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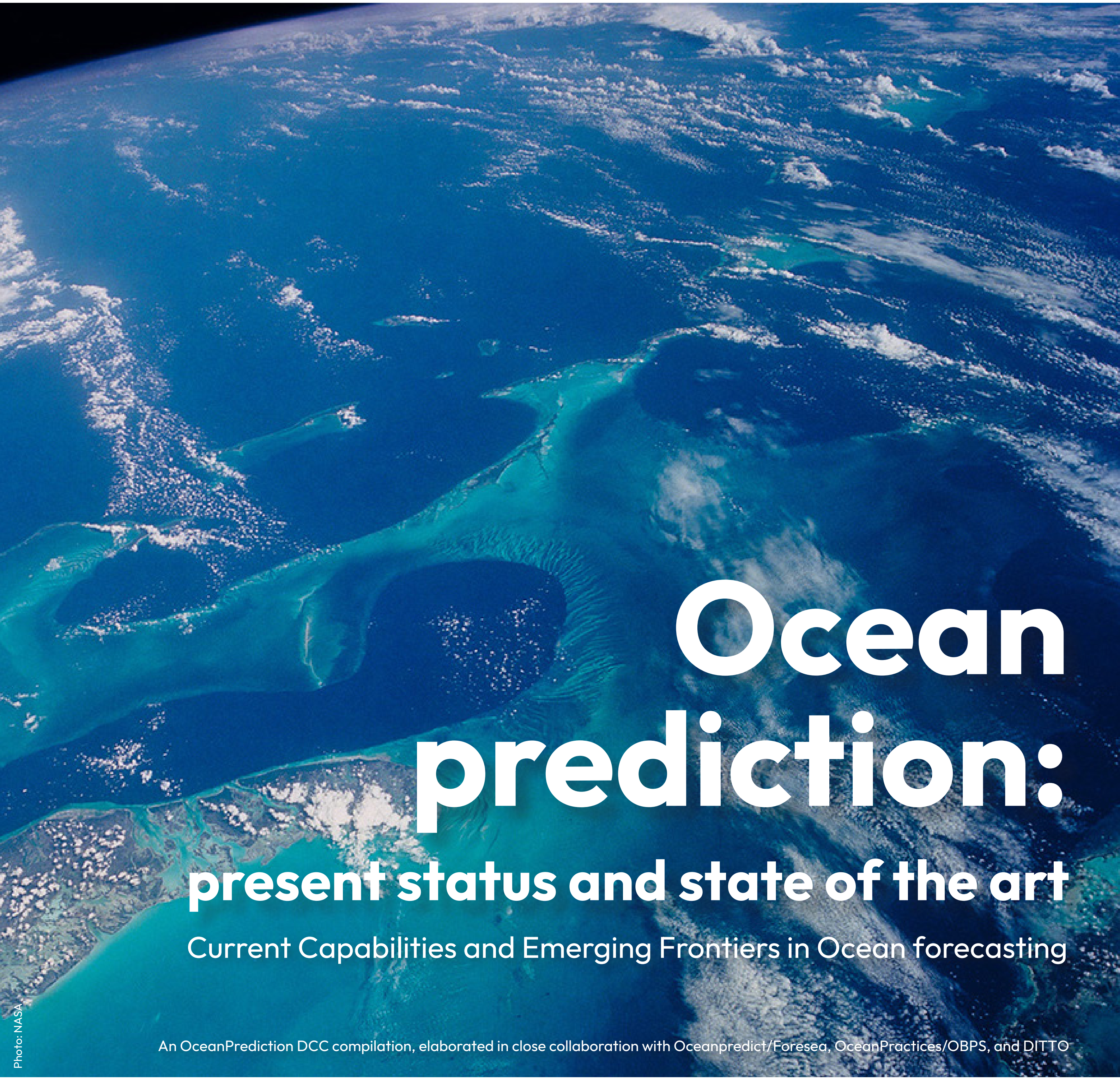

# Ocean prediction:

## present status and state of the art

Current Capabilities and Emerging Frontiers in Ocean forecasting

An OceanPrediction DCC compilation, elaborated in close collaboration with Oceanpredict/Foresea, OceanPractices/OBPS, and DITTO

Photo: NASA

2021 2030 United Nations Decade of Ocean Science for Sustainable Development

unesco Intergovernmental Oceanographic Commission

Ocean Prediction Capacity of the Future ForeSea

Ocean best practices

DITTO Digital Twins of the Ocean

## About this publication – Ocean prediction: present status and state of the art

Ocean prediction services have been improving and evolving during the last decades and today are a crucial tool for decision-making in multiple socio-economic sectors, being the backbone of many applications, including those that enhance marine safety, disaster risk reduction, and coastal zone management. This compilation describes the actual status of ocean forecasting, detailing its degree of development in the different regions of the world and the most recent advances in all the relevant specific aspects associated with the technology, such as artificial intelligence and cloud computing. This publication results from the coordinated work of a group of experts that forms the so-called "Ocean Forecasting Co-Design Team", integrated in the OceanPrediction Decade Collaborative Centre, a cross-cutting collaborative centre of the UN Decade of Ocean Science for Sustainable Development. It has been prepared in close collaboration with several Decade Programmes, which are closely linked to OceanPrediction DCC, such as Oceanpredict/ForeSea, OceanPractices, and DITTO. The result is a complete picture of the situation of ocean prediction that demonstrates its relevance and will foster future developments to overcome the present-day limitations. This compilation will be followed by a second one where gaps and ways forward on ocean forecasting and its applications will be explored.

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Álvarez Fanjul, E., Ciliberti, S. A., Pearlman, J., Wilmer-Becker, K., and Behera, S. (Eds.): Ocean prediction: present status and state of the art (OPSR), Copernicus Publications, State Planet, 5-opsr, https://doi.org/10.5194/sp-5-opsr, 2025.

## About State of the Planet

State of the Planet (SP) is a journal dedicated to the publication of scientific synthesis reports and assessments on all subjects of the Earth and environmental sciences. In a rapidly changing world, expert-based assessments of academic findings curated for a wider audience to support decision making, science communication, education, and funder mandates are becoming more and more widespread. Such reports are extensive science community efforts offering timely, state-of-the-art insight into a specific field of the Earth sciences. State of the Planet is open to any reporting and assessment initiative by (inter-) governmental agencies, environmental services, learned societies or associations of researchers that aim to publish on a regular basis.

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https://doi.org/10.5194/sp-5-opsr

eISSN 2752-0706

# Table of contents

State of the Planet - Ocean prediction: present status and state of the art | OPSR | 2025



https://doi.org/10.5194/sp-5-opsr

eISSN 2752-0706

# Table of contents

State of the Planet - Ocean prediction: present status and state of the art | OPSR | 2025




https://doi.org/10.5194/sp-5-opsr

eISSN 2752-0706

State Planet, 5-opsr, 1, 2025
https://doi.org/10.5194/sp-5-opsr-1-2025




# OceanPrediction Decade Collaborative Center: connecting the world around ocean forecasting

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Received: 17 September 2024 – Discussion started: 7 October 2024
Revised: 11 December 2024 – Accepted: 18 December 2024 – Published: 2 June 2025

**Abstract.** Operational ocean forecasting systems (OOFSs) have proven to be immensely valuable today. Numerous successful and inspiring services are operating in various regions of the world, contributing to cutting-edge applications within the marine community. This success lays a strong foundation for building a global community around ocean forecasting. However, the development and enhancement of existing forecasting systems remain challenging due to the absence of best practices, standards, and community-endorsed architectures. The OceanPrediction Decade Collaborative Center (DCC) and its associated Decade actions aim to address these challenges by leveraging the UN Decade of Ocean Science for Sustainable Development (2021–2030) and the concept of digital twinning. This paper introduces the OceanPrediction DCC and outlines the forward-looking strategies to achieve these ambitious goals. The special issue introduced by this paper is part of this broader effort.

## 1 Introduction

The United Nations Decade of Ocean Science for Sustainable Development (2021–2030), also referred to as "the Decade", was proclaimed by the 72nd session of the UN General Assembly on 5 December 2017. Coordinated by the IOC-UNESCO, the Decade seeks to promote large-scale, transformative change to shift from the "ocean we have" to the "ocean we want". The Decade supports the development of ocean data, information, and knowledge systems, driving them toward higher levels of readiness, accessibility, and interoperability. The scale of this effort must be exponentially greater than anything previously undertaken.

To guide the Decade's implementation, the IOC (Intergovernmental Oceanographic Commission) has developed an Implementation Plan (IOC-UNESCO, 2021), supported by contributions from member states, UN agencies, intergovernmental organizations, nongovernmental organizations, and relevant stakeholders. The OceanPrediction Decade Collaborative Center (DCC) is a cross-cutting structure within this plan that operates globally, fostering collaboration among the Decade actions related to ocean prediction.

Mercator Ocean International has been entrusted by the IOC-UNESCO to coordinate the OceanPrediction DCC, with the mission "to achieve a predicted ocean through a shared and coordinated global effort within the framework of the UN Ocean Decade." The center implements a community-driven agenda that allows the ocean prediction community to collaborate on activities such as communication, outreach, training, cost sharing, joint workshops, and the standardization of language and outputs. Additionally, it facilitates the co-design of an architecture necessary for developing a global ocean prediction system.

The center acts as a global convener of multidisciplinary ocean prediction expertise, collaborating with intergovernmental programs (e.g., GOOS, ETOOFS, IODE, OBPS) to establish agreements on operational infrastructure, terminology, and standards needed to deliver unified services from multiple geographic and thematic nodes

## 2 OceanPrediction DCC objectives

The objectives of the OceanPrediction DCC (https://www.unoceanprediction.org/en, last access: 6 March 2025) are as follows.

- To provide a collaborative backbone structure and a collective voice for the ocean prediction community, supporting the Decade's implementation, focusing on the following.
  - Creating a global, inclusive forum (spanning the coastal to deep sea, nowcasting to climate, biology to physics, public to private, users to scientists) and other tools to facilitate dialogue and information exchange.
  - Implementing capacity development and ocean literacy initiatives.
  - Promoting operational ocean forecasting systems (OOFSs) as a crucial tool for the blue economy and ocean policy.
- To develop a global technical and organizational structure centered on the following.
  - Co-designing, in collaboration with Ocean Decade actions and other key stakeholders, a new scenario for ocean forecasting that facilitates data sharing and interoperability while leveraging digital twin technologies.
  - Identifying needs and coordinating the development of new tools, standards, and best practices for the implementation and improvement of Ocean Forecasting Services and its applications, with a focus on a science-to-service framework and promoting interoperability and integration.
  - Aligning Decade actions with the objectives of ocean forecasting and fostering collaboration between Decade initiatives and other relevant actors.
- To support the Decade Coordination Unit (head of the Decade) by collaborating with other Decade collaborative centers and coordination offices, ensuring alignment and monitoring of Decade actions to secure their long-term legacy.

## 3 OceanPrediction DCC in the UN "Decade ecosystem"

OceanPrediction DCC will closely coordinate with the Data Sharing DCO (led by IODE) and the Observations DCO (led by GOOS) to establish a framework for developing ocean monitoring and forecasting services throughout the Decade. OceanPrediction DCC shall be responsible for promoting collaboration between Decade programs and their relevant Decade projects, as well as Decade contributors when these fall under the scope of work, all done in coordination with the mentioned DCOs.

The Decade implementation plan links each DCC and DCO to specific Decade programs, named "primary attachments". In the case of OceanPrediction DCC, these are the following.

- FORESEA has the following overarching goals: (1) to improve the science, capacity, efficacy, use, and impact of ocean prediction systems and (2) to build a seamless ocean information value chain, from observations to end users, for economic and societal benefit. These transformative goals aim to make ocean prediction science more impactful and relevant.
- Ocean Practices for the Decade Programme ("OceanPractices") will support all ocean stakeholders in securing, equitably sharing, and collectively advancing this methodological heritage.
- Digital Twins of the Ocean (DITTO) will establish and advance a digital framework on which all marine data, modeling, and simulation along with AI algorithms and specialized tools including best practices will enable shared capacity to access, manipulate, analyze, and visualize marine information.
- Global Environment Monitoring System for the Ocean and Coasts (GEMS Ocean) is designed to boost its multi-stakeholder partnership convened by UNEP, bringing together experts from earth observation, monitoring, and modeling communities, together with end users and a broad range of stakeholders to provide fit-for-purpose key information for policymaking.
- Ocean Acidification Research for Sustainability (OARS) will foster the development of the science of ocean acidification including the impacts on marine life and sustainability of marine ecosystems in estuarine–coastal–open-ocean environments.
- The NASA Sea Level Change Science Team has been conducting interdisciplinary sea level science by collecting and analyzing observational evidence of sea level change, quantifying underlying causes and driving mechanisms, and producing projections of future changes in sea level.
- France's Priority Research Program "Ocean of Solutions" aims to address ocean-related societal challenges through integrated research.

The collaboration with these programs will be particularly intensive, but additional collaborations with other programs will be established as "secondary attachments".

## 4 OceanPrediction DCC collaborative structure

To achieve its objectives, OceanPrediction DCC will establish two global collaboration structures:

- A decentralized regional structure, consisting of regional teams that focus on community development and capacity-building efforts.

– A central structure, comprising the Ocean Forecasting Global Co-design Team (OFCT) and a central office, which will liaise with various UN, EU, and national bodies. The OFCT focuses on co-design alignment and consists of experts covering different aspects of the ocean forecasting value chain (Alvarez Fanjul et al., 2022).

Having different teams for technical aspects and community building will allow efficient management: a smaller specialists team able to deliver technical results on time and a larger geographically based structure able to integrate the community and catalyze the governance and organizational component.

### 4.1 The regional teams

The OceanPrediction DCC regional teams have the following objectives:

– Act as regional nodes of OceanPrediction DCC.

– Contribute to the coordination and cooperation with ocean forecasting-related Decade actions in the region.

– Identify gaps and ways forward in the regional landscape of ocean forecasting.

– Support OceanPrediction DCC in the design and organization of regional events for capacity building, ocean literacy, and other purposes, such as courses, workshops, and hackathons.

– Advocate for regional implementation of best practices, standards, and tools derived from OceanPrediction activity.

– Collaborate with the other OceanPrediction DCC regional teams to support global actions.

– Support OceanPrediction DCC in obtaining information for the building of an atlas describing the situation of ocean forecasting around the globe (including services, institutions, interested persons, experts, and any other relevant data).

– Promote the use of OOFS in each region for decision-making purposes, including a sustainable blue economy, as well as technical, policy, and legal aspects.

The regional team distribution is based on both UNEP (United Nations Environment Programme) regional seas and GOOS Regional Alliances (GRAs), clustering some regions. The concept of the regional teams was announced at the OceanPrediction DCC kick-off meeting, an event that demonstrated the appetite for this initiative, with 1800 registered participants from all continents. At this moment we are building these teams, and several leaders are volunteering worldwide to chair each region.

– Region 1: the western Pacific and marginal seas of South and East Asia. Chair: Swadhin Behera (JAMSTEC Japan).

– Region 2: Indian seas, covering South Asian Seas and the ROPME sea area. Chair: Sudheer Joseph (INCOIS India).

– Region 3: African seas. Chair: Kouadio Affian (Ivory Coast – Chair of IOC Africa). For this region, we have decided to have several co-chairs and a subregional division to address the differences in technical development.

– Region 4: Mediterranean and Black Sea. Chair: Emanuela Clementi (MONGOOS/CMCC – Italy).

– Region 5: the northeastern Atlantic. Chairs: Ghada al Serafy and Loreta Cornacchia (EuroGOOS coastal WG, Deltares).

– Region 6: South and Central America. Chairs: Clemente Tanajura (Universidade Federal da Bahia) and Boris Dewitte (CEAZA).

– Region 7: North America. Chairs: Patrick Hogan (NOAA), and Fraser Davidson (DFO).

– Region 8: the Arctic. Chair: Heather Reagan (NERSC Norway).

– Region 9: the Antarctic. Chair: Stuart Corney (UTAS – Australia).

### 4.2 The Ocean Forecasting Co-Design Team

Ocean forecasting systems (OFSs) have proven invaluable for understanding the ocean and providing critical information for decision-making. However, challenges remain in areas like standardization, interoperability, and integration. Building an OFS from scratch, without guidance, is a daunting task, often resulting in isolated systems with limited integration into a larger framework.

This situation hampers the proliferation of forecasting services, especially in technologically less advanced countries, and hinders the growth of the ocean forecasting community and collective knowledge. The Ocean Forecasting Co-Design Team (https://www.unoceanprediction.org/en/about/technical, last access: 6 March 2025) is an international group of experts working under OceanPrediction DCC coordination, collaborating to overcome these limitations by developing a new ocean forecasting architecture. This team comprises worldwide specialists whose collective expertise covers the whole value chain. It will leverage existing technologies and initiatives, such as the digital twins, and the IPCC activities on standardization, interoperability, and integration.

As an initial step, the team assembled the current special issue and evaluated the status of operational ocean forecasting systems from both user and expert perspectives (Ciliberti et al., 2023). The team's primary objective is to design a unified ocean forecasting architecture that leverages the concept of digital twinning (Tzachor et al., 2023). This architecture aims to facilitate a simpler, modular, and more robust system development in the future. A key aspect of this development will be the establishment of well-defined building blocks, which will take the form of standards, tools, and best practices. While this new framework will benefit all forecasting services, it will be especially impactful for organizations that are just beginning their activities.

The Ocean Forecasting Co-Design Team's role is to identify this architecture and define the essential building blocks needed for its expansion. This effort will support the various Decade programs by providing clear development targets. However, the team's role is not to "code" these components directly but rather to inspire and guide the implementation of these targets by Decade programs.

## 5 Next steps

The OFCT will continue its activities, and, in the future, it is planned to address the identification of gaps in ocean forecasting and the priorities for further development. The results of these works will be published in subsequent special issues. These efforts form part of a wider strategy to promote ocean forecasting worldwide, which is summarized in the virtuous loop shown in Fig. 1.

The Ocean Prediction DCC's community, organized around the regional teams and integrating the Decade programs related to ocean forecasting, will be at the center of all the developments. This community will be articulated through the OceanPrediction DCC web page (https://www.unoceanprediction.org/en) and, more specifically, around a forum, where the community will share experiences and address doubts, as well a an atlas that will serve to identify who is who.

The description of the virtuous loop can start with the knowledge required to understand ocean forecasting techniques and their degree of development and implementation. The publications presented in this special issue and the future gap analysis mentioned above are part of this effort, which is centralized around the ETOOFS guide (Alvarez-Fanjul et al., 2022). This is a GOOS publication that compiles the basic knowledge related to the different aspects of ocean forecasting. Now the guide has been transformed into a wiki site under the OceanPrediction DCC website. This will permit the update of content by the addition of community contributions.

This compilation of common knowledge will serve as a valuable tool for capacity development, and therefore it will facilitate the construction of new operational services and

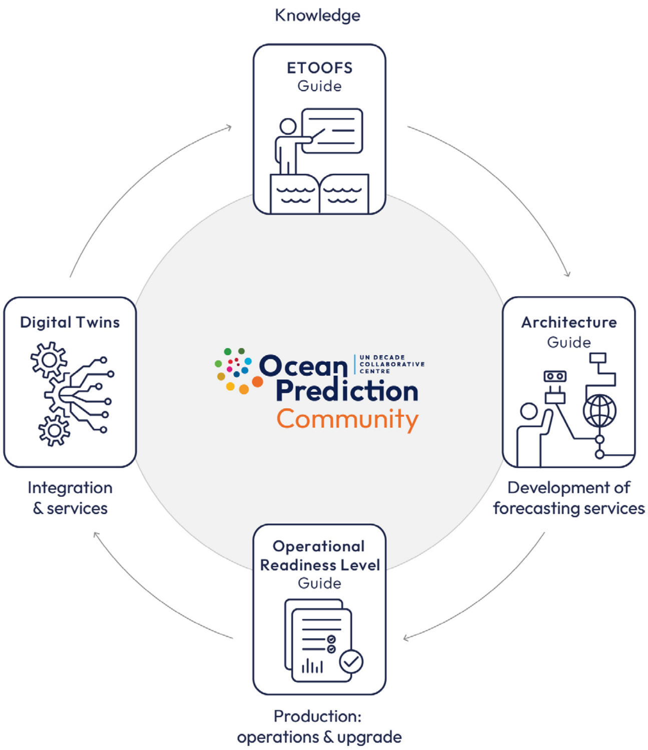


**Figure 1.** OceanPrediction DCC's virtuous loop towards the promotion of ocean forecasting.

the improvement of existing ones. To additionally facilitate this task, the OFCT has delivered the so-called "Architecture Guide", available at the resource center of the OceanPrediction DCC website. This document describes all the components and "internal wiring" required to implement a robust forecasting service. The architecture is based on "building blocks", which will take the form of data standards and tools.

Once a system is implemented, it is required to operate it properly. To facilitate this task, the OFCT has developed the Operational Readiness Level (ORL; Alvarez Fanjul et al., 2024). This is a new tool to promote the adoption and implementation of best practices in ocean forecasting. Thanks to its application, system developers will be able to assess the operational status of an ocean forecasting system. Improving the ORL qualification of a service is a means to implement best practices and standards in ocean forecasting, improving the system.

The ORL comprises three independent digits designed to certify the operational status of an ocean forecasting system. Each digit ranges from 0 (minimum) to 5 (maximum), with decimal numbers being allowed. These digits correspond to distinct aspects related to operations: the first digit reflects the reliability of the service, the second monitors the level of validation for the service, and the third assesses the various degrees of product dissemination achievable by the system.

In the last conceptual step of the virtuous loop, the data will be integrated into interoperable frameworks, such as

Digital Twins of the Ocean. This will allow a richer exploitation of the data, extracting more information useful for science and decision-making. The knowledge generated in this way will be incorporated into our common knowledge, closing the loop.

We intend for this compilation to become a relevant part of the shared knowledge that forms part of this loop, describing where ocean forecasting stands today. By examining current methods and new developments, we highlight how important ocean forecasting is for keeping our marine environment healthy and productive for future generations.

**Data availability.** No data sets were used in this article.

**Author contributions.** EÁF and PB developed the concepts described in this manuscript. EÁF prepared the manuscript with contributions from PB.

**Competing interests.** At least one of the (co-)authors is a member of the editorial board of *State of the Planet*. The peer-review process was guided by an independent editor, and the authors also have no other competing interests to declare.



**Financial support.** The OceanPrediction DCC is co-funded by the French government and by Mercator Ocean International.

**Review statement.** This paper was edited by Swadhin Behera and reviewed by Sudheer Joseph and Johannes Karstensen.

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State Planet, 5-opsr, 2, 2025
https://doi.org/10.5194/sp-5-opsr-2-2025






# Core services: an introduction to global ocean forecasting

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Received: 1 October 2024 – Discussion started: 23 October 2024
Revised: 31 January 2025 – Accepted: 13 February 2025 – Published: 2 June 2025

**Abstract.** The capacity in monitoring and forecasting the global ocean is increased nowadays, thanks to the advancements in observing and in modelling the main physical ocean processes and dynamics. This has led to the growth of core services, devoted to providing free and open data, science-driven, and based on users' needs. Here we illustrate the fundamental steps that have been developed, over the last decades, for improving the ocean value chain – from access to upstream data like observations to the delivery of products to users for downstream services and applications, with description of worldwide state-of-the-art operational ocean forecasting systems at a global scale. We also provide some examples on core service organisation, like the Copernicus Marine Service and many others, which are available today and operating for the provision of near-real-time predictions.

## 1 Introduction

Effective monitoring and prediction of the global ocean is nowadays a crucial and demanding need for supporting a wide range of applications – from maritime safety and transports to search and rescue and from offshore industry operations to addressing climate change, including management and planning of fisheries, ecosystems and aquaculture activities. It implies coordinated actions among marine core services and users through downstream applications as in the "butterfly" diagram shown in Fig. 1 from Alvarez Fanjul et al. (2022): it positions the marine core service as one of the pillars of the whole value chain, in charge of providing high quality information of the ocean state by combining observations and numerical modelling, delivered to users in a timely manner for the implementation of tailored tools for decision-making.

Therefore, a core service should have by definition the following characteristics:

- It feeds from ocean observations, from both satellite and in situ sources.
- It provides reliable access (production requirements are defined and information provided to users on target delivery time, timeliness and monitoring of dedicated key performance indicators (KPIs)) to both quality-controlled measured and forecasted ocean data.
- It is user-driven, and specific support to the users is provided.
- It generates data useful for final and intermediate users, enabling the latter to produce tailored information for final users.
- The development, evolution and operations are done under well-controlled planning, ensuring availability, timeliness and quality of the resulting products.

The concept of a "core service" was developed in the framework of the Copernicus programme, but the idea of providing reliable and up-to-date information on the state of the

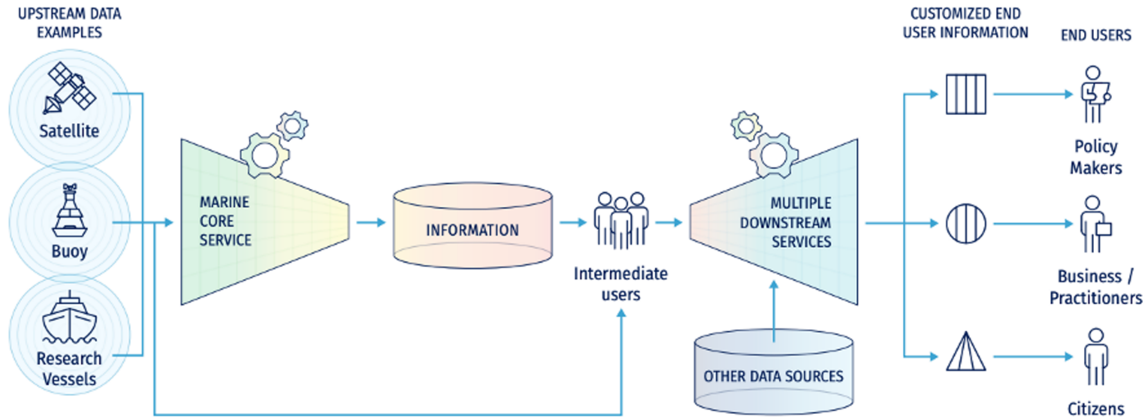


**Figure 1.** The ocean value chain (from Alvarez Fanjul et al., 2022).

environment is universal. There are other global ocean services, such as the Global Ocean Observing System (GOOS), which also provide information on the state of the world's oceans and seas. However, the specific services offered and the way in which they are organised may differ between programmes, so not all of them can be considered core services in the sense developed by Copernicus. Here we define a core service as the provision of open and free data together with dedicated user support with the characteristics described in the next section.

In this chapter, we will focus on the general characteristics of existing global ocean forecasting systems and their collocation in the framework of marine core services and existing international initiatives that support scientific networking and activities for improving and advancing numerical ocean predictions.

## 2 Global ocean forecasting systems: where we are today

The last decade has been characterised by vibrant advancements in numerical ocean modelling and observational networks that have opened new opportunities for improving global ocean monitoring and forecasting. The last review on the status of ocean forecasting systems described in Tonani et al. (2015) outlined that 12 global systems were regularly operating up to 2015 across the world – from France, UK, Norway and Italy to the USA, Canada and Brazil; from Australia to Japan; and from China to India – with an increase of 30 % with respect to 2009, when only 7 were providing forecast products. These actions were and still are supported by an international coordinated effort promoted by the Global Ocean Data Assimilation Experiment (GODAE) over three main steps.

- *Phase 1 – the experiment* (Bell et al., 2009). GODAE started in 1998 and developed over 10 years, with the main scopes of the following:
  - applying state-of-the-art ocean models and data assimilation methods for producing short-term forecast and for providing initial and boundary conditions for regional-to-coastal subsystems and
  - providing global ocean analysis to understand the ocean state, to improve predictability, and to support the design and the effectiveness of the global ocean observing system.
- *Phase 2 – "science to underpin societal needs"* (Bell et al., 2015; Schiller et al., 2015). Following the first step, over the next 10 years, GODAE OceanView consolidated the coordination by launching new activities devoted to developing predictive systems to meet users' needs. Such activities included the following:
  - the consolidation and improvement of global (and regional) systems;
  - the scientific evolution for the next generation of systems;
  - the exploitation of this capacity in other contexts, like ocean reanalysis, weather forecasting, seasonal and decadal prediction, climate change, and coastal impacts;
  - the assessment and the design of the ocean observing network.
- *Phase 3 – advancing the science of ocean prediction with OceanPredict.* In 2019, GODAE OceanView became OceanPredict, with the main scope to enhance ocean prediction within an overall operational oceanography context (The OceanPredict – Strategy 2021–2030, 2021), by working on five major drivers (https://oceanpredict.org/about/strategy/goals/, last access: 30 April 2025):
  - data assimilation – to improve ocean forecasting and also data assimilation capacity;

- verification – for monitoring and demonstrating improved accuracy and utility of ocean analysis and forecasting products resulting from OceanPredict contributions, by coordinating regular system intercomparisons and verifications;
- observing system evaluations – for contributing to projects and assessment to better determine observation impact and feeding back to the observing system community information about opportunities for further improving the impact of observations on forecasting skill;
- models – collaborating with R&D groups through OceanPredict task teams to improve ocean predictions in shelf seas and coastal environment, for biogeochemical variables and for coupled environmental prediction systems;
- visualisation – collaborating with ocean product developers and ocean services to improve visualisation and accessibility tools for predictions and observations.

The GODAE/OceanPredict Science Team, which includes more than 30 experts that are leaders in the field of operational oceanography from national, international and intergovernmental organisations, is in charge of maintaining updated information about the current global ocean forecasting capacity of the physical and biogeochemical components, including technical description of the systems and available viewing services. In Alvarez Fanjul et al. (2022), detailed complementary inventories of global ocean systems available worldwide are given. Table 1 summarises services provided by the operational centres (technical characteristics of operational ocean forecasting systems are given in Alvarez Fanjul et al. (2022), showing that state-of-the-art ocean model and data assimilation methods are used to produce standard products including main Essential Ocean Variables (EOVs)).

## 3 The Copernicus Marine Service as reference core service and its offer for the global ocean

In the framework of the EU Copernicus programme, the Copernicus Marine Service is organised to provide operational service to external users and to get user feedback to improve an user-driven service. It has been defined with the following specificities:

- Free access to reliable up-to-date and historic data is key for enhanced knowledge and better understanding of our oceans.
- Copernicus Marine Service provides data from satellites, in situ sensors and numerical models covering the global ocean and the European regional seas and associated product quality information.
- Information on past, present and future trends is made available to empower all users who want to drive the Blue Economy, for scientific innovation and to support sustainable ocean initiatives.
- Anyone can use the data – scientists, policy-makers, entrepreneurs and ordinary citizens, from all over the world.
- Services and training are tailored and adapted to different levels of expertise and familiarity with ocean data.
- Users can get help from the Copernicus Marine User support team.
- Interoperability between different producers is ensured between all the products available in the catalogue and to allow connection between the producers.
- Standards (including best practices) are defined and applied by the producers for the products (resolution, frequency, variable, time series, forecast length, etc.), the format, the quality information and the timeliness.

User feedback is organised within the core service by collecting and analysing information on access to data, the services offered and user support through surveys and training sessions, as well as through a user uptake programme in the form of projects and thanks to a group of experts (i.e. the Champion User Advisory Group) that analyses and summarises needs.

Access to the Copernicus Marine Product Catalogue is possible through https://marine.copernicus.eu/ (last access: 30 April 2025).

Copernicus Marine Service is organised around Thematic Assembly Centers (TACs) and Monitoring Forecasting Centers (MFCs) (Fig. 2). TACs process data acquired from satellite ground segments and in situ platforms to produce realtime (today) and reprocessed (30-year historic) products. They are organised by thematic hubs including sea ice, wind, sea level, in situ, ocean colour, sea surface temperature, wave and multiple observations. MFCs run ocean numerical models assimilating data provided by TAC data to generate reanalysis (30 years in the past), analysis (today) and 10 d forecasts of the ocean. They are organised in geographical areas, including the global ocean and European seas such as the Arctic Ocean, the Baltic Sea, the Atlantic European North-West Shelf, Iberian–Biscay–Irish seas, the Mediterranean Sea and the Black Sea.

Focusing on global ocean forecasting systems, the Copernicus Marine Service, through the GLO MFC, provides marine data (waves, currents, temperature, salinity, sea level and biogeochemistry) for the world's oceans, Atlantic, Indian, Pacific, Arctic and Antarctic, and the European seas. The past, present and future are covered by these data, providing information for 30 years in the past up to 10 d in the future. The portfolio of products (as summarised also in Table 1) includes the following:

**Table 1.** Updates on the inventories as given in Alvarez Fanjul et al. (2022) and by OceanPredict (https://oceanpredict.org/science/operational-ocean-forecasting-systems/ocean-products-services/, last access: 30 April 2025), with focus on provided Essential Ocean Variables (EOVs) and summary of offered service.

| System | EOV | Service |
|---|---|---|
| GIOPS (Global Ice Ocean Prediction System) 1/4° resolution | Temperature, salinity, sea surface height, zonal and meridional velocity components, sea ice concentration, sea ice thickness, northward sea ice velocity. | Daily means and 3 h average surface fields. From 2014 to present https://science.gc.ca/site/science/en/concepts/prediction-systems/global-ice-ocean-prediction-system-giops (last access: 30 April 2025) |
| ESSO-INCOIS (Earth System Science Organisation–Indian National Centre for Ocean Information Services) 1/4° resolution | Temperature, salinity, sea surface height, zonal and meridional velocity components, mixed layer depth. | 6 h average hourly fields for 5 d forecast https://incois.gov.in/ (last access: 30 April 2025) |
| MOVE (Multivariate Ocean Variational Estimation) nested grid from 1° at a global scale to 1/33° around Japan | Temperature, salinity, sea surface height, zonal and meridional velocity components, sea ice concentration. Daily mean | Daily mean from October 2020 to present, 31 d forecast for the North Pacific and 11 d forecast with a higher resolution for the Japan area. https://www.jmbsc.or.jp/jp/online/file/f-online23100.html (last access: 30 April 2025) (in Japanese) |
| OceanMAPS (Ocean Modelling, Analysis and Prediction System) 1/10° resolution | Temperature, salinity, sea surface height, zonal and meridional velocity components. | Daily means. From 2007 to present https://research.csiro.au/bluelink/global/forecast/ (last access: 30 April 2025) |
| GLO MFC (Global Monitoring Forecasting Center from Copernicus Marine Service) 1/12° resolution | Temperature, salinity, sea surface height, zonal and meridional velocity components, mixed layer depth, bottom temperature. Chlorophyll, dissolved inorganic carbon in sea water, iron, oxygen, nitrate, phosphate, silicate, primary production, alkalinity, pH, surface partial pressure of carbon dioxide in sea water, volume attenuation coefficient of downwelling radiative flux. Significant wave height, wave period, peak period, wave direction, wave maximum height, Stokes drifts, swell significant heights, swell wave directions. | Hourly, daily and monthly means from 2020 to +10 d for the physical component; daily and monthly means from 2021 to present for the biogeochemical component; hourly instantaneous from 2021 to +10 d for the wave component https://marine.copernicus.eu/about/producers/glo-mfc (last access: 30 April 2025) |
| FOAM (Forecast Ocean Assimilation Model) 1/12° resolution | Temperature, salinity, sea surface height, zonal and meridional velocity components, sea ice concentration, sea ice thickness, sea ice velocity. | Daily forecasts out to 7 d producing data with daily and 3 h frequency. https://www.metoffice.gov.uk/research/weather/ocean-forecasting/ocean-development (last access: 30 April 2025) |
| GOFS3.1 (Global Ocean Forecasting System) 1/12° resolution | Temperature, bottom temperature, salinity, sea surface height, zonal and meridional velocity components, sea ice concentration, sea ice thickness, sea ice velocity. | 3 h means. From 2018 to +4 d https://www.hycom.org/dataserver/gofs-3pt1/analysis (last access: 30 April 2025) |
| GOFS16 (Global Ocean Forecasting System) 1/16° resolution | Temperature, salinity, sea surface height, zonal and meridional velocity components. | Daily means of +5 d https://gofs.cmcc.it/ (last access: 30 April 2025) |
| NMEFC (National Marine Environmental Forecasting Center) 1/12° resolution | Temperature, salinity, velocities, sea ice. | Daily means and 5 d forecast. https://www.nmefc.cn/ybfw/seacurrent/Global (last access: 30 April 2025) |

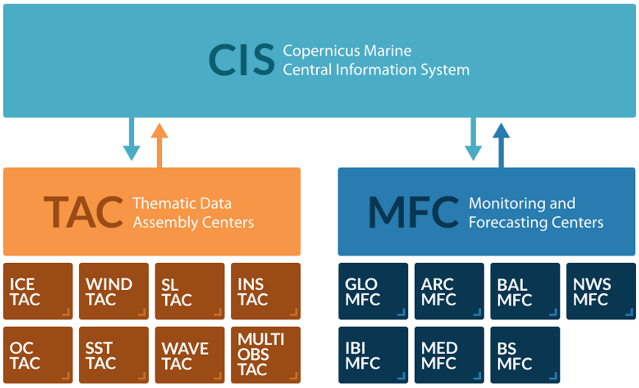


**Figure 2.** Organisation of Copernicus Marine Service including Thematic Assembly Centers (TACs), which provide ocean observations, and Monitoring and Forecasting Centers (MFCs), which provide reanalysis and forecast at a global scale and for the European seas. Exchanges with users happen through the Central Information System (CIS).

- *Near-real-time (NRT)* datasets provide physics and waves at 1/12° resolution and biogeochemistry at 1/4°, forced by ECMWF IFS atmospheric forecasting product (see https://www.ecmwf.int/en/elibrary/81235-evaluation-ecmwf-forecasts-including-2021-upgrade (last access: 30 April 2025) for a description of the systems and their evolution).
  - Global Ocean Physics Analysis and Forecast, run by Mercator Ocean International, provides analysis and forecast of the 3D ocean regularly every day. The time series is aggregated in time to reach a full 2 years' time in a sliding window to +10 d. The core model is based on NEMO (Nucleus for European Modelling of the Ocean v3.6, coupled to LIM3 sea ice model): it assimilates temperature and salinity profiles as well as sea surface temperature, sea ice concentration and sea level anomaly data, provided by corresponding TACs using the SAM2 data assimilation scheme. Details are given in Le Galloudec et al. (2023) and Lellouche et al. (2023). An example of the sea surface temperature forecast field is given in Fig. 3.
  - Global Ocean Biogeochemistry Analysis and Forecast, run by Mercator Ocean International, provides analysis and forecasts of the 3D global ocean updated weekly. The time series is aggregated similarly to the physical system. The core model is based on NEMO v3.6 online coupled to PISCES for the biogeochemical component: it assimilates satellite ocean colour provided by the OC TAC using the SEEK (Singular Evolutive Extended Kalman) data assimilation scheme. Details are given in Lamouroux et al. (2023) and Lamouroux and Tonani (2023).
  - Global Ocean Waves Analysis and Forecast, run by Météo-France, provides analysis and forecasts of the global ocean sea surface waves. The core model is MFWAM, with spectral resolution of 24 directions and 30 frequencies: it uses optimal interpolation for the assimilation of significant wave height from altimeters. Details are given in Dalphinet et al. (2023) and Aouf (2023).
- *Multi-Year (MY)* datasets provide physics at 1/12° resolution, biogeochemistry at 1/4°, and waves at 1/5°, forced by ECMWF ERA5 atmospheric reanalysis (Hersbach et al., 2020).
  - Global Ocean Physics Reanalysis, run by Mercator Ocean International, provides reanalysis of the global ocean covering the altimetry period (from 1993 onward). The core model is based on NEMO v3.1, coupled to LIM2 (Louvain-la-Neuve Sea Ice Model) and implementing the SAM2 (System assimilation Mercator) scheme for the assimilation of reprocessed observations such as satellite sea surface temperature, sea ice concentration, sea level anomaly, in situ temperature and salinity profiles. Details are given in Drevillon et al. (2023a, b).
  - Global Ocean Biogeochemistry Hindcast, run by Mercator Ocean International, provides biogeochemical hindcasts for the global ocean over a period starting in 1993. The core model is based on NEMO v3.6 coupled to PISCES. Details are given in Le Galloudec et al. (2022) and Perruche et al. (2019).
  - Global Ocean Waves Reanalysis, run by Mercator Ocean International, has provided the global wave reanalysis since 1993. The core model is MFWAM, coupled to an optimal interpolation scheme for the assimilation of significant wave height provided by altimeters. Details are given in Law-Chune (2023) and Law-Chune et al. (2023).

## 4 Other worldwide ocean services

The list of operational oceanography centres and associated services is evolving rapidly, and the centralisation and updating of this information is one of the important activities for international coordination and is carried out within the framework of OceanPredict (https://oceanpredict.org/science/operational-ocean-forecasting-systems/ocean-products-services/) and the Decade Collaborative Centre for Ocean Prediction, where a dedicated atlas is provided (https://www.unoceanprediction.org/en/atlas/people?lat=16.467694748288978&lng=23.5546875&zoom=2, last access: 30 April 2025).

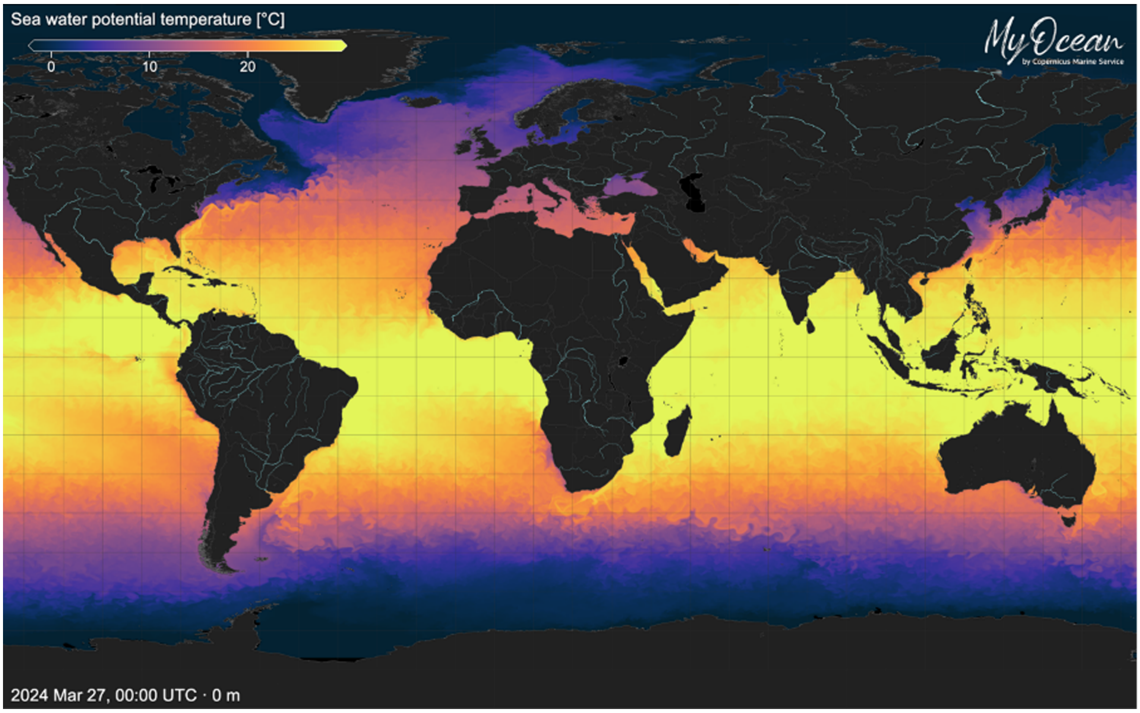


**Figure 3.** Sea surface temperature as predicted by the Global Ocean Physical Analysis and Forecasting System on the 27 March 2024: visualisation provided by the Copernicus Marine Service – MyOcean Pro Viewer.

- The National Oceanic and Atmospheric Administration (NOAA) is the reference agency in the USA that provides understanding and predictions of changes occurring in climate, weather, ocean and coasts, sharing knowledge and information and conserving and managing coastal and marine ecosystems and resources. The NOAA's National Ocean Service operates with the Center for Operational Oceanographic Products and Services (CO-OPS) for gathering accurate, reliable and timely water-level and current measurements. The NOAA's National Weather Service (https://oceanservice.noaa.gov/, last access: 30 April 2025) provides, through the Environmental Modeling Center, the Global Real-Time Ocean Forecast System products (https://polar.ncep.noaa.gov/global/, last access: 30 April 2025), delivered via FTP. Visualisation of nowcast/forecast products and reference metrics are provided as well through a dedicated web page, available at https://polar.ncep.noaa.gov/global/.

- From the collaboration between Environment and Climate Change Canada, Fisheries and Oceans Canada, and National Defence departments, the Government of Canada supports the Canadian Operational Network of Coupled Environmental PredicTion Systems (CONCEPTS; https://science.gc.ca/site/science/en/concepts, last access: 30 April 2025) for the monitoring of the met-oceanographic conditions in the country. CONCEPTS provides operational access to real-time forecasts through dedicated web services (i.e. geospatial web services and third-party websites), including bulletins produced with static images. CONCEPTS includes prediction systems like the Global Ice Ocean Prediction System (GIOPS) with delivery of 10 d forecast of daily ocean and sea ice analysis, together with regional systems (e.g. the Regional Ice Ocean Prediction System (RIOPS) and the Regional Deterministic Prediction System Coupled over the Gulf of St. Lawrence (RDPS-CGSL)) and a dedicated one for the Great Lakes (i.e. the Water Cycle Prediction System Coupled over the Great Lakes (WCPS-CGL), https://science.gc.ca/site/science/en/concepts/prediction-systems, last access: 30 April 2025).

- The European Centre for Medium-Range Weather Forecasts (ECMWF) develops and maintains an operational system called OCEAN5 (https://www.ecmwf.int/en/research/climate-reanalysis/ocean-reanalysis, last access: 30 April 2025), a global eddy-permitting ocean-sea ice ensemble with five members from 1979 to present. It includes a behind-real-time (BRT) component to produce ocean reanalysis from 1979 to present (ORAS5; https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-oras5?tab=overview, last access: 30 April 2025) and a real-time (RT) component, initialised from the last BRT analysis to compute an analysis up to real time every day using a variable assimilation window. Data are accessible through the Copernicus Climate Data Store and are used for performing past reconstruction of the ocean climate state at a global scale.

- The Australian Government Bureau of Meteorology is Australia's national weather, climate and water agency (http://www.bom.gov.au/?ref=hdr, last access: 30 April 2025). It provides marine and ocean products such as wind maps, tide predictions, sea temperature and currents, wave maps, and seasonal ocean temperature. The service is for citizens and society, so the communication is done through VHF, radio and radiofax, internet, and satellite.

- The Japan Meteorological Agency (JMA; https://www.jma.go.jp/jma/indexe.html, last access: 30 April 2025) is the reference Japanese agency for monitoring weather, earthquakes and volcano activities. The ocean component of the JMA carries out oceanographic and marine meteorological observations in the western North Pacific and seas adjacent to Japan. Additionally, it operates with a set of operational ocean data assimilation and prediction systems named MOVE for preventing coastal disasters; supporting fishery, marine transportation and marine industry; and providing the oceanic initial conditions for the coupled atmosphere–ocean forecasting systems (Hirose et al., 2019; Fujii et al., 2023; Yamanaka et al., 2023).

- The China Meteorological Administration (CMA; https://www.cma.gov.cn/en/, last access: 30 April 2025) is an operator, service-provider and regulator in weather forecasting and warning, climate prediction and public meteorological services. The National Meteorological Centre (NMC) undertakes the responsibility of issuing forecasts and warnings for 13 different types of hazardous weather conditions within the next 24 h. These include typhoons, heavy rain, severe convective weather, blizzards, cold waves, gales at sea, sandstorms, low temperatures, high temperatures, frosts, ice storms, heavy fog, and haze. The Beijing Climate Centre operates its own global ocean system for the monitoring of the ocean climate events like El Niño in the central and eastern equatorial Pacific (https://www.cma.gov.cn/en/forecast/news/202402/t20240229_6093860.html, last access: 30 April 2025).

- The National Marine Environmental Forecasting Center (NMEFC; http://www.nmefc.cn/hailiu/quanqiu.aspx, last access: 30 April 2025) is the national operation and research centre for marine environmental forecasting and marine hazard warning and provides advisory information for public policy, decision-making, and socio-economic and sustainable development, which is a public institution directly under the Ministry of Natural Resources of China.

- Mercator Ocean International (MOi; https://www.mercator-ocean.eu/, last access: 30 April 2025) is a non-profit organisation, in the process of transforming into an intergovernmental organisation, providing ocean-science-based services of general interest focused on the conservation and the sustainable use of the oceans, seas and marine resources. After running the European MyOcean projects since 2009, Mercator Ocean was officially appointed by the European Commission on 11 November 2014 to implement the European ocean-monitoring service, the Copernicus Marine Service, as part of the European Earth observation programme, Copernicus.

- The Met Office (https://www.metoffice.gov.uk/, last access: 30 April 2025) is the UK's national weather and climate service and produces operational global and regional ocean forecasts on a daily basis using the FOAM system as well as waves, storm surge and ecosystem predictions. The research effort is reinforced by a close collaboration with academic groups, including those in the National Partnership for Ocean Prediction (NPOP).

- The CMCC (https://www.cmcc.it/, last access: 30 April 2025) Foundation (Euro-Mediterranean Center on Climate Change) is an international, independent, multidisciplinary research centre that studies the interaction between climate change and society. They produce advanced climate research developing cross-cutting and multidisciplinary analyses and data that combine first-class climate modelling with climate change impact modelling and environmental economics.

- ESSO-INCOIS (https://incois.gov.in/portal/aboutus, last access: 30 April 2025) was established as an autonomous body in 1999 under the Ministry of Earth Sciences (MoES) and is a unit of the Earth System Science Organisation (ESSO). ESSO-INCOIS is mandated to provide the best possible ocean information and advisory services to society, industry, government agencies and the scientific community through sustained ocean observations and constant improvements through systematic and focussed research.

## 5 Conclusion

The development of operational ocean analysis and forecasting systems began in the late 1990s for institutional and expert users. The first systems produced analyses and forecasts of the physical ocean at intermediate resolutions (between 1° and 1/4°) and frequencies that were daily at best. The output from these systems was made available directly on supercomputers or on archive centres or ftp servers. The progress made in production systems was accompanied by progress in dissemination systems, visualisation tools, data processing and the support provided to users in order to create what are currently called core services. The horizontal resolution of global models now reaches a few kilometres, and the temporal resolution of forecasts updated daily can be hourly, with assimilated data and model forcings also having progressed in line with the targeted resolutions. Data are now distributed on cloud servers in optimised formats, enabling large volumes of data to be viewed and handled efficiently. Standardisation of the associated documentation and monitoring of operational production and user support mean that these operational products can be used more easily. The number of users of operational oceanography products has risen sharply, with some core services currently able to serve several tens of thousands of users. Digital Twin Ocean's developments will make it possible to integrate new technologies and, in the near future, will represent an important evolution in the core service for operational oceanography.

**Data availability.** No data sets were used in this article.

**Author contributions.** YD led the paper and wrote and structured the paper. All co-authors provided comments and corrections for an initial version of the paper.

**Competing interests.** At least one of the (co-)authors is a member of the editorial board of *State of the Planet*. The peer-review process was guided by an independent editor, and the authors also have no other competing interests to declare.

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**Acknowledgements.** The authors acknowledge the European Commission, Copernicus Marine Service, OceanPredict and the Decade Collaborative Centre for Ocean Prediction in the framework of the UN Decade of Ocean Science for Sustainable Development.

**Review statement.** This paper was edited by Kirsten Wilmer-Becker and reviewed by two anonymous referees.

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# Ocean forecasting at the regional scale: actual status

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Received: 15 September 2024 – Discussion started: 19 September 2024
Revised: 16 December 2024 – Accepted: 16 December 2024 – Published: 2 June 2025

**Abstract.** Operational ocean forecasting systems provide important information on physical and biogeochemical variables across global, regional, and coastal scales. Regional systems, with higher resolution than global models, capture small-scale processes like eddies and usually include tides but lack detailed land–sea interactions essential for coastal areas. These models, often nested within global systems, vary in spatial resolution (1–20 km) and may include biogeochemical components. While regional systems focus on physical parameters such as sea surface height, temperature, salinity, and currents, only a few incorporate biogeochemical processes. The growing demand for biogeochemical data has prompted advancements and more systems will include this component in the coming years.

This paper provides a preliminary overview of the current status of regional forecasting systems, discussing examples such as the Copernicus Marine Service from OceanPredict, analysing the offer in terms of covered regions, resolution, and catalogues of ocean variable products.

## 1 Introduction

Numerous oceanographic systems are providing data on physical and biogeochemical variables, spanning global, regional, and coastal scales. It can be challenging to precisely define the characteristics of a regional oceanographic system versus a global or coastal system, as there may be some overlap in the information they provide and the regions they cover. Regional models typically offer greater detail than global models due to their higher resolution and ability to capture small-scale processes such as eddies, fronts, and local features. This approach avoids the significant computational costs associated with running a global system at high resolution. Additionally, most regional models incorporate tides, which are not always included in global models. Moreover, they can be optimized for specific areas, which may have unique oceanographic characteristics and require higher resolution or tailored parameterizations (Tonani et al., 2015). However, they do not include the processes of land–sea interaction that are important for coastal areas, e.g. the dynamics of nearshore currents, sediment transport, delta and estuary processes, and some biogeochemical processes, typically solved by coastal systems. In addition, the spatial scale is a factor in differentiating global, regional, and coastal. Regional systems are directly nested into global systems and may or may not have nested coastal systems. In recent years, various approaches have been developed to increase model resolution only where needed, leveraging unstructured grid models. These models show great promise in balancing the need for high-resolution detail with manageable computational costs. As a result, the distinction between regional and coastal models has become less defined. However, differences in the processes resolved and key parameterizations remain essential for accurately representing coastal dynamics and processes versus regional. Another promising development is the use of machine-learning-based forecasting systems and hybrid models. Once properly trained, these systems can deliver accurate forecasts while significantly reducing computational costs. Although most of these systems are still under development or in pre-operational stages, they are expected to be integrated into the landscape of operational forecasting systems in the near future.

Several regional forecasting systems have been developed across the world and are currently in operation (Tonani et al., 2015; Schiller et al., 2018; Alvarez Fanjul et al., 2022). A brief overview of the main characteristics of these systems is presented in Sects. 2 and 3. Section 4 provides details on the regional systems described by OceanPredict (Tonani et al., 2015; Bell et al., 2015) and the Copernicus Marine Service (Le Traon et al., 2019), considered a representative overview of the systems currently in operation. Providing an exhaustive account of all the regional forecasting systems is outside the scope of this document and would require a dedicated survey. This need is fulfilled by the Atlas initiative (https://www.unoceanprediction.org/en/atlas/, last access: 22 February 2025), launched a few months ago by the OceanPrediction Decade Collaborative Centre (OceanPrediction DCC), aiming to map all the operational forecasting centres and their characteristics.

## 2 General characteristics

There are several factors that determine the spatial scale of a regional ocean forecasting system, including the region's size, bathymetry, and oceanographic characteristics, as well as the system's purpose. Operational systems currently have resolutions ranging from approximately 1 to 20 km. Usually, larger regions do not need the same fine resolution as smaller regions and can therefore cope with a coarser resolution. Shelf sea regional systems may require a finer spatial resolution compared to larger regions such as the North Atlantic basin. For example, in shelf areas, smaller grid cells of around 1 km are necessary, whereas in the North Atlantic, larger grid cells of 10 km or more are enough.

The resolution needed by a model grid for resolving the baroclinic eddy dynamics can be computed as a function of the first baroclinic Rossby radius of deformation, $R_\mathrm{d}$. A well-established metric used for assessing this relationship (Hallberg, 2013) is $R_\mathrm{h} = R_\mathrm{d}\sqrt{(\Delta x^2 + \Delta y^2)/2}$, where $R_\mathrm{d}$ is the first baroclinic Rossby radius of deformation and $\Delta x$ and $\Delta y$ represent the horizontal grid spacing of the model. A model is defined as eddy-resolving when $R_\mathrm{h} > 2$; otherwise, it is eddy-permitting.

The choice between a regional, global, or coastal oceanographic system will depend on a variety of factors, including the specific operational needs of the user, the oceanographic characteristics of the region of interest, and the computational resources and data availability. Regional forecasting systems must be tailored to the specific processes characterizing their target areas. This requires selecting appropriate parameterizations and designing system components accordingly. In some cases, coupling additional components may be justified if the resulting improvement in forecast accuracy outweighs the associated computational costs.

Design, components, and configurations of these systems can vary widely. Most of them use an ocean general circulation model such as NEMO (Madec and NEMO System Team, 2022), ROMS, or HYCOM and data assimilation components based on the Kalman filter or variational methods. Additionally, some systems include wave and biogeochemical model components. These model components can be stand-alone or coupled in various configurations. Most of them rely on atmospheric fields at the ocean–atmosphere boundaries because they are not coupled with an atmospheric model. Biogeochemical components are a standard feature in all the European systems of the Copernicus Marine Service, but they are missing in most other systems. Some countries, such as India, are currently developing a biogeochemical component for future use.

Regional models are often nested into a global system or another regional system, a parent model, providing them with lateral boundary forcing. Many systems, in turn, provide lateral boundaries and initialization fields to coastal systems.

Most systems provide deterministic forecasts, although a few already have the ability to produce ensemble forecasts. There is a growing interest in developing systems that can produce ensemble forecasts.

The forecast production is daily for most systems, although some run them twice per day. The forecast lead time is typically between 5 and 10 d (short to medium range) (WMO, 2021). The time resolution of their products varies from hours to days, with some fields delivered at a higher frequency of 15 min.

Ultimately, the spatial and temporal scales of a regional ocean forecasting system, as well as the selection of its components, will depend on the region's specific needs and characteristics.

## 3 Oceanographic information provided by regional systems

Regional oceanographic services play a crucial role in measuring the essential ocean variables (EOVs) defined by the Global Ocean Observing System (GOOS). EOVs are classified into four categories: physics, biology and ecosystems, biogeochemistry, and cross-disciplinary. This description is mainly focused on short-term forecasting products because most systems do not provide long climatological series of the past to understand how ocean conditions are changing over time. Several regional reanalysis studies exist, but obtaining information about the services delivering these data can be challenging. The Copernicus Marine Service offers an oper-

**Table 1.** Summary of the regions covered by regional ocean forecasting systems based on the information available from OceanPredict and the Copernicus Marine Service. The last column describes the ocean essential variables (defined by GOOS) provided by each system.

| Country/provider | Geographical area/system | Resolution | Essential ocean variables |
|---|---|---|---|
| Australia – Bluelink | Relocatable regional model along Australian coast | ∼ 2 km | Physics ($T$, $S$, currents, SSH, waves)<br>Biogeochemistry under development |
| Brazil – REMO | – Atlantic Ocean<br>– Brazilian continental margin (METAREA V) | – 1/12°<br>– 1/24° | Physics ($T$, $S$, currents, SSH) |
| Canada – Concept RIOPS | – Arctic<br>– North Atlantic and Great Lakes | – 1/4°<br>– 1/36° | Physics ($T$, $S$, currents, SSH, sea ice) |
| China – NMEFC | – Northwest Pacific<br>– Bohai Sea, Yellow Sea, and East China Sea<br>– South China Sea | – 1/20° (1/36°)<br>– 1/30°<br>– 1/30° | Physics ($T$, $S$, currents, SSH) |
| Europe – Copernicus Marine Service | – Arctic Sea<br>– Baltic Sea<br>– Northwest European Shelf<br>– Iberian–Biscay–Irish Sea<br>– Mediterranean Sea<br>– Black Sea | – 3–6 km<br>– ∼ 2 km<br>– ∼ 2 and 7 km<br>– ∼ 2–3 km<br>– ∼ 5–3 km<br>– ∼ 3 km | Physics ($T$, $S$, currents, SSH, sea ice, waves)<br>Biogeochemistry (nutrients, oxygen, carbonate system, organic carbon, optics)<br>Biology (plankton) |
| India – INCOIS | – Indian Ocean (INDOFOS)<br>– Local Indian Ocean regions (HOOFS)<br>– Indian Ocean nested into global (ITOPS-IO) | – 1/12°<br>– 1/48°<br>– 1/16° | Physics ($T$, $S$, currents, SSH)<br>Biogeochemistry under development |
| Japan – MOVE/MRI.COM | – Japanese area<br>– North Pacific | – 1/33° × 1/50°<br>– 1/10° × 1/11° | Physics ($T$, $S$, currents, SSH) |
| Republic of Korea | – North Pacific<br>– The Yellow and East China Sea (KOOFS) | – 1/28°<br>– 3 km | Physics ($T$, $S$, currents, SSH) |
| US – NOAA | West Coast Operational Forecast System (WCOFS) | 4 km | Physics ($T$, $S$, currents, SSH) |

ational service for reanalysis produced by all its regional systems, updated at least annually. However, additional services are also available. In this context, the Ocean Prediction DCC Atlas will be instrumental in providing detailed and structured information on these systems. While regional forecasting systems primarily focus on physical parameters such as temperature, salinity, currents, and sea level, some also include wave and sea ice components to provide comprehensive information about the ocean's physical characteristics.

It is important to clarify that most regional systems forecast sea level, also referred to as sea surface height. This represents the distance between the ocean surface and a reference mean sea level. This reference mean sea level depends, at each individual grid point, on the model domain and its physics (barotropic vs. baroclinic, consideration of tides, wind parameterization), as well as on the physics and characteristics of the parent model. This should be considered when comparing model data with observations (e.g. tide gauge data usually refer to national or local datums) or other models (e.g. regional versus coastal models). Additionally, approximations made by the models and their parameterization, as well as data assimilation schemes, can impact the accuracy of this information. Except for the Copernicus Marine Service, most regional systems do not deliver information on biogeochemistry and biology. These models are computationally very expensive due to the high number of variables and processes they take into account, in most cases preventing them from providing the level of detail and accuracy that users require. However, despite these limitations, there is a growing recognition of the importance of monitoring and understanding biogeochemical variables in the ocean as confirmed by the steady increase in the demand for biogeochemical products from the Copernicus Marine Service. Additional regional systems, i.e. INDOFOS in India and CSIRO-Bluelink in Australia, are currently developing a biogeochemical model that will be coupled to their systems.

## 4 Operational regional systems across the world

Different countries and organizations have developed regional ocean forecasting systems. The European Copernicus Marine System (Le Traon et al., 2019), since 2015, has a set of regional systems that cover all the European seas, the Arctic Ocean, and the northeastern Atlantic. Australia has a relocatable regional system for refining its global model around its own region. Other countries such as Brazil (Franz et al., 2021; Lima et al., 2013), Canada, China, India, Japan (Sakamoto et al., 2019), Republic of Korea, and the US have regional ocean forecasting systems or a set of them, covering the ocean and seas surrounding their coasts.

These systems use different data sources and modelling techniques, but they also have many similarities. Table 1 provides a non-exhaustive summary of the regional systems as described by OceanPredict and by the Copernicus Marine Service.

As described in Sect. 1, their geographical extension can vary from relatively small surfaces to extended areas and their horizontal grid resolution is usually of the order of 2–20 km. They do all provide the standard physical variables, but only a few also provide biogeochemical information.

Differences also exist in the level of operational readiness among the systems described, as well as in their product validation procedures and data dissemination policies. Not all this information has an open and free access policy, but all the regional systems play an important role in monitoring and forecasting the ocean.

**Data availability.** No data sets were used in this article.

**Author contributions.** MT drafted the manuscript and coordinated contributions from all partners. EC reviewed the manuscript, providing scientific insight and adding details on ocean forecasting systems from OceanPredict. MC reviewed the manuscript, contributing information on South American forecasting systems, particularly the Brazilian landscape. YM contributed information on Japanese forecasting systems. BPG provided scientific input for the definition of sea level.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** This document was prepared thanks to the framework provided by Ocean Prediction DCC, a cross-cutting structure of the UN Decade of Ocean Science for Sustainable Development, with the goal of promoting collaboration towards "a predicted ocean", one of the transformative outcomes of the decade.

**Review statement.** This paper was edited by Enrique Álvarez Fanjul and reviewed by two anonymous referees.

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State Planet, 5-opsr, 4, 2025
https://doi.org/10.5194/sp-5-opsr-4-2025


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# Solving coastal dynamics: introduction to high-resolution ocean forecasting services

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Received: 28 November 2024 – Discussion started: 12 December 2024
Revised: 9 May 2025 – Accepted: 13 May 2025 – Published: 2 June 2025

**Abstract.** Coastal services are fundamental for society, with approximately 60 % of the world's population living within 60 km of the coast. Thus, predicting ocean variables with high accuracy is a challenge that requires numerical models able to simulate processes from the mesoscale to the submesoscale, to capture shallow-water dynamics influenced by wetting–drying and resolve the ocean variables in very high resolution spatial domains. This paper introduces key aspects of coastal modelling, such as vertical structure of the mixed layer depth, parameterization of bottom roughness, and the dissipation of kinetic energy in coastal areas. It stresses the need for models to account for the nonlinear interactions between tidal currents, wind waves, and small-scale weather patterns, emphasizing their significance in refining coastal predictions. In addition, observational advancements, such as high-frequency (HF) radar and satellite missions like Surface Water and Ocean Topography (SWOT), provide unique opportunities to observe coastal dynamics. This integration enhances our ability to model physical and dynamical peculiarities in coastal waters, estuaries, and ports. Coastal models not only benefit from such high-resolution observations but also contribute to evolving observational systems, creating feedback loops that refine monitoring and prediction capabilities. Modelling strategies are also examined, including downscaling and upscaling approaches, and numerical challenges like implementing robust data assimilation schemes to refine estimations of coastal ocean states are addressed. Emerging techniques, such as advanced turbulence closure models and dynamic vegetation drag parameterization, are highlighted for their role in enhancing the realism of modelled coastal processes. Furthermore, the integration of atmospheric forcing, tidal asymmetries, and estuarine dynamics underlines the necessity for models that span the complexities of the coastal continuum. It also demonstrates the critical importance of accurately modelling coastal and estuarine systems to capture interactions between mesoscale and submesoscale processes, their connections to broader oceanic systems, and their implications for sustainable coastal management and climate resilience. This work underscores the potential of advancing coastal forecasting systems through interdisciplinary innovation, paving the way for enhanced scientific understanding and practical applications.

## 1 Introduction

High-resolution observation and modelling are needed so that marine services can be compliant with small-scale processes in the ocean, particularly in coastal areas where these processes have a significant impact on dynamics and biogeochemistry (Fig. 1). The importance of high resolution in coastal services is underscored by the coastal ocean's significance to humanity, not least because about 60 % of the world's population lives within 60 km of the coast (Rao et al., 2008). These areas are highly dynamic, subject to both direct and indirect anthropogenic impacts, respectively, such as eutrophication, overfishing, offshore wind farm development, dredging, and pollution; global warming; sea-level rise; and changes in meteorological and hydrological conditions. These combined influences frequently trigger regime shifts, coastal erosion, flooding, and the introduction of invasive species, underscoring the vulnerability and complexity of these systems.

Accurately predicting ocean variables in coastal environments is challenging due to the need to resolve mesoscale to submesoscale dynamics and their interactions with atmospheric and hydrological processes. The inherent variability of these systems requires models that can account for a wide range of phenomena, including tidal asymmetries, wetting–drying cycles, nonstationary river and atmospheric forcing, and nonlinear feedback mechanisms between tidal currents and wind waves (Staneva et al., 2017). These processes influence mixing, ocean circulation, and the accuracy of sea surface temperature predictions. Thus, high-resolution models are indispensable for capturing the fine-scale interactions that drive coastal dynamics and shape biogeochemical responses.

Observational data play a pivotal role in advancing coastal modelling. High-frequency (HF) radar and novel high-resolution satellite missions offer unprecedented opportunities to observe and understand coastal processes with fine spatial and temporal resolution (De Mey-Frémaux et al., 2019). These data sources are integral to improving the representation of physical and biogeochemical variability in the models, bridging the gap between observations and predictive frameworks. By integrating data from remote sensing and in situ platforms, coupled with advanced data assimilation techniques, models can better capture the complexity of estuarine and nearshore processes.

Science-based services in the coastal ocean are essential for ensuring efficient management, sustainable use of coastal systems, and the development of strategies that are adaptable to the changing climate, including sea-level rise. These efforts, for example, align with the marine strategy framework directive in the European context (Hyder et al., 2015).

The aim of this paper is to introduce high-resolution ocean forecasting services that address the challenges of coastal dynamics by improving predictions of physical and biogeochemical processes. It focuses on the integration of advanced modelling techniques and modern observational tools to enhance understanding of small-scale dynamics and their connections to larger ocean systems. The paper first describes the spatial scales and processes that high-resolution models address, focusing on local, regional, and transitional zones. It then explores advanced observational tools, such as satellite missions and HF radars, and their role in improving coastal forecasts. Following this, the discussion highlights numerical modelling techniques, including turbulence modelling and bottom drag parameterization, which are essential for capturing small-scale coastal dynamics. It also examines the role of data assimilation techniques and Observing System Experiments in improving prediction accuracy and guiding the design of observation networks. Finally, the paper concludes with a summary of findings, identifies current challenges, and outlines future directions for advancing coastal forecasting systems. By addressing these topics, the paper aims to support the development of more robust and adaptable tools for coastal forecasting, which are critical for sustainable management and improving resilience to environmental changes.

## 2 Typical spatial scales and processes solved by high-resolution services

High-resolution services in the coastal ocean operate at various spatial scales depending on the specific applications and objectives. These scales can range from local to regional levels, aiming to capture fine-scale processes and variations. Here are some typical spatial scales for high-resolution services:

1. *Local scale*. At the local scale, high-resolution services focus on small coastal areas, such as individual bays, estuaries, or nearshore zones. These services aim to provide detailed information and predictions for specific locations of interest. Spatial resolutions in this range can be on the order of metres to a few kilometres, allowing for precise observations and modelling of localized processes.

2. *Coastal scale*. High-resolution services at the coastal scale cover larger coastal regions, spanning multiple bays, estuaries, and coastal zones. These services provide a broader view of the coastal environment and its dynamics. Spatial resolutions in this range typically range from metres to a kilometre, enabling the capture of coastal- to regional-scale variations and interactions.

3. *Transition zones*. Transition zones refer to areas where coastal and open-ocean processes interact. These zones often exhibit complex dynamics and are of particular interest for high-resolution services. Spatial resolutions in transition zones can vary depending on the specific characteristics and objectives, but they generally aim to capture the intricate interactions between coastal and open-ocean processes.

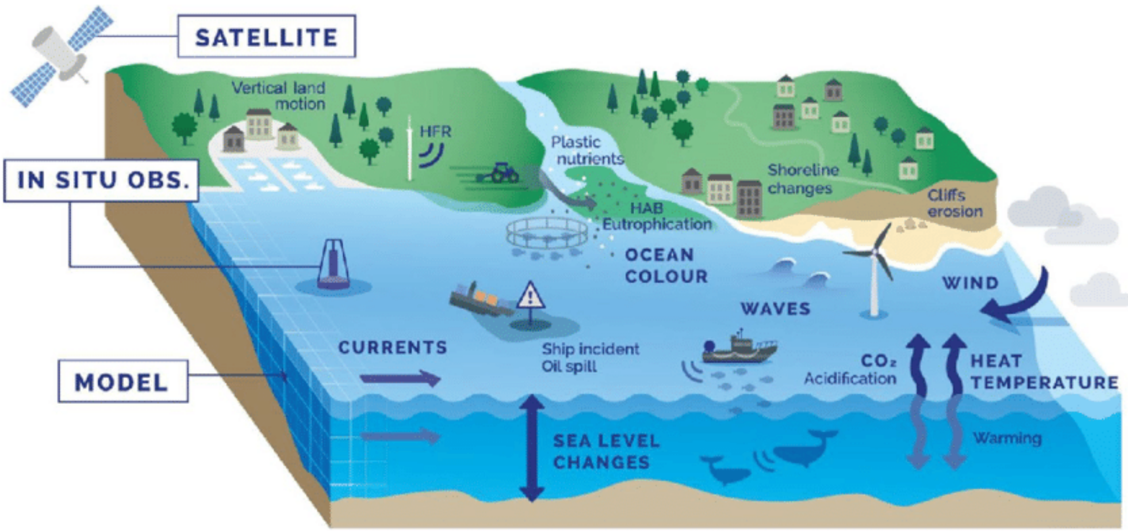


**Figure 1.** Schematic representation of the coastal zone, hazards (e.g. HAB, harmful algae bloom), metocean and biogeochemical variables, and observations and applications (adapted from Melet et al., 2020).

A collection of 11 recent studies on operational coastal services utilizing high-resolution models offers significant insights into the relevant spatial scales, objectives, and applications, thereby strengthening the analysis in this context (Sotillo, 2022). Eddies or isolated vortices, meandering currents, or fronts and filaments are characteristic features of oceanic mesoscale processes. These processes typically exhibit spatial scales ranging from 10 to 500 km, depending on geographic latitude and stratification, and timescales ranging from several days to approximately 100 d. Submesoscale processes in the ocean, on the other hand, are characterized by smaller scales, typically ranging from 1 to 10 km (McWilliams, 2016). These scales are smaller than the Rossby radius of deformation. Submesoscale processes also have shorter temporal scales, usually lasting only a few hours, and their relative vorticity is greater than the Coriolis parameter $f$. In contrast, for mesoscale motion, the relative vorticity is comparable to $f$. Overall, studying and observing submesoscale processes require advanced techniques and methods to overcome their small scale and rapid variability, but their understanding is crucial for comprehending the intricate dynamics of the ocean.

The surface and bottom mixed layers in the open ocean occupy just a tiny part of the ocean volume because these layers are much thinner than the almost viscousless ocean interior. However, in the coastal zone, drag parameterizations become increasingly important in shallow water and even more so where the impact of vegetation is significant. Furthermore, a large part of kinetic energy in the ocean is dissipated in the coastal zone, which necessitates an adequate modelling of this important small-scale process, vital for the global energy balance (Munk and Wunsch, 1998). To accurately represent the coastal dynamics and the fine structure of these layers, models need to resolve the vertical structure of the mixed layers. This requirement necessitates the use of turbulence closure models, which account for the effects of turbulence and mixing in these regions. Additionally, models for coastal processes need to consider the impact of bottom drag. The parameterization of bottom roughness, often based on the grain size distribution, allows for the inclusion of bottom drag effects. In cases where vegetation is present, drag parameterizations become even more important. A significant portion of the kinetic energy in the ocean is dissipated in the coastal zone. Therefore, it is crucial to adequately model these small-scale processes in order to maintain a balanced representation of the global energy dynamics. Understanding and accurately simulating the dissipation of kinetic energy in coastal areas contribute to a comprehensive understanding of the ocean's energy budget.

In shallow water, the variability of surface elevation caused by tides and storms becomes comparable to the water depth itself. In some coastal areas, shallow-water tides play a significant role in the overall tidal dynamics. To improve the accuracy of tidal predictions in shelf regions, it is necessary to consider higher harmonics and assess the ability of ocean models to fully resolve the tidal spectrum.

Some important processes, such as the nonlinear feedback between strong tidal currents and wind waves, cannot be ignored in the coastal zone (Staneva et al., 2016a, b, 2017). Wave–current coupling tends to decrease strong winds through wave-dependent surface roughness (Wahle et al., 2017), affects mixing and ocean circulation, and improves predictions for sea surface temperature. Further examples of the value of the incorporation of coupling in the numerical models in the coastal ocean are given by De Mey-Frémaux et al. (2019). These scientific developments of operational oceanography are in pace with the trend in the Earth system modelling to seamlessly couple different environmental prediction components of atmosphere, waves, hydrology, and ice.

The small spatial scales that are characteristic of coastal and estuarine systems require coastal models to consider ageostrophic (deviating from the Earth's rotation) and three-dimensional dynamics, primarily driven by boundary-layer processes (Fringer et al., 2019). Understanding these small-scale processes is crucial, particularly the interactions between mesoscale and submesoscale dynamics and their connection to larger-scale processes. It is essential to improve the representation of exchanges between the coastal and open ocean, as well as their coupling with estuaries and catchment areas, in order to capture the complexity of coastal systems. Accounting for high-resolution atmospheric forcing in the coastal models is essential for accurately capturing local meteorological dynamics, including wind patterns, temperature gradients, and precipitation rates. Such detailed atmospheric data drive fundamental processes like heat and momentum fluxes, profoundly influencing coastal hydrodynamics, sediment transport, and ecosystem responses. The implementation of a novel high-resolution atmospheric forcing, combined with the refinement of bulk formulae for surface flux computations, significantly enhances the performance of various high-resolution modelling systems for port environments (García-León et al., 2022). Coastal models need to accurately account for frictional balances, taking into consideration the effects of friction on the movement of water. They must also address wetting and drying processes, as well as hydrological forcing, to capture the transitions between shallow environments and larger regional scales. By incorporating these factors, models can provide a more realistic representation of coastal dynamics. In addition, the grid characteristics used in coastal models should be carefully selected to accurately represent the dominant spatial scales present in the coastal environment. Choosing grid resolutions that capture the essential features of the coastal system is crucial for obtaining reliable and meaningful results.

In the coastal ocean, characteristic timescales are significantly shorter compared to the global ocean. These timescales, typically around 1 d, are determined by various processes, including tides, inertial motion, diurnal cycles, and synoptic weather patterns. The fast-paced dynamics of the coastal ocean require models to accurately capture these shorter time scales. In estuaries, the periodicity becomes more complex due to strong tidal asymmetries and the presence of secondary circulation patterns. The interactions between tidal forcing, river flow, and estuarine geometry result in intricate and variable periodic patterns (as shown in Campuzano et al., 2022, for the Western Iberian Buoyant Plume; Sotillo et al., 2021a, for the whole European Atlantic façade; and Pein et al., 2021, for the Elbe Estuary). The periodicity observed in coastal seas is mainly influenced by external forcing signals, such as atmospheric conditions or remote ocean signals. These external signals propagate in the coastal models through the specification of lateral boundary conditions, which is a crucial aspect of modelling in coastal areas. Unlike global models that can operate without open boundaries, coastal models require careful consideration of these boundary conditions to accurately represent the interactions between the coastal and open ocean.

The predictability limit of models depends on the geophysical processes. For synoptic processes in the open ocean, this limit is on the order of weeks to months. For the coastal ocean, it is on the order of hours to days. The loss of predictability, associated with nonlinear processes, is exemplified by the growth of errors in predictive models. Assimilation of data containing spatial and temporal scales below the predictability limit is needed to address this issue. Simulations at grid resolutions that would sufficiently resolve the coastal submesoscale would require horizontal grid resolutions of approximately 1–10 m in estuaries and 0.1–1 km in coastal shelf domains. However, achieving such high resolutions poses significant computational challenges and resource demands.

By employing high-resolution services with appropriate spatial scales, scientists and stakeholders can gain a more detailed and accurate understanding of coastal processes, improve forecasting capabilities, and support effective coastal management and decision-making.

## 3 State-of-the-art data and tools for coastal forecasting

### 3.1 Required observations

Observing systems are spatiotemporally sparse in coastal regions compared to the small scales of ecosystem variability found there. A crucial challenge in observations is addressing the variety of important spatial and temporal scales within the coastal continuum, which encompasses the seamless transition from the deep ocean to estuaries through the shelf. In order to achieve this, observations should sample the multiscale, two-way interactions of estuarine, nearshore, and shelf processes with open-ocean processes. Additionally, they need to account for the different pace of circulation drivers, such as fast atmospheric and tidal processes, as well as the slower general ocean circulation and climate forcing. It is also important to accurately sample the gradients of biological production, ranging from mesotrophic estuaries to oligotrophic oceans. Given the current situation, observational practices and strategies need to be strongly coupled with numerical modelling to effectively extract the information contained in the data and advance the quality of coastal services.

Most global and regional prediction products use a combination of satellite observations and in situ observations. Traditionally, in situ observations constituted the major data source for coastal ocean monitoring. During the end of the past century, satellite observations contributed significantly to the understanding of spatial variabilities. Novel instruments, such as the acoustic Doppler current profiler (ADCP), which measures current profiles throughout the water column, enhanced our understanding of current shear and bottom stress. Nowadays, high-resolution numerical simulations in the coastal ocean are keeping pace with high-resolution observations. A similar trend is observed in coastal waters, estuaries, and ports, which are rich in different activities and interests: fishing, recreational activities, search and rescue, protection of habitats, storm forecasts, and maritime industries, as well as routine maintenance operations (De Mey-Frémaux et al., 2019).

The coastal ocean observations only are not sufficient to fully support the present-day need for high-quality ocean forecasting and monitoring because measurements may represent very localized and short-scale dynamics, and it is not straightforward to know how fully they describe the complex coastal system. Therefore, recent practices employ the synergy between observations and numerical modelling, which ensures valuable research advancements and practical implementations (Kourafalou et al., 2015a, b). The core components of operational oceanographic systems consist of a multi-platform observation network, a data management system, a data assimilative prediction system, and a dissemination/accessibility system (Kourafalou et al., 2015a; De Mey-Frémaux et al., 2019; Davidson et al., 2019). By combining observations and models through data assimilation methods, ranging from coastal to global and from in situ to satellite-based, we can assess ocean conditions and create reliable forecasts. This integration adds value to coastal observations and enables a wide range of applications (De Mey-Frémaux et al., 2019; Ponte et al., 2019), as well as providing decision-making support. For a comprehensive review of ocean monitoring and forecasting activities in both the open and coastal oceans, please refer to Siddorn et al. (2016).

High-frequency radars (HFRs) offer unique spatial resolution by providing reliable directional wave information and gridded data of surface currents in near-real time. The use of HFR networks has become an essential element of coastal ocean observing systems, contributing to high-level coastal services (Stanev et al., 2016a; Rubio et al., 2017; Reyes et al., 2022). The outputs from prediction systems extend the utility of HFR observations beyond the immediate observation area (Stanev et al., 2016b), enabling adequate estimates even where no direct observations have been made. This demonstrates how models connect observations, synthesize them, and assist in the design of observational networks. In turn, observations can guide the development of coastal models (De Mey-Frémaux et al., 2019).

Alongside ADCP data, HFR data are used for skill assessment of operational wave and circulation models (Lorente et al., 2016). Another valuable source of fine-resolution data in the coastal region is provided by colour data from satellites. In terms of sea-level observations, some challenges associated with the use of altimeter data in the coastal zone are expected to be overcome through the use of wide-swath Surface Water and Ocean Topography (SWOT) technology. SWOT is a landmark satellite mission that delivers two-dimensional sea surface height observations at high resolution across a 120 km swath. It represents a major step forward in resolving mesoscale and submesoscale features critical to coastal dynamics. Recent Observing System Simulation Experiments (OSSEs) have demonstrated that wide-swath altimetry substantially enhances ocean forecasting capabilities. For instance, a constellation of two SWOT-like wide-swath altimeters provides a $\sim 14\,\%$ reduction in sea surface height forecast error compared to a 12-nadir altimeter constellation and also improves estimates of surface currents and Lagrangian trajectories (Benkiran et al., 2024). These results highlight the importance of SWOT-type observations for resolving small-scale coastal variability and improving model–data integration.

Further advances in coastal observations are enabled by autonomous platforms such as Slocum gliders. These gliders can carry a wide array of physical and biogeochemical sensors and perform repeated transects, thus providing high-resolution observations of dynamic features such as eddies, frontal systems, and upwelling events. Their operational flexibility and ability to collect subsurface data make them valuable for both sustained monitoring and adaptive sampling strategies (Rudnick, 2016; Testor et al., 2019). In parallel, satellite technologies continue to evolve. Moreover, the Japanese geostationary meteorological satellite Himawari-8 provides high-frequency (every 10 min) and high-resolution (up to 500 m) visible and infrared imagery. These capabilities allow for near-real-time monitoring of sea surface temperature (SST), making it possible to track rapidly evolving coastal phenomena such as diurnal warming, river plumes, and thermal fronts (Kurihara et al., 2016).

These complementary in situ and remote sensing platforms represent essential components of integrated coastal observing systems, supporting the growing demand for accurate forecasts, early warnings, and data-driven decision-making tools.

### 3.2 Numerical models

Addressing specific processes in the coastal ocean and accurately modelling the transition between regional and coastal scales cannot be achieved solely by adjusting the model resolution. Certain processes, such as shallow-water tides, which are often overlooked in global and regional forecasting, play a dominant role in coastal ocean dynamics. The previous sections have highlighted the importance of a tailored approach in observational practices and numerical models for the coastal ocean. For further information on other popular coastal models, refer to the comprehensive discussion by Fringer et al. (2019).

**Table 1.** Circulation models in alphabetical order, which can be used for coastal and regional studies and/or provision of services.

| Model | Citation | C: coastal, R: regional, G: global | Finite-volume (FV) or finite-element (FE) |
|---|---|---|---|
| ADCIRC | Luettich et al. (1992); Westerink et al. (1994) | C | FE |
| COAWST | Warner et al. (2008, 2010) | C/R | FV |
| COMPAS | Herzfeld et al. (2020) | C/R | FV |
| CROCO | Marchesiello et al. (2021) | C/R | FV |
| Delft3D | Deltares (2012) | C | FV |
| FVCOM | Chen et al. (2003) | C/R/G | FV |
| GETM | Burchard and Bolding (2001) | C | FV |
| MITgcm | Marshall et al. (1997) | C/R/G | FV |
| MPAS | Ringler et al. (2013) | R/G | FV |
| NEMO | Madec et al. (2016) | C/R/G | FV |
| POMS | Blumberg and Mellor (1987); Mellor (2004) | C/R | FV |
| ROMS | Shchepetkin and McWilliams (2005) | R | FV |
| SCHISM | Zhang et al. (2016b) | C/R/G | FV/FE |
| SELFE | Zhang and Baptista, 2008 | C | FV/FE |
| SHYFEM | Umgiesser et al. (2004) | C | FE |
| SUNTANS | Fringer et al. (2006) | C | FV |
| TRIM/UnTRIM | Casulli (1999); Casulli and Zanolli (2002, 2005) | C | FV |

### 3.3 Fine-resolution nested models and their downscaling and upscaling

High-resolution coastal services must properly resolve interactions between various coastal processes, including nearshore, estuarine, shelf, drying, and flooding dynamics. Achieving this requires a resolution of approximately 10–100 m. Simultaneously, it is essential to capture open-ocean processes at a resolution of around 1 km or coarser. Common approaches employed in addressing this challenge include downscaling and multi-nesting techniques (e.g. Debreu et al., 2012; Kourafalou et al., 2015b; Trotta et al., 2017), as well as the use of unstructured-grid models (e.g. Zhang et al., 2016a, b; Federico et al., 2017; Stanev et al., 2017; Ferrarin et al., 2018; Maicu et al., 2018). Another important aspect to consider is upscaling (Schulz-Stellenfleth and Stanev, 2016), which becomes relevant when addressing the two-way interaction between coastal and open-ocean systems.

Most coastal models are one-way nested, relying heavily on forcing data from larger-scale models as the coastal system is primarily influenced by the atmosphere, the hydrology, and the open ocean. Enhancing the horizontal resolution of the North Sea operational model from 7 to 1.5 km (Tonani et al., 2019) has shown improvements in off-shelf regions, but biases persist over the shelf area, indicating the need for further enhancements in surface forcing, vertical mixing, and light attenuation.

An important consideration in downscaling and coastal modelling is the treatment of open boundary conditions (OBCs), which play a critical role in determining model fidelity near the boundaries. OBCs are typically derived from larger-scale models but often require case-specific tuning to ensure dynamic consistency and minimize reflection or spurious signals. The choice and configuration of OBCs – such as Flather-type, radiation conditions, or relaxation zones – can significantly affect the transport and energy balance within the coastal model domain. Given the diversity of physical processes and geometries encountered in coastal environments (Marchesiello et al., 2001). Models equipped with a wide suite of configurable boundary condition types offer a practical advantage, particularly in multi-scale coupled frameworks. Ensuring consistency across nested domains while preserving physical realism remains an ongoing challenge, motivating continued development and intercomparison of OBC strategies in operational and research settings.

While the downscaling of information from coarser global or regional models to high-resolution coastal models is well established, the reverse process of upscaling is more challenging and continues to be a subject of research. Two-way nested models allow assimilated information from coastal observations, typically not assimilated by larger-scale forecasting systems, to propagate beyond the coastal region while maintaining dynamic consistency. This upscaling capability has the potential to benefit regional models. Coastal observations have demonstrated their potential to improve boundary forcing or surface wind forcing in regional models.

The coupling of a coarse-resolution regional model with a fine-resolution coastal model using a two-way nesting approach has been studied in the context of the straits connecting the North Sea and the Baltic Sea. The intricate topography and narrow cross-sections of the straits result in the dominance of small-scale motions, which play a vital role in the exchange between the two seas and significantly influence Baltic Sea stratification. The two-way nesting method, designed to exchange information between the child model in the straits and the parent model in the seas, incorporates elements of data assimilation and allows for different vertical discretizations in each model. The Adaptive Grid Refinement in FORTRAN (AGRIF), originally developed by Debreu et al. (2008, 2012), has found wide application as a library for seamless spatial and temporal refinement over rectangular regions in the NEMO modelling framework (Madec and the NEMO System Team, 2024; Debreu et al., 2008)

Recent advancements in two-way nesting frameworks have demonstrated their effectiveness in improving multiscale model accuracy. The implementation of a general two-way nesting framework has enhanced the exchange of physical properties between nested grids while preserving numerical stability and computational efficiency. Additionally, the integration of two-way nesting in a global ocean model has significantly improved surface tidal accuracy, refining regional tidal dynamics without compromising large-scale coherence (Herzfeld and Rizwi, 2019; Jeon et al., 2019). Further applications of AGRIF have demonstrated improvements in hydrodynamic simulations and the estimation of environmental indicators in coastal systems, underscoring its potential to refine fine-scale hydrodynamics while ensuring consistency with larger-scale ocean processes (Petton et al., 2023).

The organization of these multi-model studies is identified by the coastal modelling community as a need. Firstly, to tackle common assessments of the wide range of overlapping (global, basin, or regional and local) models that are available for users in some coastal zones. Secondly, these multimodel validation exercises, comparing the performance of global/regional "core" model forecasts (i.e. from services such as the Copernicus Marine one) and coastal model solutions, nested into the former, are useful to identify the potential added value (and the limitations) of performed coastal downscaling with respect to the "parent" core operational solutions, in which high-resolution coastal models are nested.

Frishfelds et al. (2025) highlight the benefits of on-demand coastal modelling employing two-way nesting, emphasizing its capacity to dynamically refine coastal processes while maintaining consistency with larger-scale ocean simulations. This approach enhances the accuracy and reliability of high-resolution forecasting systems, facilitating improved representation of fine-scale coastal dynamics.

In that sense, these multi-model intercomparison exercises are key elements for many initiatives, such as the Horizon Europe project, FOCCUS (2025), that have enhanced existing coastal downscaling capabilities at their core, developing innovative coastal forecasting products based on a seamless numerical forecasting from regional models of the Copernicus Marine Service covering the EU regional seas to member states' coastal forecasting systems. Espino et al. (2022) emphasized the significance of extending Copernicus Marine Environmental Monitoring Service (CMEMS) products to coastal regions, highlighting the integration of high-resolution models and observational data to improve coastal forecasting capabilities. Their work underscores the importance of tailoring operational ocean models to better capture nearshore dynamics, ensuring more accurate and actionable predictions for end-users.

Furthermore, and from an end-user perspective, multimodel studies focused on extreme event simulations provide valuable input on the performance of operational forecasting systems. For instance, Sotillo et al. (2021b) examined Gloria, the record-breaking western Mediterranean storm, by evaluating five different model systems, including Copernicus Marine Service products (global, regional Mediterranean, and Atlantic IBI solutions) alongside two coastal nested models. Such studies play a crucial role in assessing model accuracy, leveraging local HF radar observations, and informing future improvements to regional and coastal forecasting services. In addition, it contributed to an increase in the knowledge about the model systems in operations and an outline of future model service upgrades (both in the regional and coastal services), aimed at achieving a better coastal forecasting, especially during the extreme events.

### 3.4 Unstructured-grid models for cross-scale coastal dynamics

The use of unstructured-grid models is crucial for cross-scale modelling and effectively addressing the interactions between estuaries and the open ocean. One key aspect is the accurate representation of freshwater transformation from rivers, which is often oversimplified in ocean models by specifying river runoff as a point source. Unstructured-grid models, while often employing lower-order spatial discretizations due to interpolation complexities on irregular meshes, provide enhanced flexibility in resolution placement and transition zones. This allows them to effectively capture subtidal, tidal, and intermittent processes in coastal and estuarine environments, supporting a more realistic representation of estuarine dynamics and improved coupling with estuarine models.

Compared to curvilinear and Cartesian grids, unstructured grids excel in resolving complex bathymetric features without significant grid stretching. Since bathymetry plays a fundamental role in governing the dynamics of estuaries and the near-coastal zone, unstructured-grid models offer greater accuracy and computational efficiency in numerical forecasting. Their flexibility also enables more effective resolution of multiscale dynamic features. Fine spatial resolution in unstructured-grid models allows for the resolution of secondary (transversal) circulation in estuaries and straits, thereby improving mixing and enhancing the representation of long-channel changes in stratification, as demonstrated by Haid et al. (2020). Zhang et al. (2016a) have emphasized the role of cross-scale modelling in capturing multiscale hydrodynamic interactions, particularly in tidal straits, where unstructured-grid models enhance the representation of exchange flows and stratification dynamics. As Ilicak et al. (2021) have shown, these advancements contribute to more precise simulations of estuarine and strait dynamics. Recent research has further elucidated the mechanisms governing secondary circulation in tidal inlets. Chen et al. (2023) demonstrated that subtidal secondary circulation can arise due to the covariance between eddy viscosity and velocity shear, even in predominantly well-mixed tidal environments. This finding highlights the necessity of incorporating high-resolution turbulence parameterizations within unstructured-grid models to accurately capture submesoscale and cross-channel processes, thereby improving the fidelity of numerical simulations in complex coastal and estuarine systems.

However, the construction of grids and the need to ensure reproducibility in unstructured-grid modelling still present challenges. Grid generation is not always fully automated, and subjective decisions are often made based on the specific research problem, applications, and intended services. The development of more objective grid construction methods and reproducibility standards is an ongoing concern in unstructured-grid modelling (Candy and Pietrzak, 2018). One significant advancement is the introduction of the JIGSAW mesh generator (Engwirda, 2017), which enables the creation of high-quality unstructured grids designed to satisfy specific numerical requirements. JIGSAW produces centroidal Voronoi tessellations with well-centred, orthogonal cell geometries that are particularly suitable for mimetic finite-volume schemes. JIGSAW incorporates mesh optimization strategies tailored to geophysical fluid dynamics and has been increasingly adopted in ocean modelling applications.

Moreover, the generation of unstructured meshes is a critical component in configuring coastal and estuarine ocean models, as it directly influences numerical accuracy, computational efficiency, and the ability to represent complex shoreline and bathymetric features. Tools such as OceanMesh2D offer MATLAB-based workflows for high-quality, two-dimensional unstructured mesh generation, facilitating user control over mesh density and coastal geometry resolution (Roberts et al., 2019). Similarly, OPENCoastS provides an open-access, automated service that streamlines the setup of coastal forecast systems, integrating mesh generation, model configuration, and forecast production (Oliveira et al., 2019, 2021). The OCSMesh software developed by NOAA represents another important advancement. It enables data-driven, automated unstructured mesh generation tailored for coastal ocean modelling, offering a robust framework to ensure mesh quality, reproducibility, and interoperability with NOAA modelling systems (Mani et al., 2021). Together, these developments represent the ongoing progress toward objective, reproducible, and user-oriented mesh generation in support of high-resolution coastal ocean modelling.

### 3.5 Observing System Simulation Experiments, Observing System Experiments, and data assimilation

Data assimilation in coastal regions presents challenges due to the presence of multiple scales and competing forcings from open boundaries, rivers, and the atmosphere, which are often imperfectly known (Moore et al., 2019). Data assimilation is particularly challenging in tidal environments (especially for meso- and macro-tidal environments and not so in micro-tidal coastal zones; De Mey et al., 2017; Stanev et al., 2011; Holt et al., 2005). Studies by Oke et al. (2002), Wilkin et al. (2005), Shulman and Paduan (2009), Stanev et al. (2015, 2016a), and others have demonstrated the value of assimilating HF radar observations to improve the estimation of the coastal ocean state.

Observing System Simulation Experiments (OSSEs) and Observing System Experiments (OSEs) are widely used techniques for assessing and optimizing ocean observational systems. OSSEs involve numerical simulations that test the potential impact of hypothetical observations on forecast models before actual observations are made, enabling improved planning and cost-effective observational strategies. In contrast, OSEs assess the impact of existing observations by systematically removing certain datasets from assimilation systems and evaluating the resulting degradation in model performance. OSSEs and OSEs have the capability to incorporate diverse observing systems, including satellite-based observations, HF radars, buoys with low-cost sensors, and autonomous vehicles. These approaches are useful for refining data assimilation techniques and guiding the development of future observational networks. For further details, we refer readers to Oke and Sakov (2012) and Fujii et al. (2019), who provide comprehensive discussions on the methodologies and applications of OSSEs and OSEs in operational oceanography. An in-depth review of OSSE methodologies, as well as insights into how OSSE and OSE methodologies contribute to improving ocean forecasting, designing observational systems, and refining numerical models, is given in Zeng et al. (2020). These approaches can help identify gaps in existing coastal observing networks, assess operational failure scenarios, and evaluate the potential of future observation types. Pein et al. (2016) used an OSE-type approach to investigate the impact of salinity measurements in the Ems Estuary on the reconstruction of the salinity field, identifying observation locations that are more suitable for model–data synthesis. This type of analysis can contribute to the design and optimization of both existing and future observational arrays, especially in coastal regions where fine resolution is required.

### 3.6 Riverine forcing and its role in coastal ocean modelling

Rivers play a critical role in shaping coastal circulation and stratification by delivering freshwater, nutrients, and sediments that influence estuarine and shelf dynamics. The treatment of riverine inputs in ocean models remains a key source of uncertainty, especially when estuarine plume dynamics and mixing processes are unresolved. In many coarse-resolution systems, river discharge is prescribed via simplified surface or salinity fluxes, which may misrepresent the spatial structure and strength of river plumes (Sun et al., 2017; Verri et al., 2020). To address this, high-resolution and regional-scale models increasingly incorporate momentum-carrying river inflows or artificial estuarine channels (Herzfeld, 2015; Sobrinho et al., 2021). For instance, Nguyen et al. (2024) demonstrated how high-resolution modelling in the German Bight captures the hydrodynamic and biogeochemical responses to extreme river discharge events, showing significant implications for salinity, stratification, and nutrient dispersion during floods. These findings underscore the importance of resolving riverine inflow variability and extreme events in coastal ocean prediction systems.

Recent work has also focused on operational strategies for river forcing (Matte et al., 2025 in this report), including real-time discharge data integration (e.g. from GloFAS; Harrigan et al., 2020) and estuary box models that approximate sub-grid plume behaviour (Sun et al., 2017). These approaches aim to enhance predictive capabilities while maintaining computational feasibility in global-to-coastal modelling chains. Choosing the appropriate river input strategy is therefore application-dependent and strongly influenced by spatial resolution and target phenomena.

### 3.7 Integration of AI in coastal modelling and forecasting

The integration of artificial intelligence (AI) and machine learning (ML) techniques in ocean and coastal forecasting has rapidly evolved, providing novel methodologies for improving predictive accuracy, computational efficiency, and data assimilation in operational models. Recent advances in AI-based approaches for parameterizing subgrid-scale processes, hybrid modelling techniques, and ensemble forecasting highlight the transformative potential of these methods in coastal modelling (Heimbach et al., 2025 in this report).

Machine learning applications in coastal ocean modelling primarily focus on two domains: (1) enhancing conventional physical models by integrating ML-based parameterizations and error corrections and (2) fully data-driven approaches that employ neural networks as surrogate models (Zanna and Bolton, 2020; Bolton and Zanna, 2019). The former leverages ML techniques to optimize numerical model performance by improving subgrid parameterizations, bias correction, and data assimilation strategies, while the latter explores the potential of deep learning algorithms such as Fourier neural operators (FNOs) and transformer-based architectures for high-resolution ocean forecasting (Bire et al., 2023; Wang et al., 2024).

Data assimilation, a critical component of operational forecasting, benefits from AI-enhanced methodologies that improve state estimation and predictive skill. AI-driven data assimilation frameworks, such as the combination of deep learning with variational assimilation (4D-VarNet) (Fablet et al., 2023), have demonstrated superior performance in coastal and regional models. Hybrid approaches incorporating AI techniques into numerical models have been applied to refine coastal simulations, allowing for better representation of multi-scale interactions (Brajard et al., 2021). Furthermore, convolutional neural networks (CNNs) have been successfully used for downscaling sea surface height and currents in coastal areas, addressing challenges related to observational gaps and improving model resolution (Yuan et al., 2024).

Coastal high-resolution models often suffer from errors stemming from inaccuracies in numerics, forcing (e.g. open boundaries, meteorological inputs), and unresolved physical processes. AI-based methods have been increasingly applied to address these challenges, particularly in the realm of subgrid-scale parameterization. AI-enabled parameterizations of mesoscale and submesoscale processes using deep learning techniques, such as residual networks and generative adversarial networks (GANs), have shown promising results in reducing bias in numerical simulations (Gregory et al., 2023; Brajard et al., 2021). Additionally, hybrid methods combining physics-based models with ML correction schemes have demonstrated improved predictive skill for regional and coastal ocean models (Perezhogin et al., 2023).

The use of ML for extreme event prediction has gained increasing attention in the context of operational coastal forecasting. AI models trained on historical storm data and high-resolution numerical simulations have been utilized to enhance storm surge predictions and improve early warning systems (Xie et al., 2023). Transformer-based models, originally developed for atmospheric forecasting, have been adapted for ocean applications, achieving competitive skill in eddy-resolving ocean simulations (Wang et al., 2024).

The integration of AI in ensemble forecasting further contributes to uncertainty quantification, providing probabilistic predictions for extreme coastal events. Bayesian inference techniques, combined with ML-based ensemble prediction, offer a framework for optimizing multi-model ensembles and reducing systematic errors in operational forecasts (Bouallègue et al., 2024; Penny et al., 2023). The synergy between ML-driven emulators and traditional ensemble forecasting techniques has the potential to enhance coastal hazard predictions, particularly in regions prone to high-impact events.

Despite the advancements in AI for coastal modelling, several challenges remain. The interpretability and robustness of ML-based solutions need further improvement, particularly for operational applications requiring high levels of reliability (Bonavita, 2024). Additionally, integrating ML models with real-time observational data streams, including remote sensing and high-frequency radar (HFR) networks, remains an ongoing area of research (Reichstein et al., 2019). The extension of ML-based ocean forecasting to seasonal and interannual timescales also poses challenges related to long-term stability and physical consistency (Beucler et al., 2024).

## 4 Summary and outlook

The critical importance of high-resolution coastal modelling is demonstrated in addressing the complexities of dynamic coastal systems. Coastal areas are shaped by the interplay of mesoscale and submesoscale processes, strong tidal currents, atmospheric and hydrologic forcing, and significant anthropogenic pressures. Advanced techniques, including turbulence closure models for capturing vertical mixing and parameterizations of bottom roughness and vegetation drag for representing energy dissipation, are essential for accurately modelling these systems. The nonlinear interactions between tidal currents and wind waves emerge as a particularly influential factor, affecting ocean circulation and improving the accuracy of sea surface temperature predictions.

It is shown that the integration of high-resolution observational data, such as HF radar for surface currents and the SWOT satellite mission for sea surface topography, has the potential of substantially enhancing the resolution and reliability of coastal models. These data facilitate a detailed characterization of processes in transition zones spanning estuaries, nearshore areas, and the open ocean. Improved coupling between regional and local models has advanced the representation of boundary conditions and enabled simulations of small-scale dynamics, essential for capturing the complexity of the coastal continuum.

The application of data assimilation techniques addresses the rapid variability inherent in coastal processes, highlighting the challenges and limitations of predictability in these highly dynamic environments. Strategies to extend the accuracy of short-term and localized forecasts are provided, leveraging multiscale data integration to refine predictions. The ability to simulate interactions between atmospheric conditions, hydrological inputs, and oceanographic processes strengthens the foundation for more accurate modelling. This contribution underscores the importance of bridging observational and modelling gaps to achieve a comprehensive understanding of coastal systems. It highlights the necessity of integrating small-scale dynamics with broader processes to better inform sustainable coastal management practices. By aligning advanced techniques with high-resolution data, this work offers a pathway for more robust representations of coastal ocean dynamics and supports informed decision-making in the face of growing environmental and societal challenges.

Several directions for advancing coastal ocean modelling to address evolving environmental and societal challenges are highlighted. Future efforts should focus on integrating emerging observational technologies, such as high-resolution satellites (e.g. SWOT), autonomous platforms like gliders and drones, and hyperspectral imaging. These tools, combined with machine learning techniques for data analysis, can bridge gaps in spatial and temporal data coverage, providing a richer understanding of coastal dynamics.

Developing coupled modelling systems that seamlessly integrate atmospheric, hydrological, and oceanographic processes will be essential for capturing the complexities of the land–ocean continuum. Incorporating river runoff, estuarine dynamics, and nearshore processes into such systems will significantly enhance the scope and accuracy of predictions. Addressing computational challenges associated with high-resolution modelling is equally critical; this includes leveraging high-performance computing and cloud-based processing and optimizing numerical schemes to achieve efficient and precise simulations.

Improving data assimilation techniques through ensemble approaches and probabilistic forecasting is another priority. These methods will better integrate multiscale observational data, reduce uncertainties, and enhance the reliability of predictions in dynamic environments. Concurrently, there is a pressing need to explore the impacts of climate change on coastal systems, including sea-level rise, increased storm intensity, and shifting precipitation patterns. Understanding these impacts will guide the development of adaptive strategies and strengthen resilience in vulnerable coastal zones.

The future of coastal modelling also depends on fostering interdisciplinary collaboration, engaging expertise from oceanography, meteorology, hydrology, and ecology. By aligning scientific research with societal needs and practical applications, collaborative frameworks can ensure the relevance and effectiveness of modelling efforts. Additionally, applying artificial intelligence to optimize model parameterization, grid design, and predictive analyses will unlock new capabilities for simulating small-scale processes like sediment transport and ecosystem responses.

Finally, enhancing global and regional coordination for coastal monitoring and modelling will be vital. Strengthening networks to ensure consistency in data and modelling approaches can foster international collaboration, facilitating the exchange of best practices and resources. These collective advancements promise to deepen our understanding of coastal systems and provide robust tools to manage and protect these critical areas sustainably in the face of ongoing and future challenges.

**Data availability.** No data sets were used in this article.

**Author contributions.** JS conceptualized the study, analysed data, and wrote this article. All authors contributed to the writing of the article and quality control.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** Joanna Staneva and Angelique Melet acknowledge the EU Horizon Europe project FOCCUS, "Forecasting and observing the open-to-coastal ocean for Copernicus users" (grant agreement 101133911). Joanna Staneva acknowledges the EU Horizon Europe project LandSeaLot Land-Sea Interface: Let's Observe Together! (grant agreement 101134575).

We thank the editors, in particular Kirsten Wilmer-Becke, Stefania Ciliberti, and Enrique Alvarez, for their kind support and coordination. We are also grateful to the two reviewers for their helpful and constructive comments, which improved the manuscript. Special thanks are given to Stefania Ciliberti for her support during the final submission and proofreading of an earlier draft.

**Financial support.** Joanna Staneva and Angelique Melet were supported by the EU Horizon Europe project FOCCUS, "Forecasting and observing the open-to-coastal ocean for Copernicus users" (grant agreement 101133911). Joanna Staneva was supported by the EU Horizon Europe project LandSeaLot Land-Sea Interface: Let's Observe Together! (grant agreement 101134575).

**Review statement.** This paper was edited by Kirsten Wilmer-Becker and reviewed by two anonymous referees.

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# A description of existing operational ocean forecasting services around the globe

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Received: 13 September 2024 – Discussion started: 29 October 2024
Revised: 25 April 2025 – Accepted: 30 April 2025 – Published: 2 June 2025

**Abstract.** Predicting the ocean state in support of human activities, environmental monitoring, and policy-making across different regions worldwide is fundamental. To properly address physical, dynamical, ice, and biogeochemical processes, numerical strategies must be employed. The authors provide an outlook on the status of operational ocean forecasting systems in eight key regions including the global ocean: the West Pacific and Marginal Seas of South and East Asia, the Indian Seas, the African Seas, the Mediterranean and Black Sea, the North East Atlantic, South and Central America, North America (including the Canadian coastal region, the United States, and Mexico), and the Arctic.

The authors initiate their discussion by addressing the specific regional challenges that must be addressed and proceed to discuss the numerical strategy and the available operational systems, ranging from regional to coastal scales. This compendium serves as a foundational reference for understanding the global offering, demonstrating how the diverse physical environment – ranging from waves to ice – and the biogeochemical features besides ocean dynamics can be systematically addressed through regular, coordinated prediction efforts.

## 1 Introduction

The vast and dynamic nature of the world's oceans plays a critical role in shaping global climate, supporting biodiversity, and sustaining human economies. Accurate ocean forecasting is essential for a variety of applications, including maritime navigation, fisheries' management, disaster preparedness, and climate research. As such, the ability to predict ocean conditions with precision is of paramount importance to scientists, policymakers, and coastal communities alike.

Over the past few decades, significant advancements have been made in the field of ocean forecasting, driven by improvements in observational technologies, numerical modeling, and computational capabilities. Satellite remote sensing, autonomous underwater vehicles, and enhanced buoy networks have expanded our ability to monitor oceanic parameters with unprecedented resolution and coverage. Concurrently, sophisticated numerical models, integrating physical, chemical, and biological processes, have improved the accuracy and reliability of ocean predictions.

Despite these advancements, the status of ocean forecasting varies widely across different regions of the world. Factors such as technological infrastructure, scientific expertise, and financial resources influence the development and implementation of forecasting systems. Some regions have established comprehensive and highly accurate forecasting capabilities, while others struggle with limited data availability and outdated methodologies.

This paper aims to provide a comprehensive overview of the current state of ocean forecasting services across various regions globally (reanalysis services are not contemplated). By examining the technological, scientific, and operational aspects of forecasting systems in different parts of the world, we seek to identify both the strengths and gaps in existing capabilities.

The main inventory for operational ocean forecasting services existing today is the atlas of these services hosted on the OceanPrediction Decade Collaborative Center (DCC) website (https://www.unoceanprediction.org/en/atlas, last access: 8 May 2025) In this already growing inventory more than 150 worldwide systems are described in detail showing a comprehensive picture of the activity in this field (Fig. 1).

The following sections describe, starting with global systems and analyzing region by region, the situation across different regions of the world ocean.

## 2 Global ocean forecasting services

Historically, global ocean forecasting efforts were initially focused on naval operations and scientific research, with early models developed to support strategic planning and military navigation. The advent of global observing systems, such as satellite altimetry and Argo floats, provided unprecedented datasets, leading to significant improvements in model accuracy.

With the establishment of initiatives such as the Global Ocean Data Assimilation Experiment (GODAE) in the late 1990s and early 2000s, operational oceanography moved toward a coordinated, global-scale framework. These efforts laid the foundation for modern global ocean forecasting services, which now provide continuous, high-resolution forecasts tailored for various sectors, including fisheries, shipping, offshore energy, and climate services.

Today, global operational ocean forecasting systems are operated by multiple institutions worldwide, using state-of-the-art ocean circulation and sea ice models coupled with data assimilation techniques. These models are forced by atmospheric reanalysis and forecast systems, integrating satellite and in situ observations to improve the accuracy of predictions. The outputs of these systems are crucial for understanding ocean dynamics, predicting extreme events such as hurricanes and marine heat waves, and supporting policy decisions related to climate change adaptation and marine resource management.

Table 1 shows the global systems already registered in the OceanPrediction DCC Atlas and their main characteristics. All the detailed information about these systems can be found at the OceanPrediction DCC Atlas. To the knowledge of the authors, only a few systems remain to be incorporated into this inventory: LICOM, operated by the Institute of At-

**Table 1.** Global ocean forecasting services on the OceanPrediction DCC Atlas.

| System | Organization | Forecasted Essential Ocean Variables (EOVs) | Numerical model(s) | Horizontal grid type | Maximum resolution |
|---|---|---|---|---|---|
| Global Ocean Analysis and Forecast System (Copernicus Marine GLO-MFC) | Mercator Ocean International | Currents, salinity, sea ice concentration, temperature, sea state (waves), biogeochemistry variables | NEMO, MFWAM, and PISCES | Regular | 9 km |
| FIO Ocean Forecasting System | First Institute of Oceanography | Currents, ocean surface heat flux, salinity, sea ice concentration, sea state (waves), temperature | MOM – GFDL and MASNUM wave model | Curvilinear (MOM) and Regular (MASNUM) | 10 km |
| neXtSIM-F | Nansen Environmental and Remote Sensing Center | Sea ice concentration | neXtSIM – Next Generation Sea Ice Model | Regular | 4 min |
| Global FOAM | Met Office | Currents, salinity, sea ice concentration, sea surface height (sea level), temperature | NEMO and WAVEWATCH III | Curvilinear | 7 km |
| INCOIS global HYCOM | Indian National Centre for Ocean Information Services | Currents, salinity, sea surface height (sea level), temperature | HYCOM – HYbrid Coordinate Ocean Model | Regular | 25 km |
| MOVE-JPN | Meteorological Research Institute | Currents, ocean surface heat flux, ocean surface stress, salinity, sea ice concentration, sea surface height (sea level), temperature | MRI.COM V4 | TriPolar coordinate system | 15 min |
| Real-Time Ocean Forecasting System (RTOFS) | National Oceanic and Atmospheric Administration | Currents, salinity, temperature | HYCOM | TriPolar coordinate system | 9 km |
| Hurricane Forecast Analysis System (HAFS) | National Oceanic and Atmospheric Administration | Currents, salinity, sea state (waves), temperature | HYCOM | Curvilinear | 1 km |
| INPE wave prediction system | National Institute for Space Research | Sea state (waves) | WAVEWATCH III | Regular | 15 min |
| INCOIS-WAVEWATCH III | Indian National Centre for Ocean Information Services | Sea state (waves) | WAVEWATCH III | Regular | 8 km |
| Global Ocean Forecasting System GOFS16 | Centro Euro-Mediterraneo sui Cambiamenti Climatici | Currents, ocean surface heat flux, salinity, sea ice concentration, sea surface height (sea level), temperature | NEMO | TriPolar coordinate system | 3 km |
| Global Ice Ocean Prediction System | Environment and Climate Change Canada | Currents, salinity, sea surface height (sea level), temperature, sea ice properties (concentration, thickness, snow depth, temperature, internal pressure) | NEMO and CICE | TriPolar coordinate system | 12 km |
| Chinese Global Operational Oceanography Forecasting System | National Marine Environmental Forecasting Center | Currents, salinity, sea ice concentration, sea surface height (sea level), temperature | MaCOM | Unstructured | 5 min |
| JCOPE-FGO | Japan Agency for Marine-Earth Science and Technology | Currents, salinity, sea state (waves), sea surface height (sea level), temperature | POM | Regular | 10 km |

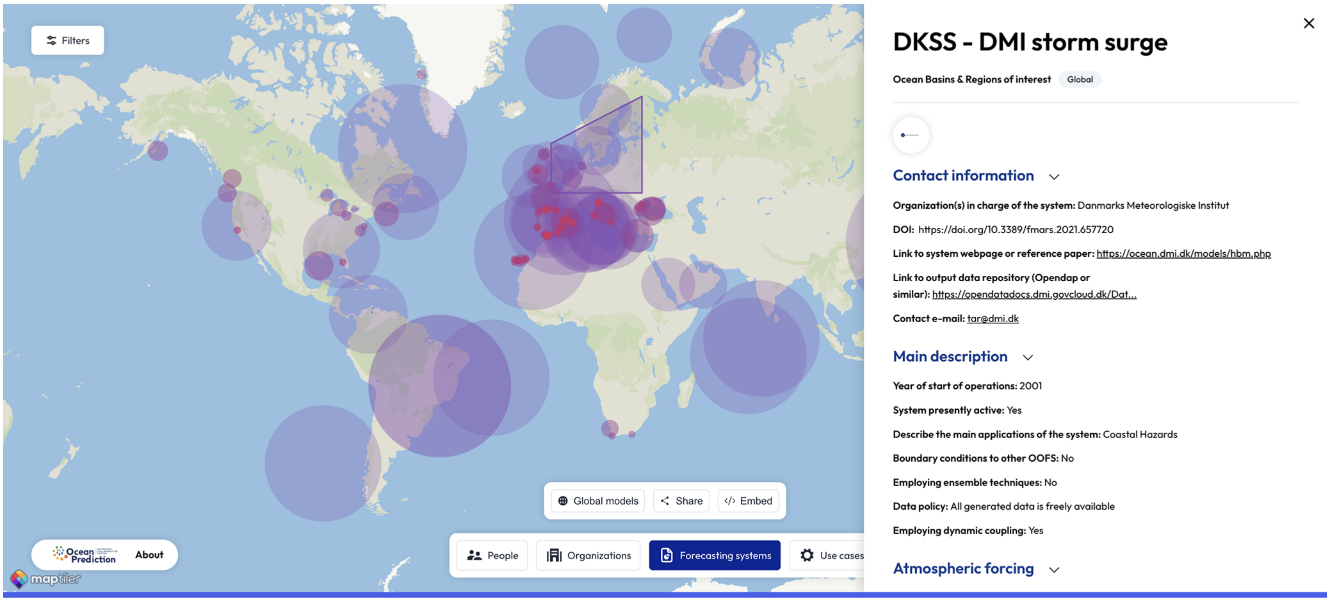


**Figure 1.** The OceanPrediction DCC Atlas (https://www.unoceanprediction.org/en/atlas/models, last access: 8 May 2025).

mospheric Physics (China), and NAVY-ESPC and GOFS3, both developed by the Naval Research Laboratory (USA).

Other interesting characteristics can be derived from the replies not shown in the area. For the circulation models, the number of vertical layers ranges from 29 to 98, $Z$ coordinates being the most used system (four systems). All the systems (except some wave systems) use data assimilation, but only two make use of ensemble techniques.

The data sources employed for assimilation change from one system to another, the ones used being ARGO profiles, satellite altimetry, satellite sea surface temperature (SST), buoy data, drifters, XBT, and gliders. Six systems use dynamic coupling between different models or model components. All systems, but one, provide third parties with data, directly or after a specific request. Surprisingly, almost half of the systems declare not being validated operationally. The forecast horizon is usually between 5 and 10 d.

It is interesting to note that in regions where regional and coastal systems are scarce, global services have become a main source of information for many applications. In African seas, for example, outputs from the global services are disseminated on a local web portal. Bandwidth is cited as the most common problem affecting the accessibility of global forecast services. Some countries provide bulletins in pdf format, and some add local value to global services by developing and disseminating optimized metrics. Examples of the variety of use types are provided here:

– *Mauritius* (using Copernicus Marine Global Ocean Monitoring and Forecasting (GLO-MFC) products). The Mauritius Oceanography Institute provides a web portal, available at https://moi.govmu.org/gmes/forecast (last access: 8 May 2025) (affiliated with GMES and Africa) that outputs a regional subset of global sea-state forecasts. Monthly bulletins are targeted at users from the marine and fisheries' realm for monitoring purposes and are a source of information for researchers and the scientific community.

– *Kenya* (using INCOIS). The Kenyan Meteorological Department provides daily and weekly marine forecast bulletins (https://meteo.go.ke/, last access: 8 May 2025).

– *Mozambique* (using INCOIS). The Integrated Ocean and Information System for Mozambique is developed by the INCOIS project Hyderabad and the Regional Integrated Multi-Hazard Early Warning System (RIMES).

– *South Africa* (using the NCEP Global Ensemble Forecast System – Wave (GFS-Wave), available at https://www.nco.ncep.noaa.gov/pmb/products/gfs/, last access: 8 May 2025, and Copernicus Marine GLO-MFC products). The South African Weather Service uses the National Centers for Environmental Prediction – Global Forecast System (NCEP GFS), as well as currents from the Copernicus Marine Service forecasts, to run an operational regional and coastal wave and storm surge model (Barnes and Rautenbach, 2020). Additionally, they disseminate regional information based on Copernicus Marine forecasts.

– *South Africa* (using Copernicus Marine GLO-MFC products). Regional value was added to Copernicus Marine products, e.g., marine heat waves, location of the Agulhas Current (e.g., distance from shore), and SST anomalies in an operational service. The tools are currently being integrated into the web portal.

## 3 West Pacific and Marginal Seas of South and East Asia

In the West Pacific and Marginal Seas of South and East Asia (WPMSEA), ocean forecasting systems are particularly important due to the region's vulnerability to tropical cyclones, tsunamis, and other oceanic phenomena, as well as socio-economic development needs.

### Regional and coastal forecasts

In this region, it is very frequent that the regional systems also include nested coastal applications, so the description is merged into a single section.

The Japan Coastal Ocean Predictability Experiment (JCOPE; https://www.jamstec.go.jp/jcope/htdocs/e/jcope_consortium.html, last access: 8 May 2025) system, developed by the Japan Agency for Marine-Earth Sciences and Technology (JAMSTEC) based on the Princeton Ocean Model (POM; Blumberg and Mellor, 1987), is a dynamic ocean monitoring and forecasting system (Miyazawa et al., 2009, 2021). Originally tailored for the western North Pacific at eddy-resolving resolutions, JCOPE is now extended to cover the global ocean with a new eddy-resolving quasi-global ocean reanalysis product, the JCOPE Forecasting Global Ocean (JCOPE-FGO). The model covers the global ocean from 75° S to 75° N except for the Arctic Ocean, with a horizontal resolution of $0.1° \times 0.1°$ and 44 sigma levels. The validation against observational data demonstrates JCOPE-FGO's effectiveness, while assessments using satellite data show its capability in representing upper-ocean circulation (Kido et al., 2022). The significance of river forcing for accurately representing seasonal variability is emphasized by highlighting the inclusion of updated global river runoff in JCOPE-FGO and its significant impacts on near-surface salinity.

Kyushu University in Japan operates several real-time ocean forecasting systems based on the Research Institute for Applied Mechanics Ocean Model (DREAMS; https://dreams-c1.riam.kyushu-u.ac.jp/vwp/html/vwp_about.html.ja, last access: 8 May 2025) system. This 3-dimensional ocean model is formulated in spherical coordinates with a horizontal resolution of approximately 1.5 km and features 114 vertical levels (Liu and Hirose, 2022). Its domain covers a rectangular region southwest of Japan, including part of the East China Sea Shelf and the deep Okinawa Trough.

The Mass Conservation Ocean Model (MaCOM) model (Feng et al., 2024) is a newly established and operated global circulation model developed at National Marine Environmental Forecasting Centre (NMEFC) in China (Fig. 2). This model adopts a complete physical framework, the key features of which are mass conservation, enthalpy conservation, and salt conservation, and which is based on pressure coordinates. The MaCOM system is used from global ($\sim 10$ km) to coastal ($\sim 100$ m) forecasts and replaces several previously used models in NMEFC. The LASG/IAP Climate System Ocean Model (LICOM) Forecast System (LFS) is another forecast system from China that maintains a horizontal resolution of $3600 \times 2302$ grids ($1/10°$) and 55 vertical levels. Assessments indicate that LFS performs well in short-term marine environment forecasting. For example, LFS is also able to forecast the marine heat waves around the China Sea, especially in the South China Sea and East China Sea (Yiwen et al., 2023). The surface wave–tide–circulation coupled ocean model developed by the First Institute of Oceanography (FIO-COM) is another global model with an emphasis on tidal mixing (Qiao et al., 2019). The model is developed in close partnership with the Intergovernmental Oceanographic Commission of UNESCO Sub-Commission for the Western Pacific (WESTPAC). MaCOM ocean forecast systems also provide regional as well as coastal forecasts on scales from kilometers to meters with various applications from oil spill forecasts and fishery to ice drifts and marine heat waves.

The BMKG Ocean Forecast System (BMKG-OFS; https://maritim.bmkg.go.id/ofs, last access: 8 May 2025) is an advanced forecasting system developed by Indonesia's Meteorological, Climatological, and Geophysical Agency (BMKG) to provide accurate and timely oceanographic information for the Indonesian seas (Fig. 3). Launched in 2017, BMKG-OFS offers up to 7 d forecasts on various ocean parameters, including wind, waves, swell, currents, sea temperature, salinity, tides, sea level, and coastal inundation. The system utilizes the WAVEWATCH III model to predict sea wave conditions and the Finite Volume Community Ocean Model (FVCOM) to provide information on ocean currents, salinity, and sea temperature at various depths. There is a plan to improve the horizontal and vertical resolutions and an atmospheric-ocean-wave model.

Two major South Korean institutes, the Korea Hydrographic and Oceanographic Agency (KHOA) and the Korea Institute of Ocean Science and Technology (KIOST) (whose details are provided in the OceanPredict National Report, 2020, https://oceanpredict.org/science/operational-ocean-forecasting-systems/system-reports/, last access: 14 May 2025), operate ocean forecasting systems to support various activities. Since 2012, KHOA has operated the Korea Ocean Observing and Forecasting System (KOOFS), consisting of nested ocean and atmospheric models with horizontal resolutions ranging from 4 to 25 km. These models generate daily forecasting data covering regional, sub-regional, coastal, and port areas, with resolutions as fine as 0.1 km for major port areas.

Since 2017, KIOST has also operated the Ocean Predictability Experiment for Marine environment (OPEM) (Jin et al., 2024), a regional ocean prediction system that provides weekly 10 d forecasts for the western North Pacific and

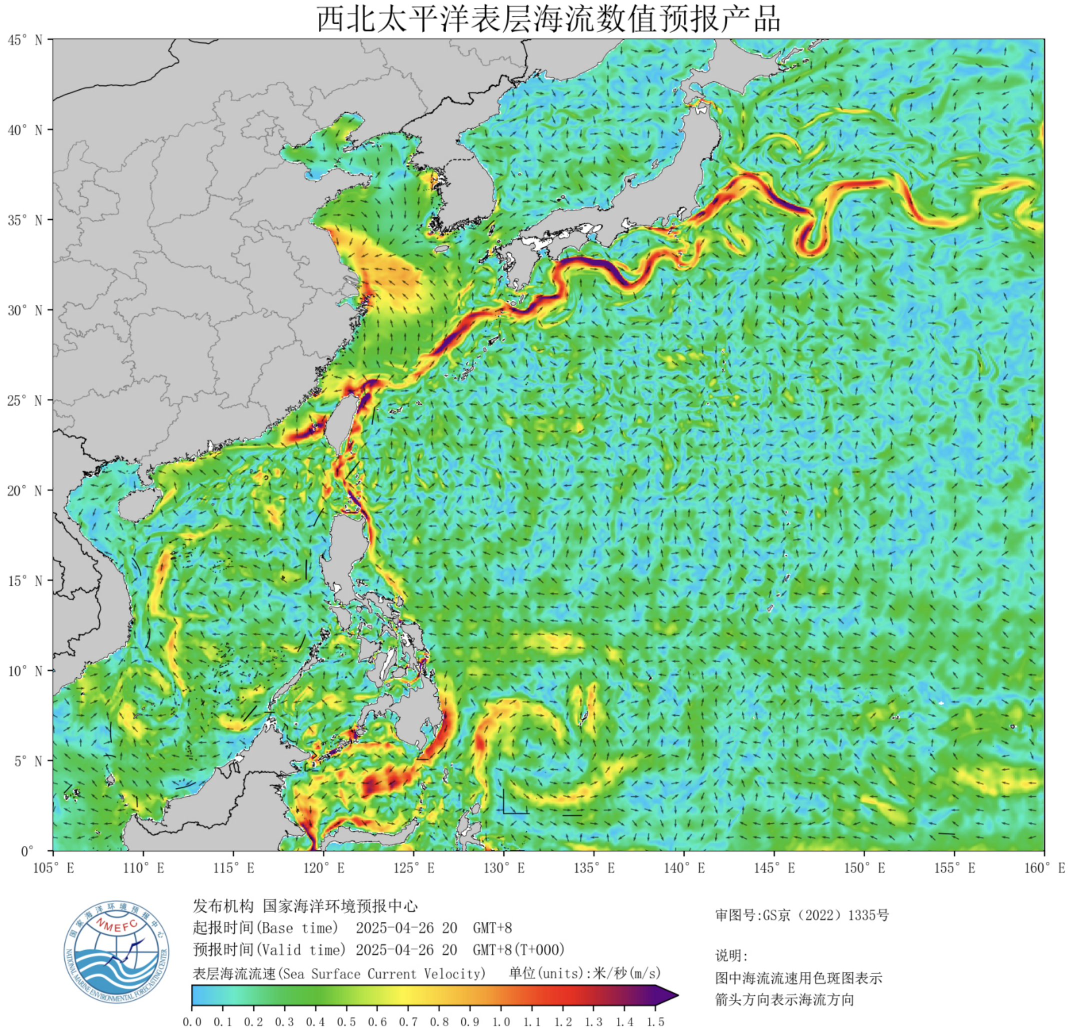


**Figure 2.** Surface currents derived from the MaCOM system (source: https://english.nmefc.cn/ybfw/seacurrent/WestNorthPacific, last access: 8 May 2025).

has shown strong performance in simulating ocean conditions around the Korean Peninsula, particularly in response to extreme events such as typhoons and coastal upwelling. In 2020, a sub-coastal model with a resolution of ∼300 m was established, nested within the coastal model, which itself has a resolution of 1 km. In addition to these major oceanographic centers, some universities are also developing coastal forecasting systems.

Bluelink (https://research.csiro.au/bluelink/global/forecast/, last access: 8 May 2025) is an Australian ocean forecasting initiative established in 2003 through a collaboration between the Commonwealth Scientific and Industrial Research Organisation (CSIRO), the Bureau of Meteorology, and the Australian Department of Defence. It aims to develop and maintain world-leading global, regional, and littoral ocean forecast systems to support defense applications and provide a national ocean forecasting capability for Australia. Bluelink's operational system, the Ocean Modelling and Analysis Prediction System (OceanMAPS; http://www.bom.gov.au/marine/index.shtml, last access: 8 May 2025), provides 7 d forecasts of ocean conditions, including currents, temperature, salinity, and sea level, on a near-global scale. These forecasts are crucial for various sectors, including maritime industries, defense applications, and climate research, aiding in decision-making and enhancing safety at sea (Brassington et al., 2023). Version 4, operational since 2022, uses the ensemble Kalman filter (EnKF).

## 4 Indian Seas

Forecasting Essential Ocean Variables (EOVs) for the Indian Seas comes with several hurdles compared to other regions due to the complex nature of the ocean dynamics and the specific characteristics of the Indian Ocean region such as the land-locked northern boundary. Major processes that

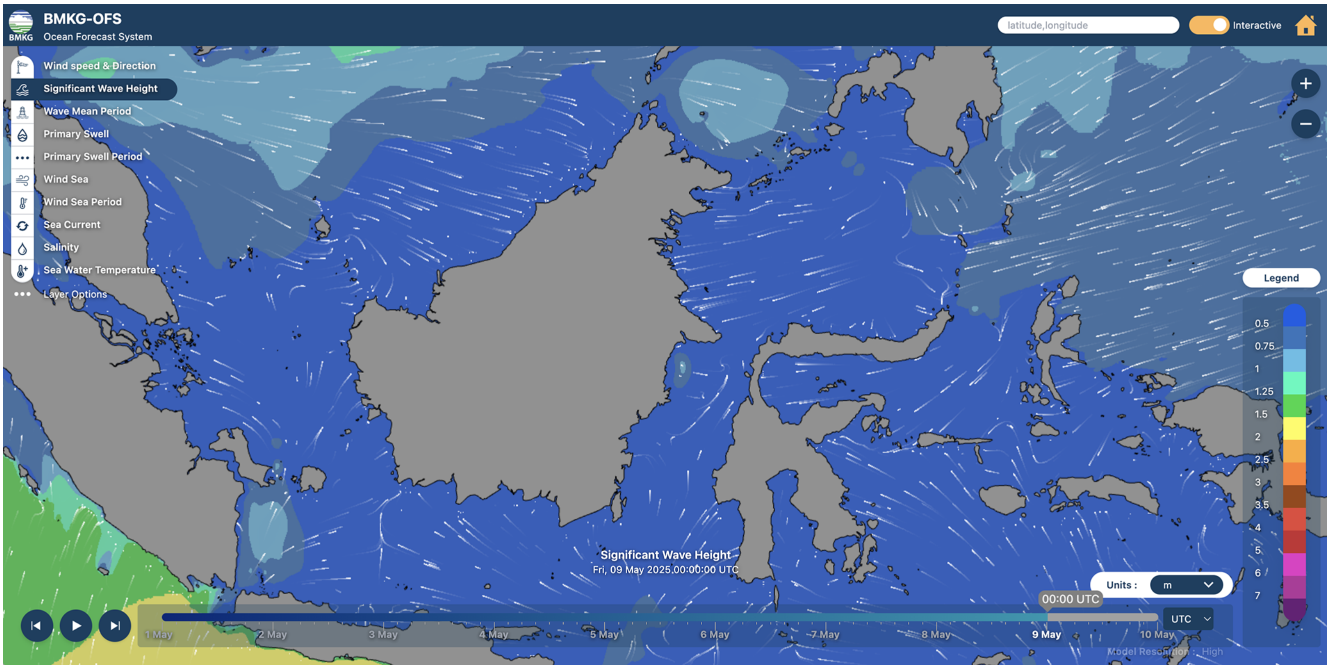


**Figure 3.** Significant wave height derived from BKMG-OFS system (source: https://peta-maritim.bmkg.go.id/ofs/, last access: 14 May 2025).

make forecasting difficult in the region include the monsoon system, which brings abrupt and significant variability in wind patterns, precipitation, and oceanic processes. The Indian Ocean is characterized by seasonally reversing circulation patterns under the influence of monsoonal winds, coastal upwelling, and interactions with neighboring ocean basins. Comprehensive and high-quality observational data for initializing and validating ocean forecast models are scarce, particularly in remote areas and during extreme weather events. The Indian Seas have a complex coastline with extensive estuaries, deltas, and coral reef systems. Coastal processes, including tides, waves, and sediment transport, interact with ocean circulation and impact nearshore areas. Accurately representing these coastal processes in forecasting models poses challenges due to the high spatial variability and the need for high-resolution data and modeling techniques.

### 4.1 Regional systems

The Indian National Centre for Ocean Information Services (INCOIS) operates two regional ocean forecasting systems utilizing the Hybrid Coordinate Ocean Model (HYCOM) and the Regional Ocean Modeling System (ROMS). The regional INCOIS-HYCOM has the highest resolution of approximately 6.9 km, followed by regional INCOIS-ROMS with approximately 9.2 km resolution. Regional INCOIS-HYCOM is forced with atmospheric variables from the NCEP GFS and uses and assimilates sea surface temperature (SST) data derived from the Advanced Very High Resolution Radiometer (AVHRR) sensor, along-track sea level anomalies, and in situ profiles from various observing platforms using the Tendral Statistical Interpolation (T-SIS) scheme data assimilation (DA) method (Srinivasan et al., 2022), taking boundary conditions from INCOIS global HYCOM described earlier (Table 1).

ROMS from INCOIS uses atmospheric forcing from the National Centre for Medium Range Weather Forecasting (NCMRWF; https://www.ncmrwf.gov.in/, last access: 8 May 2025) Unified Model (NCUM) atmospheric system. It assimilates SST and vertical profiles of temperature and salinity from in situ platforms using a local ensemble transform Kalman filter (LETKF) DA method. Data visualization and products from these models are available through a web interface (https://incois.gov.in/portal/osf/osf.jsp, last access: 8 May 2025) to users, and data are made available to users on request.

INCOIS also provides operational wave forecasts through its integrated Indian Ocean Forecasting System (INDOFOS; https://incois.gov.in/portal/osf/osf_rimes/index.jsp, last access: 8 May 2025). These forecasts are essential for maritime safety, navigation, and various ocean-based activities. INCOIS utilizes the third-generation wind wave model WAVEWATCH III (Tolman, 2009) (Fig. 4).

### 4.2 Coastal systems

INCOIS ROMS-Coastal is the only coastal model identified for the Indian Seas. It has approximately 2.3 km spa-

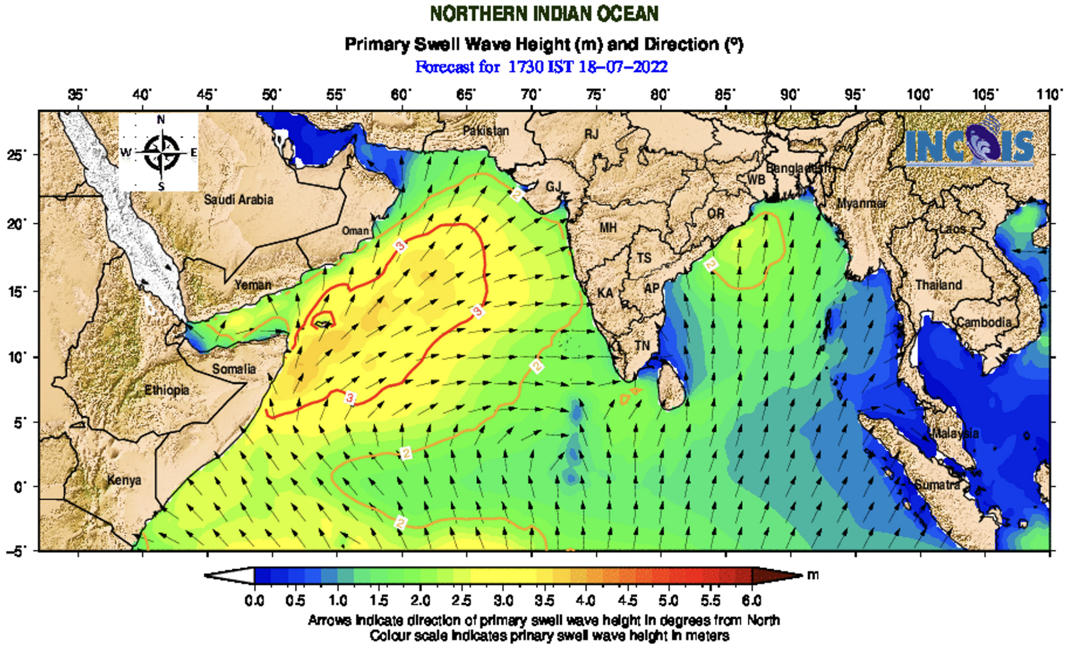


**Figure 4.** Example of wave forecast produced by INCOIS.

tial resolution, which is forced with the same NCUM atmospheric variables as in the case of ROMS and does not assimilate any data but takes initial and boundary conditions from the 9.2 km regional setup of ROMS. Data visualization and products are made available through a dedicated INCOIS web portal, available at https://incois.gov.in/portal/osf/osf.jsp (last access: 8 May 2025), and data are available to users on request.

## 5 African Seas

The African Seas can be subdivided into six regions, based on distinct ecosystem characteristics: the Canary Current large marine ecosystem (LME), the Guinea Current LME, the Benguela Current LME, the Agulhas–Somali Current LME, the Red Sea LME and the Mediterranean Sea LME. Aside from the Mediterranean Sea LME, which will be discussed separately, an overview of the landscape with respect to operational ocean forecast services will be provided below. Operational ocean modeling is a developing field, with limited capacity in most parts of Africa. Operational services in these regions therefore depend largely on core global products and vary in levels of complexity, from disseminating locally relevant information via monthly bulletins to limited area forecast models that use global products at their boundaries. While various types of ocean forecast services exist to support national priorities, two consortia have been developed through Global Monitoring for Environment and Security (GMES; https://gmes.rmc.africa/, last access: 8 May 2025) and Africa to provide more regional support for marine and coastal operations. These are Marine and Coastal Operations for Southern Africa and the Indian Ocean (MarCOSIO; https://marcosio.org/, last access: 8 May 2025) and Marine and Coastal Areas Management in North and West Africa (MarCNoWA; https://geoportal.gmes.ug.edu.gh/#/, last access: 8 May 2025). These platforms currently make use of global services for Earth observations (EOs) as well as marine forecast products that in some cases are optimized for local conditions.

### 5.1 Regional systems

There are a limited number of regional forecast systems optimized specifically for African Seas.

- The Iberia Biscay Irish Marine Forecasting Centre (IBI-MFC; https://marine.copernicus.eu/about/producers/ibi-mfc, last access: 8 May 2025) Ocean Physics, Waves and Biogeochemistry Analysis and Forecast products, provided by the Copernicus Marine Service, are suitable for use by regional services in north and northwest Africa.

- The INCOIS project Hyderabad and the Regional Integrated Multi-Hazard Early-Warning System (RIMES; https://rimes.int/, last access: 8 May 2025) have developed an integrated high-resolution regional ocean forecasting system that encompasses the ocean regions of Madagascar, Mozambique, and the Seychelles.

- The Integrated Red Sea Model (iREDS-M1) has been developed by the King Abdullah University of Science and Technology in Saudi Arabia. Its atmospheric and ocean (wave and general circulation) models are running on an operational basis to provide short-range forecasts for the Red Sea (Hoteit et al., 2021).

- The South African Weather Service (SAWS; https://www.weathersa.co.za/; last access: 8 May 2025) provides regional wave, wave–current interaction and tide forecasts, downscaled from global services, none of which are assimilative (Barnes and Rautenbach, 2020). They also provide an empirically derived algorithm-based forecast of the sea ice edge for METAREA VII (de Vos et al., 2021).
- The MarCNoWA focuses on delivering Earth observation (EO) services to coastal and marine environments and fisheries:
  - provision of potential fishing zone charts overlaid with vessel traffic,
  - monitoring and forecasting of oceanography variables,
  - forecast of ocean conditions,
  - oil spill monitoring,
  - generation of coastal vulnerability indices and mapping of coastal habitats.

  Through a network of national stakeholders, regional fisheries and environmental bodies, academia, private sector, and researchers, the project is to impact decision making in the beneficiary countries. It downscales Copernicus Marine products and provides forecasts (Forecasts – Global Monitoring for Environment and Security & Africa, https://gmes.rmc.africa/, last access: 14 May 2025).
- The forecasting system GCOAST (Geesthacht Coupled cOAstal model SysTem; https://www.hereon.de/institutes/coastal_systems_analysis_modeling/research/gcoast/, last access: 8 May 2025), developed by Hereon, is implemented at regional scale for the western coast of Africa. GCOAST (available at https://www.hereon.de/institutes/coastal_systems_analysis_modeling/research/gcoast/index.php.en, last access: 8 May 2025) is built upon a flexible and comprehensive coupled model system, integrating the most important key components of the regional and coastal systems and, additionally, allowing information from observations to be included. The operational modeling system is developed based on a downscaling approach from the Copernicus Marine GLO-MFC forecast products at $1/12°$ resolution, focusing on the western African coast. The wind wave model is based on WAM (WAve Modeling). The atmospheric forcing is taken from ECMWF.

## 5.2 Coastal systems

Operational ocean forecast services for African coasts include the following:

- The National Coastal Forecasting System for Mozambique (FEWS-INAM) provides 3 d ocean and meteorological forecasts in the form of daily bulletins and text messages to support operations at sea. It uses global NCEP GFS data to provide meteorological and wave boundaries and GLOSSIS (https://www.deltares.nl/en/expertise/projects/global-storm-surge-information-system-glossis, last access: 8 May 2025) for the storm surge boundary conditions. The forecasts include wave information, tide and surge water levels, and atmospheric weather information. This system was developed by a consortium, including Mozambique's Met Office INAM31, Deltares, UK Meteorological Office, and the DNGRH.
- SAWS provides higher-resolution wave forecasts, optimized for key coastal regions as well as storm surge forecasts. The information is disseminated on their web portal (https://marine.weathersa.co.za/Forecasts_Home.html, last access: 14 May 2025)
- The SOMISANA (A sustainable Ocean Modelling Initiative: a South African Approach, available at https://somisana.ac.za/, last access: 8 May 2025) has developed two limited-area downscaled bay-scale operational forecast systems for key areas around the South African coastline, which are (i) Algoa Bay and (ii) the southwest cape coast. The models run daily and provide 5 d forecasts of currents, temperature, and salinity through the water column (Fig. 5). The models are forced by the GFS atmospheric forecasts at the surface and by the Global Ocean Analysis and Forecast system provided by Copernicus Marine Service at the lateral boundaries. The model outputs can be explored at https://somisana.ac.za/. The validation reports are available for the two operational forecast models.
- Coastal and fluvial flood forecasting has been developed in response to the extreme storm surge and flooding events on the KwaZulu-Natal coast of South Africa by Deltares and the local municipality (details available in the informative leaflet at https://publications.deltares.nl/EP4040.pdf, last access: 8 May 2025). The coastal (Delft3d) and fluvial (SWMM) models are run in forecast mode (Delft-FEWS) every 6 h and provide 3 d forecasts. As inputs, they use global forecast services from the ECMWF and the NCEP.

The coastal forecasting system developed in response to extreme storm surge, waves, and flooding events along the eastern coast of Ghana utilizes advanced modeling techniques and global forecast services. The coastal model

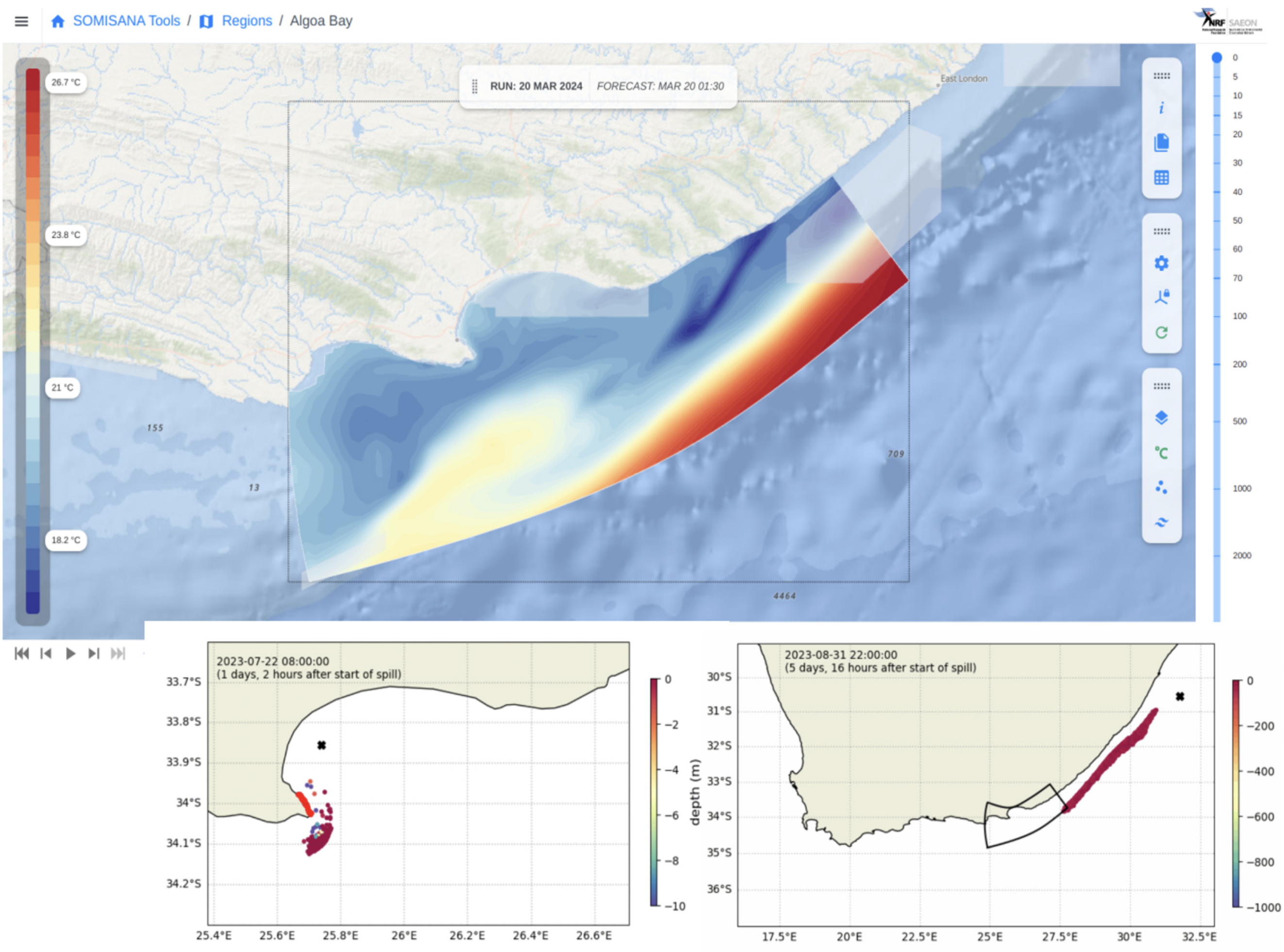


**Figure 5.** The web portal of the bay-scale forecast system developed by the SOMISANA team in South Africa. The web portal allows users to explore the variables as well as scrutinizing various depth levels of the forecasts. The insets show the oil spill tracking functionality, developed using the OpenDrift software, that allows for the seamless integration of the global and regional, bay-scale forecasts in tracking the spill.

employed in this system is a flexible and modular modeling platform GCOAST for regional and coastal applications. The hydrodynamical model is based on SCHISM (Semi-implicit Cross-scale Hydroscience Integrated System Model; https://ccrm.vims.edu/schismweb/, last access: 8 May 2025), which is coupled with the wind wave model (WWM). The coastal forecasting modeling platform ensures a flexible grid for the eastern coast of Ghana, with a resolution ranging from 50 m in the estuaries up to 1 km. The system is designed to provide both hindcasts and forecasts. For hindcast simulations, it uses the GLORYS12 reanalysis (Global Ocean Physics Reanalysis, product ID: GLOBAL_REANALYSIS_PHY_001_030; available at https://data.marine.copernicus.eu/product/GLOBAL_MULTIYEAR_PHY_001_030/description, last access: 8 May 2025). For forecasts, it uses the GLO-MFC (product ID: GLOBAL_ANALYSIS_FORECAST_PHY_001_024). Atmospheric forcing is provided by the ECMWF operational forecast products. At the boundaries, the model is coupled to the Global Ocean Physics Reanalysis GLORYS12 provided by the Copernicus Marine Service (as part of the GLO-MFC product catalogue) and produced by Mercator Ocean International. The coastal forecasting system incorporates tidal forcing from the Finite Element Solution 2014 (FES2014; Lyard et al., 2021) global ocean tide model, which provides tidal elevations and currents on a 1/16° grid and has demonstrated significant improvements over previous versions, particularly in coastal and shelf regions. This comprehensive approach ensures that stakeholders receive timely and accurate information to prepare and respond effectively to extreme events along the eastern coast of Ghana. In addition to its predictive capability, the system also supports environmental resilience. It integrates mangrove vegetation into the modeling platform to assess and promote nature-based solutions for coastal protection. This component enables the evaluation of scenarios in which mangrove cover is varied to estimate its potential to mitigate wave energy and reduce coastal erosion. The implementation builds on the findings of recent studies demonstrating the buffering role of mangroves against hydrodynamic forces in the coast of Ghana, contributing to sustainable coastal management strategies. These insights guide the design of adaptive coastal management strategies based on nature-based interventions (Jayson-Quashigah et al., 2025).

## 6 Mediterranean and Black Sea

The beginning of the 21st century can be considered the starting point of the Mediterranean and Black Sea's operational forecasting services thanks to the favorable conjunction of several aspects:

- A general concept of operational oceanography was emerging worldwide.
- The advent of new ocean monitoring technologies allowed for multiplatform systems, including both in situ monitoring and satellite remote sensing, that in addition to the development of internet network connections started providing open data with a near-real-time availability (Tintorè et al., 2019).
- The development of numerical modeling and prediction systems gave rise to the release of the first ocean forecast of the Mediterranean Forecasting System (MFS) in 2000, which provided regular and freely available 10 d predictions of the Mediterranean Sea dynamics with a spatial resolution of 7 km (Pinardi et al., 2003).
- The first Black Sea nowcasting and forecasting systems, developed during the first decade of 2000, were implemented in the framework of the ARENA (http://old.ims.metu.edu.tr/black_sea_goos/projects/arena.htm, last access: 8 May 2025) and of the EU FP6 ECOOP (European COastalshelf sea OPerational observing and forecasting system) projects.
- The Mediterranean scientific community started to get organized to establish a Mediterranean Operational Oceanography Network (MOON), which in 2012 became the Mediterranean Operational Network for the Global Ocean Observing System (MonGOOS; https://mongoos.eurogoos.eu/, last access: 8 May 2025). Also, the Black Sea Community, within the Global Ocean Observing System, has been established into the Black Sea GOOS (https://eurogoos.eu/black-sea/, last access: 8 May 2025).

In the following, some details on the services implemented in the Mediterranean and Black Sea are provided at regional scale, for the whole basins, and at coastal scale (here the global services are not considered since these basins have strongly regional dynamics and maintain a connection to the global ocean through the narrow Strait of Gibraltar, in the case of the Mediterranean Sea, therefore, this section will only consider regional and coastal services).

### 6.1 Regional systems

There are a limited number of regional forecast systems optimized specifically for African Seas.

During the last decades, major developments have been undertaken to improve the operational forecasting systems of the Mediterranean and Black Sea, first in a pre-operational phase within MyOcean EU projects leading to the Copernicus Marine Service since 2015. The Mediterranean (Med-MFC; Coppini et al., 2023) and the Black Sea (BS-MFC; Ciliberti et al., 2022) Monitoring and Forecasting Centers can be considered the core services for these regions (Fig. 6).

They provide, every day, 10 d forecast fields at around 4 and 2.5 km resolution, in the Mediterranean and Black Sea respectively, for the whole set of Essential Ocean Variables, including currents, temperature, salinity, mixed layer thickness, sea level, wind waves, and biogeochemistry, which are freely available to any user (scientists, policymakers, entrepreneurs, and ordinary citizens, from all over the world) though the Copernicus Marine Data Store. To support users, tailored services and training, adapted to different levels of expertise and familiarity with ocean data, are also provided.

Three operational systems compose both the Med-MFC and the BS-MFC: the physical component, which is based on the NEMO (Gurvan et al., 2022) ocean general circulation model (OGCM); the wave component, which is based on the third-generation spectral model, WAM (The Wamdi Group, 1988); and the biogeochemical component, which is based on the Biogeochemical Flux Model (BFM; Vichi et al., 2020) and on BAMHBI (Grégoire et al., 2008; Capet et al., 2016) for the Mediterranean and Black Sea, respectively. The systems assimilate in situ and satellite data, including sea level anomalies, along-track altimetry data, significant wave height, sea surface temperature, and chlorophyll-*a* concentration, provided by the corresponding Copernicus Marine Thematic Assembly Centers, and are jointly and constantly improved following users' needs. These Mediterranean and Black Sea core services, by providing accurate boundary conditions in a timely manner, enable the implementation of higher-resolution and relocatable forecasting systems in different areas and support the development of many downstream applications and services.

In addition to the abovementioned core services, other forecasting systems are implemented at regional scale such as the following:

- A high-resolution Mediterranean and Black Sea system based on the MITGCM (Massachusetts Institute of

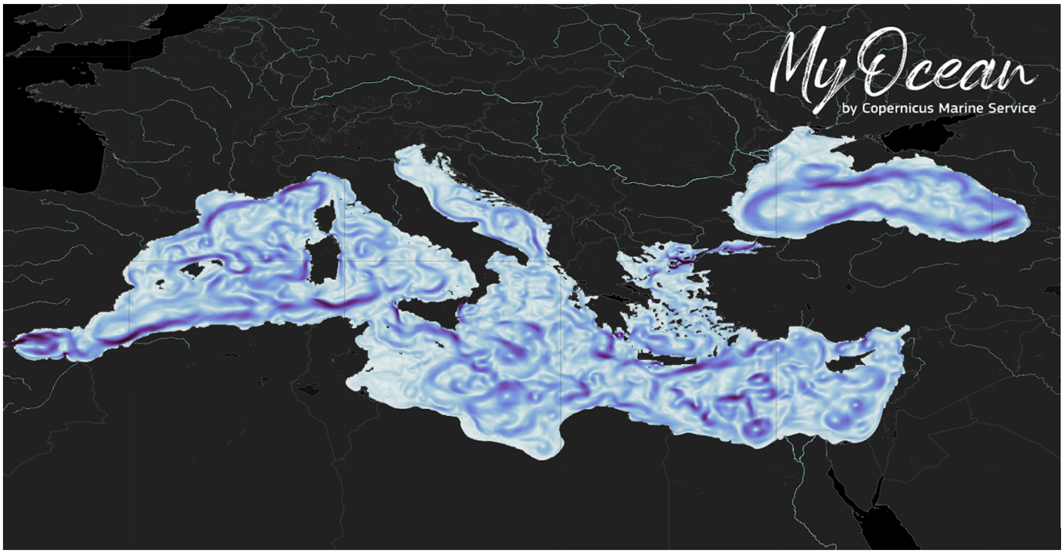


**Figure 6.** Mediterranean and Black Sea Forecasting Systems sea surface currents visualization as provided by the Copernicus Marine Service.

Technology General Circulation Model; Marshall et al., 1997) described in Palma et al. (2020). The system includes tides, is resolved at a 2 km resolution (and higher resolution in specific areas), and is nested in the Med-MFC. This system has been used as a basis to develop a 1/16° model to assess present and future climate in the Mediterranean Sea focusing on sea level change – MED16 (Sannino et al., 2022).

- The KASSANDRA (http://kassandra.ve.ismar.cnr.it:8080/kassandra, last access: 8 May 2025) storm surge forecasting system for the Mediterranean and Black Sea is based on the coupled hydrodynamic SHYFEM (Umgiesser et al., 2004) and wave (WAVEWATCH III) models, allowing for very high resolution in specific areas (Ferrarin et al., 2013).
- The MFS (Mediterranean Forecasting System; https://medforecast.bo.ingv.it/, last access: 8 May 2025) is developed at INGV (National Institute of Geophysics and Volcanology, Italy) with 1/16° resolution and is based on NEMO and implementing a 3D variational data assimilation scheme (OceanVar; Dobricic and Pinardi, 2008).
- The physical and wave ocean system MITO (Napolitano et al., 2022) provides 5 d forecasts of the Mediterranean Sea circulation based on the MITGCM and is forced by the Copernicus Mediterranean physical and wave forecasting products to generate 5 d forecasts data at a horizontal resolution up to 1/48° degree.
- The POSEIDON (https://www.poseidon.hcmr.gr, last access: 8 May 2025) basin-scale Mediterranean forecasting system ($\sim$ 10 km resolution) ocean and ecosystem state is developed at HCMR (Hellenic Centre for Marine Research, Greece). This includes a hydrodynamic model, based on POM (Blumberg and Mellor, 1987), which assimilates satellite and in situ data (Korres et al., 2007), and a biogeochemical model, based on ERSEM (European Regional Seas Ecosystem Model; Baretta et al., 1995; Kalaroni et al., 2020a, b).
- The CYCOFOS wave forecasting system provides 5 d forecasts of the Mediterranean and the Black Sea (Zodiatis et al., 2008) based on WAM and is forced by the SKIRON high-frequency winds.

### 6.2 Coastal systems

Several coastal systems are developed and implemented in the Mediterranean and Black Sea, not only for operational uses but also for research purposes by a wide research community. These modeling systems generally make use of community models that are widely used by the scientific community for a diverse range of applications including the hydrodynamical, waves and biogeochemical marine components. In the following, several of them are illustrated, providing main information and references for more details.

#### 6.2.1 Hydrodynamics

- The IBI-MFC Physics Analysis and Forecasting System (https://data.marine.copernicus.eu/product/IBI_ANALYSISFORECAST_PHY_005_001/description, last access: 8 May 2025) provides operational analysis and forecasting data at 1/36° resolution, implementing the NEMO model integrated with a data assimilation scheme SAM2, which allows for a multivariate assimilation of sea surface temperature together with all available satellite sea level anomalies and in situ observations.

- The Sistema de Apoyo Meteorológico y Oceanográfico de la Autoridad Portuaria (SAMOA; Álvarez Fanjul et al., 2018; Sotillo et al., 2019; García-León et al., 2022) provides operational downstream services and a significant number of high-resolution forecasting applications, based on Copernicus Marine forecasting services and the Spanish Meteorological Agency (for atmospheric forecast), including 20 atmospheric models, 21 wave models, and 31 circulation models. ROMS (Regional Ocean Modeling System) is implemented at a resolution of 350 to 70 m.
- The WMOP model (Juza et al., 2016; Mourre et al., 2018) based on ROMS is a downscaling of the Copernicus Mediterranean system, with a spatial resolution of 2 km and covering the western Mediterranean basin from the Strait of Gibraltar to the longitude of the Sardinia Channel. It is implemented by SOCIB (Balearic Islands Coastal Observing and Forecasting System) and is run operationally on a daily basis, producing 72 h forecasts of ocean temperature, salinity, sea level, and currents.
- A high-resolution numerical model, developed as part of an operational oceanography system in the frame of the Sistema Autonomo de Medicion, Prediccion y Alerta en la Bahia de Algecira (SAMPA) project is implemented by Puertos Del Estado (Spain), providing operational ocean forecast data in the complex dynamical areas of the Strait of Gibraltar and the Alboran Sea.
- The MARC (Modelling and Analyses for Coastal Research) and ILICO (Coastal Ocean and Nearshore Observation Research Infrastructure) are implemented using the MARS3 model in the Bay of Biscay–English Channel–northwestern Mediterranean Sea at 2.5 km horizontal resolution and nested in the Copernicus Marine global system.
- The Tyrrhenian and Sicily Channel Regional Model (TSCRM; Di Maio et al., 2016; Sorgente et al., 2016) is based on a regional implementation of POM at 2 km resolution and is nested into the Copernicus Mediterranean Analysis and Forecasting system.
- The Southern Adriatic Northern Ionian coastal Forecasting System (SANIFS; Federico et al., 2017) is a coastal-ocean operational system based on the unstructured-grid finite-element 3D hydrodynamic SHYFEM model reaching a resolution of a few meters. It is a downscaled version of the Med-MFC physical product and provides short term forecast fields.
- The Aegean and Levantine eddy-resolving model (ALERMO; Korres and Lascaratos, 2003) is based on POM implemented at $1/48°$ resolution and nested into the Copernicus Mediterranean Analysis and Forecasting system.
- The Cyprus Coastal Ocean Forecasting and Observing System (CYCOFOS; Zodiatis et al., 2003, 2018) is specifically developed to provide a sub-regional forecasting and observing system in the eastern Mediterranean (including the Levantine Basin and the Aegean Sea). The latest system is forced by the Copernicus Med-MFC physical forecasting system and implements POM at 2 km resolution to produce initial and open boundary conditions in specific locations.
- The TIRESIAS Adriatic forecasting system is based on the unstructured grid 3D hydrodynamic model SHYFEM and represents the whole Adriatic Sea together with the lagoons of Marano–Grado, Venice, and the Po Delta (Ferrarin et al., 2019). It is a downscaled version of the Med-MFC physical product and provides 3 d forecast fields.

#### 6.2.2 Waves

- The IBI-MFC Waves Analysis and Forecasting system (Toledano et al., 2022) is based on MF-WAM (Meteo-France WAM). It is implemented at $1/36°$ resolution and produces wave forecasts in the western part of the Mediterranean Sea twice a day.
- The SAPO (Autonomous Wave Forecast System; https://static.puertos.es/pred_simplificada/Sapo/d.corunia/sapoeng.html, last access: 8 May 2025) based on WAM is implemented at several Spanish ports with a 72 h forecast horizon, and it is nested within the PORTUS forecast system, an operational wave forecast for Spanish Port Authorities.
- The WAMADR setup of ECMWF WAM is implemented by the Slovenian Environment Agency for the Adriatic and central Mediterranean domain with a horizontal resolution of 72 h and a spatial resolution of 1.6 km. The model is forced by a hybrid ALADIN SI and ECMWF surface wind product and runs daily.
- Several coastal and local wave applications providing wave information near the harbors, as well as boundary conditions for specific wave agitation inside the port applications, use the SWAN model (Booij et al., 1999).

#### 6.2.3 Biogeochemistry

- The IBI-MFC Biogeochemical Analysis and Forecasting System (https://data.marine.copernicus.eu/product/IBI_ANALYSISFORECAST_BGC_005_004/

description, last access: 8 May 2025) is implemented using the PISCES (Aumont et al., 2015) model at 1/36° horizontal resolution.

- The Northern Adriatic Reanalysis and Forecasting system (NARF) and the CADEAU physical-biogeochemical reanalysis (Bruschi et al., 2021) implement the MITgcm–BFM coupled models in the Northern Adriatic Sea, reaching up to 750 m with a further high resolution (∼ 125 m) and nesting in the Gulf of Trieste (https://medeaf.ogs.it/got; last access: 8 May 2025).

## 7 North East Atlantic

Operational oceanography in European countries was mainly operated at a national level until the 1990s. In 1994, the European part of the Global Ocean Observing System (EuroGOOS, https://eurogoos.eu/, last access: 8 May 2025) was founded. It grouped these national endeavors into a network of European monitoring and forecasting systems and initiated several regional and thematic working groups to support specific developments. Since the early 1990s, the European Commission has been actively funding programs to support ocean monitoring and forecasting through, for instance, its series of MyOcean projects (2009–2015) and its ongoing ambitious Copernicus Earth observation program, which includes the Copernicus Marine Service component.

Due notably to the coordinating efforts provided by the Copernicus Marine Service over the last decade, the North East Atlantic region is now well equipped in terms of operational marine forecasting services. Also, each segment of the North East Atlantic coastline is included in at least one regional system, such that global forecast services are seldom used directly, except for the provision of boundary conditions to downstream forecast systems. An inventory of operational marine and coastal models around Europe was compiled out of a survey conducted in 2018–2019 among members of EuroGOOS and its related network of regional operational oceanographic systems (Capet et al., 2020), addressing the purposes, context, and technical specificities of operational ocean forecast systems (OOFSs). Here, we re-focus this analysis on the North East Atlantic by excluding the Arctic, Mediterranean, and Black Sea basins from the original analysis. It should be noted that this inventory only includes OOFSs actively reported to the survey and might therefore be incomplete. A further expansion of the North East Atlantic OOFS inventory is expected from the OceanPrediction DCC Atlas.

Besides the three Copernicus Marine regional forecast services, the inventory includes 35 other regional OOFSs and 32 coastal OOFSs, arbitrarily identified as systems with a spatial resolution below 3 km and a longitudinal and latitudinal domain extent below 5°.

### 7.1 Regional systems in the framework of the Copernicus Marine Service

The major marine core service for the North East Atlantic is provided by the Copernicus Marine Service and its three regional Monitoring Forecasting Centres (MFCs) dedicated to the Iberian, Biscay, and Irish seas (IBI-MFC); European Northwestern Shelves (NWS-MFC; https://marine.copernicus.eu/about/producers/nws-mfc, last access: 8 May 2025); and Baltic Sea (BAL-MFC; https://marine.copernicus.eu/about/producers/bal-mfc, last access: 8 May 2025), respectively (Fig. 7).

In terms of modeling, each of these three MFCs is composed of dedicated components addressing ocean circulation (PHY), biogeochemistry (BGC), and wave dynamics (WAV). These systems operate under the coordinated umbrella of Copernicus Marine Service and therefore benefit from homogenized protocols in terms of operational data production, validation, documentation, and distribution (Le Traon et al., 2019). Products and related documentation can be accessed through the central Copernicus Marine Data Store, together with observational datasets including in situ, remote sensing, and composite products for the Blue (physics and hydrodynamics), Green (biochemistry and biology), and White (sea ice) ocean. Operational data delivery is provided through online data selection tools and a variety of automatic protocols (e.g., Subset, FTP, WMTS), which effectively enables a number of operational downstream services to depend directly on those core services. A catalogue of such downstream usage and its potentialities is exposed on the Copernicus Marine Use Cases portal (https://marine.copernicus.eu/services/use-cases, last access: 8 May 2025).

### 7.2 Other regional systems

The 35 regional forecasts systems that are not operated by Copernicus Marine are mostly operated by national entities and provide data free of charge to relevant users in 71 % of the cases. They address circulation (80 % of the regional OOFSs), wave dynamics (23 %), and biogeochemistry (14 %), as well as Lagrangian drift dynamics, for the sake of oil spills and search and rescue services. Of these 35 systems, 12 report a dependence on the Copernicus Marine products (including GLO-MFC forecast products) in terms of open-sea boundary conditions. Many of these systems (10) benefit from the SMHI e-Hype products to constrain river discharge. Regarding atmospheric conditions, the majority (22 regional OOFSs) rely on Pan-European products (typically provided by ECMWF), but regional atmospheric products are also exploited, as qualitative operational products are provided by national agencies in most European countries.

### 7.3 Coastal systems

A total of 32 coastal OOFSs are reported in the EuroGOOS Coastal Working Group (CWG) inventory for the North Sea,

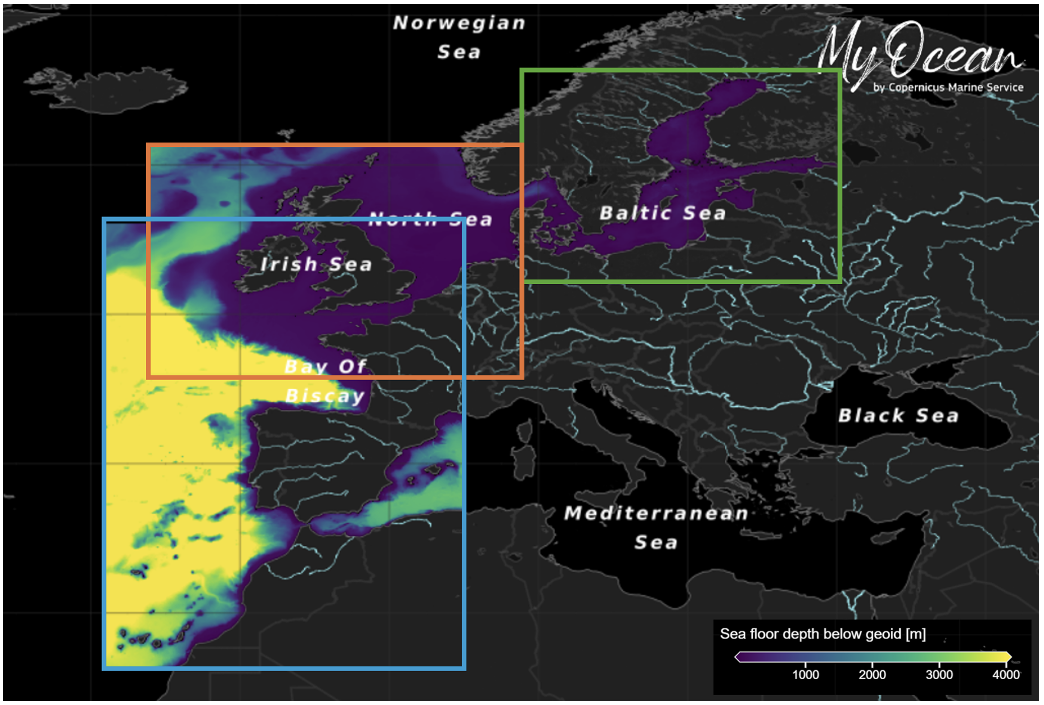


**Figure 7.** The Copernicus Marine regional monitoring and forecasting centers operating in the area: IBI-MFC (in blue), NWS-MFC (in orange), and BAL-MFC (in green). The map shows bathymetry (m) and the composite regions obtained from the MyOcean Viewer (https://marine.copernicus.eu/access-data/ocean-visualisation-tools, last access: 14 May 2025).

Baltic Sea, and European shelves, addressing circulation (68 % of the coastal OOFSs), biogeochemistry (29 %), and wave dynamics (4 %). Again, these OOFSs are mostly operated by public entities (although this is recognized as a potential bias in the survey, as discussed in Capet et al., 2020) and provide, in the vast majority of cases, forecast data that are freely accessible to relevant users.

Among coastal OOFSs, the usage of land and atmospheric forcing data from specific national sources is much more common than for regional systems, indicating that adequate products are available at local scales. Besides, several coastal system operators rely on their own atmospheric or hydrology model to obtain adequate boundary conditions. One could highlight that 15 of the 35 reporting coastal OOFSs provide forecasts at a spatial resolution below 500 m, at least in some parts of their domain. In general, such systems also consider fine bathymetry, with a minimal water depth of under 5 m (Fig. 8).

According to the survey, which was in almost all cases answered by model operators, OOFSs in the North East Atlantic are relevant for marine safety, oil spills, and sea level monitoring concerns (Fig. 9). However, the survey did not consider the extent to which provided information was effectively exploited by downstream operators. To a lesser extent, some systems address biochemical issues such as water quality, harmful algal blooms, or coastal eutrophication.

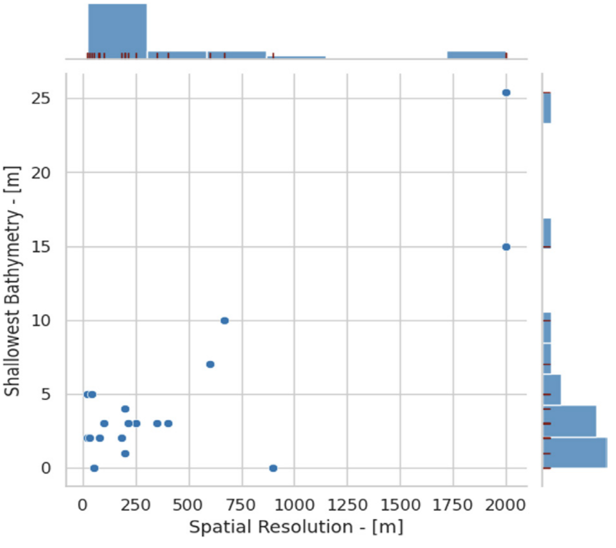


**Figure 8.** Joint and marginal distribution of the minimal water depth and spatial grid resolution, for all North East Atlantic coastal model domains illustrated in Fig. 7.

## 8 South and Central America

The development of short-range ocean forecasting systems in South and Central America is relatively recent with respect to other systems in Europe, North America and East

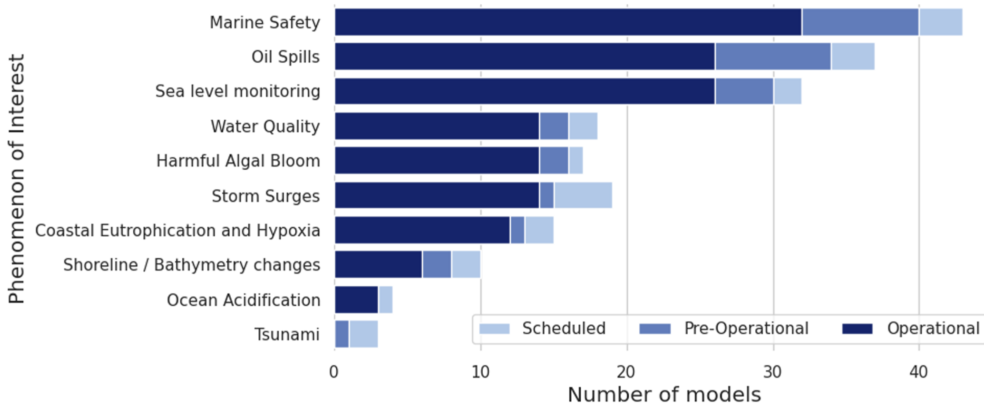


**Figure 9.** Number of regional and coastal models considered by their providers to be relevant for a proposed set of downstream sectorial applications and phenomenon of interest. Based on the 2018–2019 EuroGOOS CWG survey (Capet et al., 2020).

Asia. They are very heterogeneous, reflecting their different needs, local observational systems, and infrastructure. Operational systems are present today in Argentina, Brazil, Chile, Colombia, Panama, and Peru, with a focus on regional- and basin-scale domains in the western Pacific, South Atlantic, and the Caribbean Sea and on tackling forecasts on short-term to seasonal timescales. All of them are rapidly evolving considering the outstanding scientific and technical knowledge gained by the oceanographic global community and the permanent increase in computational resources. Some details about some of these systems are presented below.

### 8.1 Regional systems

In Brazil, a few regional (and coastal) forecast systems exist, considering the vast oceanic area under Brazilian jurisdiction (branded as Blue Amazon), which currently total $4.4 \times 10^6$ km$^2$, approximately half of the Brazilian terrestrial area, with the possibility of reaching $5.7 \times 10^6$ km$^2$ in the future (Franz et al., 2021). The forecasting service results are not available for the public in general due to restrictions imposed by public–private partnerships and other constraints.

The first operational ocean forecast system with data assimilation in Brazil was implemented in the Brazilian Navy Hydrographic Center in 2010 based on the Hybrid Coordinate Ocean Model (CHM-HYCOM) and on an optimal interpolation scheme, developed by the Oceanographic Modeling and Observation Network (REMO) (Lima et al., 2013). Since 2014, CHM-HYCOM forecasts have been initialized by the REMO Ocean Data Assimilation System (RODAS) (Augusto Souza Tanajura et al., 2014; Tanajura et al., 2020), based on the optimal interpolation scheme, which can assimilate SST analysis, along-track or gridded sea level anomalies (SLAs), and $T$–$S$ vertical profiles. The ensemble members are chosen according to the assimilation day from a previous free run. The most recent CHM-HYCOM + RODAS configuration produces 5 d forecasts daily and encompasses the entire North, equatorial, and South Atlantic with $1/12°$ horizontal resolution, to generate boundary conditions for a regional domain grid covering the METAREA-V (35.8° S–7° N, 20° W) with a horizontal resolution of $1/24°$, both with 32 vertical hybrid layers. Other models are also employed operationally in CHM. ADCIRC is employed in Guanabara Bay, São Sebastião and Ilha Bela proximities, and Sepetiba Bay, as well as in Santos and Paranaguá ports.

Regarding the Argentine Sea, the Modelling System for the Argentine Sea (MSAS) is used to model the barotropic component of the ocean state of the southwestern Atlantic continental shelf. MSAS is based on the Coastal and Regional Ocean Community Model (CROCO; http://www.croco-ocean.org, last access: 8 May 2025). Dinápoli et al. (2023) modified the source code to resolve the depth-averaged horizontal momentum and continuity equations, as well as consider spatially varying bottom friction. MSAS covers the Southwestern Atlantic Continental Shelf with a trapezoidal shape designed to avoid a significant number of land points and ensure the regular spatial resolution of 8 km in both directions. Along the boundaries, the model is forced with tides and continental discharges, whereas in the interior of the domain, the ocean surface is forced by atmospheric pressure and surface wind stress (Dinápoli et al., 2020a, 2021, 2023). In addition, MSAS has been used to conduct several scientific studies on the barotropic nonlinear interactions in the region (Dinápoli et al., 2020b), the tidal resonance over the continental shelf (Dinápoli and Simionato, 2024), and the genesis and dynamics of the storm surges along the coast (Alonso et al., 2024; Dinapoli and Simionato, 2025; Dinapoli et al., 2024). Recently, the Asynchronous Ensemble Square Root Filter (4DEnSRF; Sakov et al., 2010; Whitaker and Hamill, 2002) DA scheme was also incorporated as part of MSAS. The 4DEnSRF scheme is currently used to produce optimal initial conditions for the forecasts by assimilating tidal gauges and remote sensing observations. Because of the large and nonlinear impact of the wind uncertainty on the regional barotropic dynamics (Dinápoli et al., 2020a), an ensemble wind forecast is used. Dinápoli et al. (2023) used the 31-member ensemble from NCEP's Global Ensemble Forecast System, together with a set of perturbations of the tides. Since the atmospheric ensemble provides the wind field, rather than the wind stress, the former is estimated using the parameterization of Simionato et al. (2006). The incorporation of 4DEnSRF into MSAS forecasts, together with an ensemble post-processing technique developed by Dinápoli and Simionato (2022), has improved the 96 h forecasts by reducing the model bias and correcting the timing of the strong storm surges that affect the northern part of the Southwestern Atlantic Continental Shelf. It is important to mention that MSAS is running pre-operatively, and its solutions will be made public in the future. Relevant developments have been achieved with regard to wind wave modeling. The numerical model WAVEWATCH III was regionalized and validated with direct observations from a number of buoys scattered in the Southwestern Atlantic Continental Shelf.

In Peru, a large effort in climate modeling has been undertaken in the 2000s so far to develop sub-seasonal forecasts and anticipate the significant socio-economic consequences of the El Niño–Southern Oscillation (ENSO). The Geophysical Institute of Peru (IGP) has recently implemented a regional Earth system model in forecast mode called IGP RESM-COW v1. This system released in December 2023 (Montes et al., 2023) is based on CROCO (Debreu et al., 2012) coupled to the WRF atmospheric model through the OASIS coupler (Craig et al., 2017) and now serves as an additional forecasting tool for establishing the recommendations by the ENFEN (Estudio Nacional del Fenómeno El Niño), a governmental body responsible for monitoring, studying, and predicting the El Niño phenomenon and its impacts on the country. The IGP RESM-COW v1 has a horizontal resolution of 12 km for the ocean component and 30 km for the atmospheric component. The domain covers the entire Peruvian territory and part of the eastern Pacific. The current implementation takes as input the forecasts of the NOAA CFSv2 global climate model that have been corrected using a combination of reanalysis data (GLORYS outputs and the NCEP Final Analysis (FNL) data) and the climatological averages of the NCEP coupled forecast system model version 2 (CFSv2) and of a 22-year-long simulation of the IGP RESM-COW v1 model. This allows forecasts of oceanic and atmospheric conditions to be made up to 7 months in advance (Segura et al., 2023). In addition, the Navy of Peru via the Dirección de Hidrografía y Navegación (Dihidronav) implemented the WAVEWATCH III for representing the wave behavior at the northern, central and southern off Peru with a prediction up to 5 d (https://www.naylamp.dhn.mil.pe/dhn2/secciones/Pronosticos/pronosticosolas/Peru_Olas.php, last access: 8 May 2025). This product is available for the scientific community and the public interested in understanding wave conditions (https://cpps-int.org/index.php/wave-watch, last access: 8 May 2025). Operation systems are also under development at IMARPE (Instituto del Mar del Peru, https://www.gob.pe/imarpe, last access: 8 May 2025) based on the CROCO system, which targets the aquaculture industry in the central Peru region (Arellano et al., 2023). IMARPE and IGP also produce forecasts of ocean conditions at regional scale (Equatorial Kelvin wave amplitude in the Eastern equatorial Pacific) at sub-seasonal timescales based on shallow water models (Mosquera-Vasquez et al., 2014).

As part of a 10-year-long national program (CLAP), CEAZA (Center for Advanced Studies in Aride Zones) is also currently developing an operational forecast system for the Coquimbo region (central Chile) based on CROCO initialized by Mercator forecasts in order to inform the fishery industry and the public. The 7 d lead time forecasts are to be provided through a mobile app (https://app.ceaza.cl/, last access: 14 May 2025) along with real-time observations (temperature, oxygen) from a buoy at Tongoy bay, a hot spot for the scallop aquaculture industry. The system is based on a CROCO configuration at 3 km resolution (Astudillo et al., 2019) and is coupled to a simple biogeochemical model (BioEBUS) that has been tuned and validated for the western coast of South America (Montes et al., 2014; Pizarro-Koth et al., 2019).

In Colombia, the Marine Meteorological Service (SMM; in Spanish), hosted by the Dirección General Marítima (DIMAR) as part of the Ministry of Defense, has co-developed the Integrated Forecast System for Comprehensive Maritime Security (SIPSEM; in Spanish; Urbano-Latorre et al., 2023) over the last 8 years. SIPSEM is an ecosystem of climate services (Goddard et al., 2020) for met-oceanographic applications, providing a suite of demand-driven and actionable information to ensure maritime safety and protect life at sea, while contributing to international regulations in the SOLAS, SAR, IALA, PIANC, IMO, and WMO conventions. Focusing on the ocean component, SIPSEM uses CROCO involving different domains and nests, tailored for the different applications and coastal complexities. Application on a regional scale in the Colombian Caribbean and Pacific employs a horizontal resolution equal to 9.16 km. Different CROCO forecast systems are nested in global forecasts produced by HYCOM + NCODA, Copernicus Global Ocean Physics Analysis and Forecast, and the US Global Navy Coastal Ocean Model. They are forced with the Weather and Research Forecast Model (WRF) with 27 km of horizontal resolution nested in GFS forecasts. For wind-generated wave prediction, daily WAVEWATCH III (Tolman et al., 2002) forecasts are used for local and regional areas with 3.7 and 18.5 km and are periodically calibrated by fine-tuning various model parameters to best represent the local observations. SWAN (Booij et al., 1999) is also used in nearshore and ports applications. Some key SIPSEM forecasts are publicly available via a web portal, available at https://meteorologia.

dimar.mil.co/ (last access: 8 May 2025), developed targeting the general user.

### 8.2 Coastal systems

Regional to coastal operational models for the Brazilian Coast started to be developed in 2018 by the Centre for Marine Studies (CEM), from the Federal University of Paraná (UFPR), in collaboration with MARETEC, a research center of the Instituto Superior Técnico (IST – Universidade de Lisboa) from Portugal, through the application of the MOHID modeling system. This initiative, called Brazilian Sea Observatory (BSO), was initially supported by the User Uptake program from Copernicus Marine Service. In order to deliver high-resolution forecasts of the Brazilian coast, an operational modeling system was developed based on a downscaling approach from the GLO-MFC physical analysis and forecast system at 1/12° resolution, focusing on the southeastern Brazilian shelf, including estuarine systems with important port activities and large environmental protection areas. Nowadays, the operational modeling system includes a model covering the southeastern Brazilian shelf with a horizontal resolution of 1/24°; a model covering the coasts and adjacent shelf of the states of Santa Catarina, Paraná, and São Paulo with a horizontal resolution of 1/60°; and high-resolution models ($\sim$ 120 m) for coastal systems (Florianópolis bays, Babitonga Bay, and Paranaguá Estuarine Complex). The system is maintained by CEM/UFPR. Furthermore, an operational model was developed for the north of Brazil, encompassing the states of Amapá, Pará, and Maranhão and the Amazon River and Pará River estuaries, with a horizontal resolution ranging from 1/24 to 1/60°. The atmospheric forcing comes from the WRF model implemented by the Brazilian National Institute for Space Research (INPE) with 7 km of horizontal resolution. The operational models have a vertical discretization reaching about 1 m of resolution near the surface.

In Chile, efforts to implement operational forecasting systems were initially led by the Navy, with a focus on swell forecasting for the entire Chilean coast or some key sites. These efforts have recently diversified to address issues around marine resource management (industrial and artisanal fisheries, aquaculture) and extreme event prediction. They are mostly based on the use of the CROCO WRF models. As part of the University of Concepción, COPAS Coastal Center is currently developing a forecast coupled system (CDOM-Portuario) based on WRF (https://www.mmm.ucar.edu/models/wrf, last access: 8 May 2025), WAVEWATCH III, SWAN, and CROCO to deliver 3 to 6 d forecasts of oceanic and weather conditions in the harbors of Coronel (378° S), Arica (17.5° S), and Antofagasta (21.5° S). The system is currently delivering operational products at 1 km resolution in uncoupled mode (offline). It targets a resolution of 300 m in fully coupled mode. The national Fisheries Development Institute (IFOP) has recently developed an operational system called CHONOS-MOSA for the south part of central Chile (Reche et al., 2021), focused on the inland seas of the Los Lagos and Aysén regions. It provides forecasts at a 3 d lead time based on CROCO at 1.2 km. The atmospheric forcing is derived from a forecast run based on WRF at 3 km with open boundary conditions from the Global Forecast System (NCEP GFS). Ocean boundary conditions are from GLO-MFC physical forecast products, and river runoffs from 35 point sources are used based on the FLOW products. Forecasts are provided online at https://chonos.ifop.cl/ (last access: 20 May 2024).

Besides these initiatives funded by the academic and public sectors, there are some private companies that also provide ocean and atmospheric forecasting for port operations in Chile. Siprol SpA provides wave, wind, and wave forecasts. They also provide wave forecasting for Ecuador. Also, the company PRDW provides the Automated Wave Forecast System (AWFOS), with 3 h to 10 d forecasting using a mathematical model coupled with a global wave model wave for deep waters. PRDW also provides forecasting for various sites in South American countries. Finally, the port of San Antonio, the first port in Chile in terms of port operations, is using models from the Direction of Port Construction (Dirección Obras Portuarias) in collaboration with the National Institute of Hydraulic of Chile (https://www.dop.pelcam.io/about, last access: 14 May 2025). The wind forecasting is provided by the San Antonio Port Company (EPSA). In all the above, the model used and the validation and details in the model configuration are unknown. Coastal applications employ a resolution of 1.83 km, and port applications employ a grid with resolutions varying from 750 to 150 m. The daily prediction system also involves an ensemble of CROCO forecasts, continuously calibrated using a pattern-based approach for the regional domain, and an additional local calibration for the coastal domains at higher resolutions.

## 9 North America

The marine environment characterizing North America – from the icy Arctic waters to the warm ones of the Gulf of Mexico – is deeply influenced by complex biogeochemical and physical processes. The coastal and open-ocean regions of Canada, the United States, and Mexico need to be accurately forecasted to support the blue economy, ecosystem management, and disaster preparedness. This section provides an overview of existing ocean forecasting systems in the region from a regional to a coastal scale, highlighting prediction capabilities and main challenges they are expected to address.

### 9.1 Regional systems

Due to the strong economic impacts noted above, work on operational oceanography began in Canada in the late 20th century. The first system for the GSL included a baroclinic ice–ocean model at 5 km resolution (Saucier et al., 2003). Shortly thereafter, a similar system was implemented for Hudson Bay (Saucier et al., 2004). The GSL system was coupled to an atmospheric model (Pellerin et al., 2004) and later implemented at the Canadian Meteorological Centre (Smith et al., 2013a). A system was also put in place for the Grand Banks (Wu et al., 2010).

The developments of these foundational systems led to recognition within the Government of Canada of the potential benefits that could be achieved through the development and implementation of a hierarchy of operational oceanographic systems and products. As a result, the Canadian Operational Network for Coupled Environmental PredicTion Systems (CONCEPTS; https://science.gc.ca/site/science/en/concepts, last access: 8 May 2025) initiative was put in place between Environment Canada, the Department of Fisheries and Oceans, and the Department of National Defence (Smith et al., 2013b; https://science.gc.ca/site/science/en/concepts). The CONCEPTS initiative developed strong ties to Mercator Ocean to accelerate the development of a Canadian ocean assimilation capacity to complement the expertise in ice–ocean modeling and atmosphere–ice data assimilation. This effort produced the Global Ice Ocean Prediction System (GIOPS; https://science.gc.ca/site/science/en/concepts/prediction-systems/global-ice-ocean-prediction-system-giops, last access: 8 May 2025; Smith et al., 2016), which paved the way for the first ever operational global medium-range fully coupled atmosphere–ice–ocean forecasting system (Smith et al., 2018). Subsequently, a 16 d and monthly ensemble coupled forecasting system was implemented (Peterson et al., 2022), based on the same ice–ocean model configuration and initialized using GIOPS analyses.

In 2017, the Canadian Government agreed to take responsibility for METAREA regions 17 and 18 of the Global Marine Distress and Safety System. This required the dissemination of warnings for the weather and ice hazards over a pie-shaped region stretching from the Bering Strait to north of Greenland and up to the North Pole. As a result, the Regional Ice Ocean Prediction System (RIOPS; https://science.gc.ca/site/science/en/concepts/prediction-systems/regional-ice-ocean-prediction-system-riops, last access: 8 May 2025; Smith et al., 2018) was developed to produce analyses and forecasts over METAREA 17 and 18 regions but also including all Canadian coastal waters from 44° N in the Pacific Ocean through the Arctic and down to 26° N in the Atlantic Ocean. RIOPS evolved from an initially ice-only system (Buehner et al., 2016; Lemieux et al., 2016) based on the development of the CREG12 ocean configuration (Dupont et al., 2015).

As part of the Year of Polar Prediction (YOPP; Goessling et al., 2016) from 2017–2019, a pan-Arctic high-resolution coupled atmosphere–ocean system was developed and run operationally to support Arctic field campaigns and operational activities. This system, called the Canadian Arctic Prediction System (CAPS; Casati et al., 2023), used the RIOPS ice–ocean configuration coupled to a 3 km resolution atmospheric model to produce 48 h forecasts. This system was retired following YOPP but is now in the process of being reinstalled in 2025.

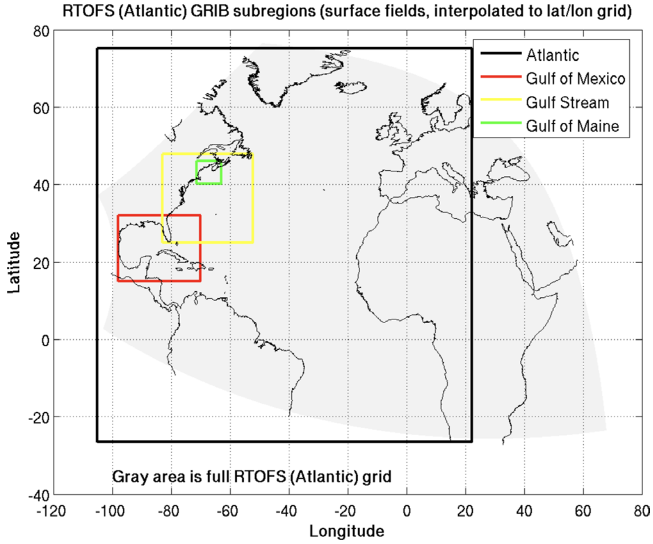


**Figure 10.** RTOFS high-resolution oceanic model spatial domain including subregions (source: https://ocean.weather.gov/index.php, last access: 8 May 2025).

In the United States, the National Oceanic and Atmospheric Administration (NOAA) and the Department of the Navy jointly pushed for the development of robust operational forecasting systems from a regional to a coastal scale to provide support safe maritime operations, including tropical cyclone predictions, search and rescue, response to marine emergencies, and operations near the marginal sea ice zone (Davidson et al., 2021).

NOAA operates different ocean forecasting systems to support monitoring in the US region. The (Atlantic) Real-Time Ocean Forecast System (RTOFS; https://polar.ncep.noaa.gov/ofs/download.shtml, last access: 8 May 2025) is a regional data-assimilating nowcast–forecast system operated by the NCEP, based on the HYCOM model. The grid is telescopic and orthogonal, varying from approximately 4–5 km near the US east coast to almost 17 km near west Africa (Fig. 10) (Mehra and Rivin, 2010). The system runs on a daily basis with a 24 h assimilation hindcast and produces 2D ocean forecasts on hourly basis for sea surface height (m), sea surface salinity (PSU), sea surface temperature (°C), sea surface currents ($m\,s^{-1}$), and mixed layer thickness (m) and 3D ocean forecasts over 40 pressure levels up to 5 d (120 h) for salinity (PSU), temperature (°C), currents ($m\,s^{-1}$), and mixed layer thickness (m).

The NOAA Ocean Prediction Center (OPC), as part of NCEP, maintains and develops five operational desks that run in 10 h shift for the Atlantic Regional, the Atlantic High Seas, the Pacific Regional, the Pacific High Seas, and the Outlook. They are devoted to producing gridded forecasts for hazards, winds, waves, weather and ice accretion, focusing only on US exclusive economic zones. Products for the Atlantic and the Pacific Regional desks include 24 h surface and wind and wave forecasts, while the Atlantic and Pacific High Seas desks produce analysis two times per shift and 48 h forecasts. The Pacific High Seas includes Alaska and Arctic projections in addition to forecast products. The Outlook desk provides medium-range forecasts for 72 and 96 h (source: https://www.weather.gov/marine/, last access: 14 May 2025). In such a context, specific operational services are operated to provide valuable support for any meteo-marine emergency occurring in the region.

The operational Hurricane Analysis and Forecast System (HAFS; https://www.aoml.noaa.gov/hurricane-analysis-and-forecast-system/, last access: 8 May 2025) of NCEP has provided a reliable and skillful model on tropical cyclone track and intensity since 2023. It is forced by atmospheric fields provided by the NOAA Global Forecast System (NCEP GFS) and uses the RTOFS fields as ocean initial and boundary conditions. HAFS is configured with two storm-centric domains with nominal horizontal resolutions of 6 and 2 km, respectively.

The NOAA Tide Predictions (https://tidesandcurrents.noaa.gov/tide_predictions.html, last access: 8 May 2025) system provides tidal forecasts in specific stations located on the west coast, on the east coast, on the gulf coast, in the Pacific, and on the Caribbean islands. Queries are allowed on hourly, 15 min, and 6 min frequencies.

The Instituto de Ciencias de la Atmósfera y Cambio Climático at the Universidad Nacional Autónoma de México (UNAM) has developed and currently maintains a regional forecast system that includes meteorology (for Mexico and adjacent regions), ocean circulation (currently the Gulf of Mexico), waves (global and regional with higher resolution), sea level, tides and storm surge, volcanic ash dispersion, oil spill dispersion in the ocean, and fire smoke dispersion.

The different components of the system began to work in different years, and UNAM has tried to keep them working every day of the year, being successful at more than 99 % of the time. This system of models is the base of other systems that are developed for other institutions such as the Mexican National Weather Service, PEMEX (e.g., the national oil company), and CENAPRED, which is part of the national civil system protection. Table 2 summarizes the main characteristics of systems operating in Mexico.

The operational ocean circulation model for the Gulf of Mexico circulation operates at a resolution of $1/25°$ of a degree using HYCOM, generating hourly output on a daily basis. The model utilizes a distinct bathymetry and coastline compared to the HYCOM Consortium's model. Surface forcings are provided by our WRF model, while global HYCOM data are used for open boundary conditions. Initial conditions are derived from global HYCOM, with a restart from the previous forecast if necessary. We are currently developing an in-house data assimilation technique for improving initial conditions. UNAM employs the WAVEWATCH III model on a structured grid for wave forecasting. A global wave model, driven by the Global Forecast System at a 1° resolution, provides boundary conditions for two regional models: one covering the Gulf of Mexico and the northwestern Caribbean Sea and the other covering the eastern tropical Pacific. Both regional models operate at a 15 km resolution, utilizing hourly surface forcings from our WRF model. Storm surge forecasting is conducted using the ADCIRC model on a nonstructured mesh in two domains: one covering the Gulf of Mexico and the northwestern Caribbean Sea and the other covering the eastern tropical Pacific. The model resolution along the coastline of these domains is at least 500 m resolution. Open boundary conditions are provided by eight tide components from the TP9 model, with surface forcings obtained from our WRF model. The model produces forecasts for up to 120 h, with hourly outputs.

## 9.2 Coastal systems

In the fourth phase of growth in Canadian operational oceanography there was a recognition of the need for improved coastal surface currents to support environmental emergency response (e.g., for oil spills) and for electronic marine navigation (e-Nav) as part of the Government of Canada's Ocean Protection Plan (OPP). Supported by OPP funding, the CONCEPTS initiative developed a 2 km Coastal Ice-Ocean Prediction System (CIOPS) for the east and west coasts (Paquin et al., 2024). The ocean analyses for CIOPS are now used to initialize coupled atmosphere–ice–ocean forecasts covering the Great Lakes and Canadian east coast as part of the Water Cycle Prediction System (Durnford et al., 2018). As a result, the coupled GSL system was retired in 2021.

A cascade of grids was then used to provide boundary conditions from CIOPS for six port ocean prediction systems (POPSs). The POPS domains include Kitimat, Vancouver Harbor, and Fraser River on the west coast and Canso, St. John Harbor, and the St. Lawrence Estuary on the east coast (DFO, 2023). These systems provide high-resolution surface currents for electronic navigation, with resolutions down to 20 m (Paquin et al., 2020).

While various biogeochemical modeling applications have been made for Canadian coastal regions, these have yet to culminate in an organized operational service. Discussions are underway regarding the specific needs and how these can be met (Lavoie et al., 2025).

The operational CONCEPTS system products are available through the Meteorological Service of Canada Open Data platform (Data list/Liste des données – MSC Open Data/Données ouvertes du SMC), including direct data access and geospatial web services (Fig. 11). Data are also available for download and visualization from the Ocean

**Table 2.** Principal characteristics of the core services operating in Mexico.

| Component | Model | Domain | Resolution | Start date |
|---|---|---|---|---|
| Meteorology | WRF-UNAM (https://pronosticos.atmosfera.unam.mx/operativo/index.php/meteorologia, last access: 8 May 2025) | 122.5 to 75.0° W and 0.0 to 37.0° N | 15 km/5 km | 2007 |
| Ocean circulation | HYCOM-UNAM (https://pronosticos.atmosfera.unam.mx/hycom/index.php, last access: 8 May 2025) | 18.0 to 32.0° N and 98.0 to 76.0° W | 1/25° | 2014 |
| Waves | WAVEWATCH III-UNAM | 15.0 to 38.0° N and 100.0 to 75.0° W | 15 km | 2009 |
| Tides and storm surge | ADCIRC-UNAM (https://pronosticos.atmosfera.unam.mx/operativo/index.php/marea-de-tormenta, last access: 8 May 2025) | Two domains: (a) one for the Gulf of Mexico and (b) the other for the eastern tropical Pacific of Mexico | Variable, with higher resolution near the shoreline which is 500 m | 2017 |
| Volcanic ash dispersion | FALL3D-WRF-UNAM (https://pronosticos.atmosfera.unam.mx/operativo/index.php/dispersion-de-cenizas, last access: 8 May 2025) | For the Popocatépetl volcano: 101.0 to 96.0° W and 17.0 to 21.0° N | 5 km | 2017 |
| Oil spill module | Quetzal-UNAM (https://pronosticos.atmosfera.unam.mx/hycom/index.php/modelacion-de-derrames-de-petroleo, last access: 8 May 2025) | Can be applied in regions that have meteorology and oceanic data. Mainly the Gulf of Mexico | Almost continuous since it is Lagrangian | 2023 |
| Smoke module | Tezcatlipoca-UNAM (https://pronosticos.atmosfera.unam.mx:20001/, last access: 8 May 2025) | Can be applied in any region with wind data from model (at least the same as our WRF) | Almost continuous since it is Lagrangian | 2023 |

Navigator (https://www.oceannavigator.ca/public/, last access: 8 May 2025).

At the coastal scale, many OOFSs are operated by NOAA/NCEP to support safety and navigation.

- In the North Pacific, five systems are available:
  - The West Coast Operational Forecast System (WCOFS; https://tidesandcurrents.noaa.gov/ofs/wcofs/wcofs.html; last access: 14 May 2025) is a high-resolution forecasting system that operates on the west coast, providing 3 to 7 d forecasts for sea level, currents, temperature, and salinity. The system is based on ROMS, implemented in a spatial domain that stretches along the western coast of the North American continent from 24° N (Mexico) to 54° N (British Columbia), with a horizontal resolution that varies from 2 to 4 km. It assimilates SST, sea surface currents (SSUV), and SLAs using the 4DVAR scheme (Kurapov et al., 2017).

- The Cook Inlet Operational Forecast System (CIOFS; https://tidesandcurrents.noaa.gov/ofs/ciofs/ciofs.html, last access: 8 May 2025) generates water levels, water temperature and salinity, and winds' nowcast and forecast up to 48 h, four times per day. The system is based on ROMS and uses an orthogonal grid with horizontal resolution that spans 10 m within the estuaries and navigation channels to 3.5 km near offshore waters.

- The Salish Sea and Columbia River Operational Forecast System (SSCOFS; https://tidesandcurrents.noaa.gov/ofs/dev/sscofs/sscofs_info.html, last access: 8 May 2025) provides nowcast and forecast for water levels, currents, water temperature, and salinity, incorporating river forcing from available observations and tidal forcing. The model has an unstructured triangular grid. The resolution varies from ∼ 100 m along the shoreline to 500 m in deeper parts of Puget Sound and the Georgia Basin and increases to

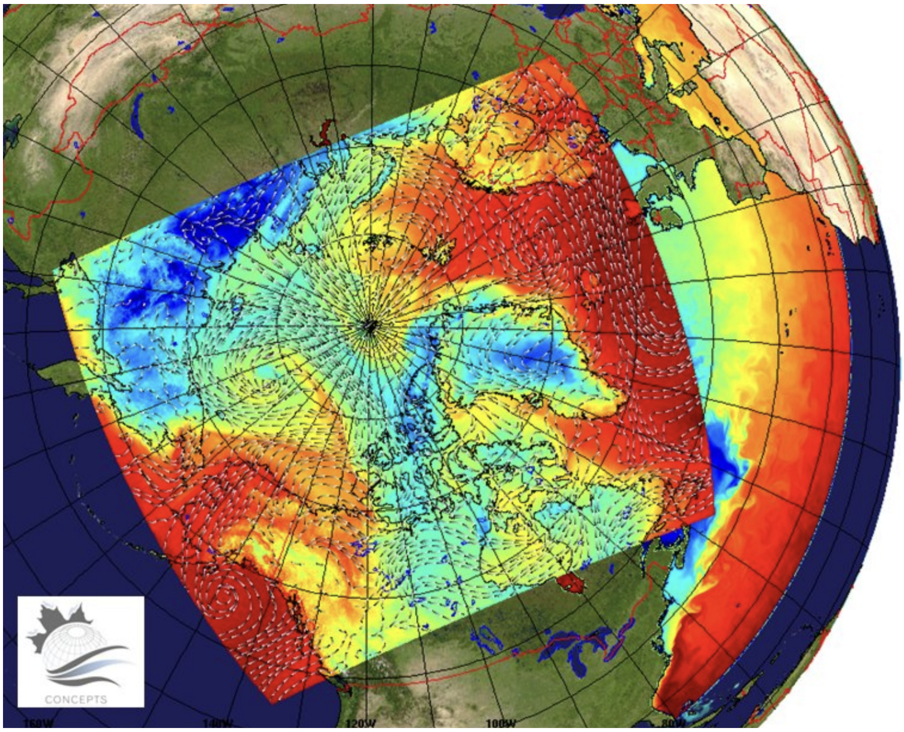


**Figure 11.** Model domain used for the CONCEPTS Canadian Arctic Prediction System (CAPS), which includes a 3 km resolution atmospheric configuration coupled to the RIOPS ice–ocean configuration. The atmospheric surface temperature and winds are overlaid on a map of sea surface temperature for RIOPS. Note that the ice–ocean domain has been extended to include the North Pacific Ocean down to 44° N.

10 000 m over the continental shelf. Resolution in the Columbia River varies between 100 and 200 m.

  - The San Francisco Bay Operational Forecast System (SFBOFS; https://tidesandcurrents.noaa.gov/ofs/sfbofs/sfbofs_info.html, last access: 8 May 2025) is based on FVCOM for providing nowcasts and forecasts of water levels, temperature, and salinity in the San Francisco Bay and in the San Francisco Bay Entrance. The grid has a minimum depth of 0.2 m and maximum depth of 106.8 m. Grid resolution ranges from 3.9 km on the open-ocean boundary to approximately 100 m near the coast, indicating the flexibility of the grid size based on bathymetry from the deep ocean to the coast. Additionally, the higher resolution along the navigational channels within the bay, from approximately 100 to 10 m, provides detailed current features.

- In the Great Lakes, four FVCOM-based operational systems are available:

  - the Lake Erie Operational Forecast System (LEOFS; https://tidesandcurrents.noaa.gov/ofs/leofs/leofs_info.html; last access: 8 May 2025) at horizontal resolution from 400 m to 4 km, with higher resolution along the shoreline and in the shallow western basin and coarser resolution for the open waters in the middle and eastern basins;

  - the Lake Michigan and Huron Operational Forecast System (LMHOFS; https://tidesandcurrents.noaa.gov/ofs/lmhofs/lmhofs_info.html, last access: 8 May 2025), at horizontal resolution from 50 m to 2.5 km, with higher resolution along the shoreline and in the shallow western basin and coarser resolution for the open waters in both lakes;

  - the Lake Ontario Operational Forecast System (LHOFS; https://tidesandcurrents.noaa.gov/ofs/loofs/loofs_info.html, last access: 8 May 2025), at horizontal resolution from 200 m to 2.5 km, with higher resolution along the shoreline;

  - the Lake Superior Operational Forecast System (LSOFS; https://tidesandcurrents.noaa.gov/ofs/lsofs/lsofs_info.html, last access: 8 May 2025), at horizontal resolution 200 m to 2.5 km, with higher resolution along the shoreline.

- In the Gulf of Mexico, two systems are available:

  - The northern Gulf of Mexico Operational Forecast System (NGOFS2; https://tidesandcurrents.noaa.gov/ofs/ngofs2/ngofs.html, last access: 8 May 2025) is based on FVCOM with a resolution from

10 km on the open ocean to approximately 600 m near the coast. Additional refinement of the grid is provided within the bays from 45 to 300 m. The system runs four times per day, providing a forecast up to 48 h.

  - The Tampa Bay Operational Forecast System (TBOFS; https://tidesandcurrents.noaa.gov/ofs/tbofs/tbofs_info.html, last access: 8 May 2025), based on ROMS, has a resolution from 100 m to 1.2 km. It has been designed to include the whole of Tampa Bay and the shelf to properly represent the dynamics at the entrance to the bay.

- In the Atlantic, five ROMS-based systems provide nowcasts and forecasts up to 48 h four times per day:

  - the Chesapeake Bay Operational Forecast System (CBOFS; https://tidesandcurrents.noaa.gov/ofs/cbofs/cbofs_info.html, last access: 8 May 2025), with a resolution spanning 30 m to 4 km;

  - the Delaware Bay Operational Forecast System (DBOFS; https://tidesandcurrents.noaa.gov/ofs/dbofs/dbofs_info.html, last access: 8 May 2025), with a resolution ranging from 100 m up to 3 km;

  - the Gulf of Maine Operational Forecast System (GoMOFS; https://tidesandcurrents.noaa.gov/ofs/gomofs/gomofs_info.html, last access: 8 May 2025), at 700 m resolution approximately, with forecast horizon up to 72 h;

  - the New York and New Jersey Operational Forecast System (NYOFS; https://tidesandcurrents.noaa.gov/ofs/nyofs/nyofs.html, last access: 8 May 2025), which provides water levels and currents using a grid with horizontal resolution from 5 m to 7.5 km;

  - the St. John's River Operational Forecast System (SJROFS; https://tidesandcurrents.noaa.gov/ofs/sjofs/sjofs_info.html; last access: 8 May 2025), with horizontal resolution from 80 m to 4 km.

Academia, governmental institutes, and the private sector cooperate for improving numerical modeling, engaging the enterprise to accelerate scientific research and excellence in US coastal predictions. Examples of coastal systems that are developed in the United States include the following:

- The Coastal Storm Modeling System (CoSMoS), developed by the United States Geological Survey (USGS), is a storm-induced coastal flooding, erosion, and cliff failures system for the north-central coast, San Francisco Bay, southern California, and the central California coast (Barnard et al., 2014).

- The West Florida Coastal Ocean Model (WFCOM), developed by the USF College of Marine Science in Florida, is an unstructured grid FVCOM in the eastern Gulf of Mexico that provides water level (storm surge) forecasts as well as surface currents and surface salinity (Zheng and Weisberg, 2012).

- The South Florida Hybrid Coordinate Ocean Model (SoFLA-HYCOM) Shelf Circulation, developed by the University of Miami, has a resolution that spans 1/25° to 2 m close to the coast and includes shelf areas, shallow embayment, and the deep Straits of Florida (between Florida and Cuba) (Kourafalou et al., 2009).

- LiveOcean, developed by the University of Washington – Coastal Modelling Group, is mainly used for research applications. It provides 3 d forecasts of currents, temperature, salinity, and many biogeochemical variables in the US Pacific Northwest. The model horizontal resolution is 500 m in the Salish Sea and near the Washington coast, growing to 3 km at the offshore boundaries (source: https://faculty.washington.edu/pmacc/LO/LiveOcean.html, last access: 14 May 2025).

## 10 Arctic region

In contrast to lower-latitude models, Arctic Ocean forecast models are focused on simulating the correct sea ice conditions, with the ocean below the mixed layer being of secondary importance on short timescales. However, this situation is expected to change with the retreating ice cover in the Arctic Ocean driving impacts on ocean ecosystems and increased activity across the Arctic region. There are 10 global models that are used for Arctic forecasting. There are also several regional models available and a handful of coastal models. Most models with Arctic forecasts are from national institutes that either represent large centers with dominant global forecasting platforms, have a large amount of Arctic research, or have an interest in maintaining a model due to having a border with the Arctic.

Given the focus around sea ice, there are several similarities across all forecasting systems, regardless of the domain. Firstly, all models must have a sea ice component. Almost all models use CICE as their sea ice model, with multiple sea ice thickness categories. The Arctic Ice Ocean Prediction System (ArcIOPS) uses the sea ice model in MITgcm, while VENUS uses the ice component of POM, the GLO-MFC physical analysis and forecasting system uses LIM2 and the Met Office FOAM and coupled models use CICE currently but will move to using SI3 in the future. The FIO-COM10 model uses the SIS sea ice model. The majority of forecasting models with an ocean component use HYCOM or NEMO for their ocean model; the exceptions are ArcIOPS (MITgcm), NOAA PSL (POP2), and FIO-COM10 (MOM5).

Most of the models have an ice–ocean coupling and use an atmospheric forcing that has been created for a weather forecast; examples are those from ECMWF, the Regional Deterministic Prediction System, and NAVGEM. Four of the models identified – one regional model (NOAA PSL CAFS) and three global models (NAVY-ESPC, Met Office coupled system and ECMWF) – are fully coupled to the atmosphere.

Another similarity between all models is the output variables. Those models with an ocean component provide standard variables (temperature and salinity) with most also providing velocities and sea surface height. Each model also provides the standard sea ice variables (sea ice concentration, sea ice thickness, and sea ice velocities) as outputs, generally at hourly resolution. Additionally, all models use some form of data assimilation over the initial part of the simulation before the forecast begins (usually one day). This is an important part of Arctic forecasting given that the ability to forecast sea ice depends heavily on the initial conditions. Most models assimilate the standard ocean variables (SST, sea surface salinity (SSS), sea surface height (SSH), and temperature and salinity profiles) and sea ice concentration.

Finally, perhaps one of the most important considerations for users is whether the data are readily available and easily downloadable. The requirement for this varies greatly depending on the user, but those needing information on ships in the Arctic, for example, will need quick access across potentially low bandwidth. All models related to the Copernicus Marine Service (neXtSIM-F, TOPAZ5, Arctic Ocean Biogeochemistry Analysis and Forecast, and Global Ocean Physical Analysis and Forecasting) are available to download for free from the Copernicus Marine website, and there is a visualization tool on the information page. Most other modeling systems have data for download and a visualization, although sometimes in different places; these are the Barents-2.5km, NOAA ice drift, NOAA PSL, RIOPS, GIOPS, GOFS3.1, and RTOFS. The systems from DMI and GOFS16 have a web page displaying the forecasts. As noted in Sect. 9, the CONCEPTS systems (GIOPS, RIOPS, CIOPS) are available through the Meteorological Service of Canada Open Data platform (Sect. 9 provides additional details). The ArcIOPS, FIO-COM10 and NAVY-ESPC systems are well-documented in the literature, but it is hard to find a website that states where/if downloading is available. The latter suggests some outputs are available for researchers if they register for a login, but it is not stated how other users can access the data. Similarly, it is difficult to find information on how to access outputs from the Met Office FOAM and its coupled data assimilation counterpart. For the global ECMWF model, some data are available, but users must pay for other variables.

There are strong crossovers between the global and regional models, and therefore specific details of both domains (covering the full Arctic) are provided below together, followed by the Arctic coastal forecasts.

## 10.1 Regional systems

Several institutions are operating regional services in the Arctic

- The Arctic Ice-Ocean Prediction System ArcIOPS, available at http://www.oceanguide.org.cn/IceIndexHome/ThicknessIce (last access: 8 May 2025; Liang et al., 2019), is managed by the National Marine Environmental Forecasting Center, China. It spans the Arctic region down to 55° north. It uses MITgcm and provides 168 h forecasts at 18 km resolution.

- The Danish Meteorological Institute (DMI) operates an ocean forecasting system utilizing the HYCOM-CICE model (Ponsoni et al., 2023; https://ocean.dmi.dk/models/hycom.uk.php, last access: 8 May 2025). This coupled ocean and sea ice model covers the Atlantic Ocean north of approximately 15° S and the Arctic Ocean, including Greenlandic waters. The system features a horizontal resolution ranging from about 4–5 km in the Arctic regions to approximately 10 km further south. It is forced by atmospheric data from the European Centre for Medium-Range Weather Forecasts (ECMWF) and produces 144 h forecasts twice daily, at 00:00 and 12:00 UTC.

- The neXtSIM-F forecasting system (Williams et al., 2021; https://data.marine.copernicus.eu/product/ARCTIC_ANALYSISFORECAST_PHY_ICE_002_011/description, last access: 8 May 2025) is a standalone sea ice model developed by the Nansen Environmental and Remote Sensing Centre (NERSC). It utilizes the neXtSIM model, forced by the TOPAZ ocean forecast and ECMWF atmospheric forecasts. The system assimilates OSI SAF (https://osi-saf.eumetsat.int/, last access: 8 May 2025) sea ice concentration products daily, adjusting initial conditions and applying compensating heat fluxes to enhance forecast accuracy.

- The National Institute of Polar Research (NIPR; https://www.nipr.ac.jp/sea_ice/e/forecast/, last access: 8 May 2025) in Japan provides Arctic Sea ice forecasts through its Arctic Sea Ice Information Centre. These forecasts are disseminated periodically, with reports typically released in May, July, August, and October each year. The May to August reports focuses on predicting the opening dates of Arctic sea routes and the sea ice distribution through September, while the October report forecasts sea ice distribution for the period of sea ice extension from October onward.

- The NOAA Physical Sciences Laboratory (PSL; https://psl.noaa.gov/forecasts/seaice/about.html, last access: 8 May 2025) operates the Coupled Arctic Forecast System (CAFS), an experimental sea ice forecasting model. CAFS is a fully coupled ice–ocean–atmosphere model adapted from the Regional Arctic System Model (RASM) and includes components such as the Weather Research and Forecasting (WRF) atmospheric model, the Parallel Ocean Program (POP) ocean model, the Los Alamos Community Ice Model (CICE), and the Community Land Model (CLM). All components run at a horizontal resolution of 10 km. The system is initialized with the NOAA Global Forecast System (NCEP GFS) analysis and Advanced Microwave Scanning Radiometer 2 (AMSR2) sea ice concentrations. CAFS produces 10 d sea ice forecasts daily, with outputs posted online at 02:00 UTC.

- The Regional Ice-Ocean Prediction System (RIOPS; https://science.gc.ca/eic/site/063.nsf/eng/h_97620.html, last access: 8 May 2025; Smith et al., 2021) is operated by the Canadian Meteorological Centre (CMC). It employs the Nucleus for European Modelling of the Ocean (NEMO) coupled with the Los Alamos Sea Ice Model (CICE). The system is forced by atmospheric data from the Global Deterministic Prediction System (GDPS) and provides a forecast horizon of up to 48 h. The model domain covers the North Pacific Ocean from the Bering Strait and the whole of the Arctic Ocean and the North Atlantic down to 26° N, with a horizontal resolution of approximately 3–4 km over the Arctic Ocean. A fully coupled forecast system called the Canadian Arctic Prediction System, which uses RIOPS and a pan-Arctic atmospheric configuration at 2.5 km resolution, is currently being reinstated (see Sect. 8 for details) following its retirement in 2021.

- The TOPAZ5 system (https://data.marine.copernicus.eu/product/ARCTIC_ANALYSISFORECAST_PHY_002_001/description, last access: 8 May 2025) is maintained by the NERSC. It utilizes the HYCOM model coupled with the Ensemble Kalman Filter for data assimilation. The system is forced by atmospheric data from the ECMWF and provides a forecast horizon of up to 10 d. The model domain encompasses the North Atlantic Ocean and the Arctic Ocean with a horizontal resolution of approximately 6.25 km.

- The VENUS forecasting system (Yamaguchi, 2013) is operated by the Norwegian Meteorological Institute (MET Norway). It employs the NEMO ocean model coupled with the LIM3 sea ice model. The system is forced by atmospheric data from the AROME-Arctic weather prediction model and provides a forecast horizon of up to 66 h. The model domain covers the Barents Sea and adjacent Arctic waters with a horizontal resolution of 4 km.

There are several characteristics to be highlighted in these systems:

- Most models are either coupled ice–ocean or coupled ice–ocean–atmosphere models. However, there are a few exceptions to this. The regional model neXtSIM-F is a standalone sea ice model that uses TOPAZ5 ocean and ECMWF atmosphere forecast forcings and therefore only outputs sea ice variables. It is the only model to use a Lagrangian framework and a non-standard rheology. TOPAZ5 is the only model that has a version with a coupling to ECOSMO, a biogeochemical model, and additionally assimilates chlorophyll for input to this.

- The lowest resolution of the provided models is the regional ArcIOPS, at around 18 km. The resolution of the regional models is comparable to the global models.

- Apart from RIOPS, which runs for 84 h at hourly resolution, most models covering the full Arctic domain provide outputs for 5 to 10 d, ranging from hourly output to daily output. NOAA ice drift and NAVY-ESPC provide forecasts for up to 16 d; the latter can also give information for up to 45 d but at a lower resolution.

- Some models also provide additional sea ice variables; RIOPS, for example, and its global equivalent GIOPS, provide ice pressure, while TOPAZ5 provides sea ice type, albedo, and snow depth. The VENUS models include wave information. TOPAZ5 running with ECOSMO outputs several biogeochemical variables including dissolved inorganic carbon, oxygen, nitrate, chlorophyll, and phytoplankton.

- The VENUS model is unique in that it provides map-based forecasts for aiding ship navigation (generally in support of research cruises) and is deployed on demand rather than running continuously.

### 10.2 Coastal systems

There are a few coastal models available in the Arctic region.

- The coastal version of the DMI forecast model covers the Greenland region at 4–5 km resolution and uses HYCOM-CICE like its regional version. It produces forecasts up to 144 h ahead and is updated twice a day.

- The Barents-2.5km model (https://ocean.met.no/models, last access: 8 May 2025) covers the Barents Sea and Svalbard region (Röhrs et al., 2023). ROMS is run at a spatial resolution of 2.5 km with an Arctic-specific atmospheric forcing, AROME-Arctic, providing forecasts up to 66 h ahead, and is updated every 6 h.

- The "storm surge" service (https://ocean.met.no/models, last access: 8 May 2025) is a ROMS model run in barotropic mode, covering the northern North Atlantic, Barents Sea, and Svalbard up to the entrance to the Arctic Basin. It uses the MEPS 2.5 km atmospheric model for outputs, providing forecasts for 120 h updated every 6 h. Its main purpose is to simulate sea level and storm conditions.

– The CIOPS-E system (Paquin et al., 2024) is a 1/36° (around 2 km) resolution NEMO-CICE coupled model that is forced by the High-Resolution Deterministic Prediction System atmospheric forcing and covers the east coast of Canada. During its assimilation, it also uses RADARSAT satellite images. In addition to standard sea ice and ocean variables, it outputs snow depth on sea ice and ice pressure at hourly frequency for the following 48 h.

## 11 Conclusions

The global landscape of ocean forecasting services demonstrates a solid and mature foundation, particularly through the widespread availability and reliability of global models. These models provide essential large-scale information and underpin the functionality of numerous regional and coastal systems. However, despite their robustness, global models often lack the resolution required to address the finer-scale dynamics necessary for many localized applications, particularly in coastal zones and regions with complex bathymetry or strong human–ocean interactions.

A clear disparity exists in the coverage and capabilities of regional and coastal forecasting systems. Some areas, particularly in developed regions, benefit from dense, high-resolution services, while others – especially in less-resourced coastal regions – remain underrepresented or underserved. Furthermore, while physical and wave modeling systems have seen significant advancements and widespread implementation, biogeochemical models lag behind in both availability and operational maturity. This gap limits our ability to provide comprehensive ecosystem forecasts and hampers decision-making related to marine biodiversity, fisheries, and water quality.

Looking forward, emerging technologies such as artificial intelligence (AI; Heimbach et al., 2025, in this report) hold immense potential to bridge these gaps. AI techniques can enhance model downscaling, fill data-sparse regions, and optimize system performance, thereby reducing disparities in forecasting capacities globally. However, while technological solutions are making impressive advancements and can have a great impact in the implementation of the ocean value chain (Ciliberti and Coro, 2025, in this report; Porter and Heimbach, 2025, in this report) they remain insufficient on their own. Continued efforts in community building, knowledge sharing, and capacity development are paramount. Initiatives such as those promoted under the United Nations Decade of Ocean Science for Sustainable Development provide critical platforms for fostering collaboration, developing shared tools, and ensuring equitable access to forecasting capabilities across all regions.

In this context, the OceanPrediction DCC Architecture (Alvarez Fanjul et al., 2024a) offers a significant opportunity to promote the development of robust ocean forecasting services worldwide. By providing a structured, modular framework for the development of forecasting systems, it facilitates interoperability, scalability, and the integration of these systems. The concept of the Operational Readiness Level for ocean forecasting (Alvarez Fanjul et al., 2024b), developed within the DCC framework, will contribute to the quality of the system by supporting the application of best practices. These tools, when combined, have the potential to accelerate the creation of new regional and coastal systems, while simultaneously enhancing the quality, reliability, and user engagement of existing ones.

By aligning technological innovation with inclusive community-driven approaches, the global ocean forecasting community can work towards a more comprehensive, high-resolution, and biogeochemically informed future, better serving society's growing and diverse needs.

**Data availability.** No data sets were used in this article.

**Author contributions.** MC designed, supervised, and validated the overall manuscript. All authors contributed to writing and revising the paper. Section 2 was additionally revised by EAF. EAF and MC conceptualized and wrote Sect. 1. WM wrote Sect. 3, SJ wrote Sect. 4, JV and JS wrote Sect. 5, EC wrote Sect. 6, and AC and GES co-wrote Sect. 7. BD, MD, IM, DN, CGS, CAST, and MC collaborated on Sect. 8, while GCS, PH, SC, and JZH contributed to Sect. 9. HR wrote Sect. 10. EAF and MC also contributed to the Conclusions.

**Competing interests.** At least one of the (co-)authors is a member of the editorial board of *State of the Planet*. The peer-review process was guided by an independent editor, and the authors also have no other competing interests to declare.

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**Acknowledgements.** The authors appreciated the effort of the reviewers, whose constructive comments and suggestions greatly improved the quality of this paper.

**Review statement.** This paper was edited by Swadhin Behera and reviewed by Pierre-Yves Le Traon and one anonymous referee.

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State Planet, 5-opsr, 6, 2025
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# A description of ocean forecasting applications around the globe

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Received: 13 September 2024 – Discussion started: 22 November 2024
Revised: 10 March 2025 – Accepted: 26 March 2025 – Published: 2 June 2025

**Abstract.** Operational oceanography can be considered the backbone of the blue economy: it offers solutions that can support multiple UN Sustainable Development Goals by promoting the sustainable use of ocean resources for economic growth, livelihoods and job creation. Given this strategic challenge, the community worldwide has started to develop science-based and user-oriented downstream services and applications that use ocean products as provided by forecasting systems as main input. This paper provides examples of stakeholder support tools offered by such applications and includes sea state awareness, oil spill forecasting, port services, and fishing and aquaculture. Also emphasized is the important role of ocean literacy and citizen science to increase awareness of and education about these critical topics. Snapshots of various applications in key world ocean regions, within the framework of the OceanPrediction Decade Collaborative Centre (DCC), are illustrated, with

emphasis given on their level of maturity. Fully operational examples can be used as inspiration for export to other areas.

## 1 Introduction

The World Bank defines the blue economy as the sustainable use of ocean resources for economic growth and improved livelihoods and jobs while preserving the health of the ecosystem. The blue economy has the potential to help address many of the UN Sustainable Development Goals including no poverty, zero hunger, affordable and clean energy, decent work and economic growth, climate action, and life below water. Various programmes and associated actions of the UN Decade of Ocean Science for Sustainable Development (https://oceandecade.org/, last access: 4 May 2025) are designed to provide the science to support the blue economy as well as ensuring the resilience of both marine ecosystems and coastal populations. A key objective of several of the programmes is the development of improved coast-to-ocean forecasts and predictions and, most essentially, their uptake by and usefulness to coastal stakeholders. To achieve this and to support the development of a sustainable blue economy, the operational oceanography community should be able to support the development of downstream applications in which model data are transformed into tailored information for end users. These applications are intended to create applied solutions to various societal, environmental and scientific challenges from which both public entities and private companies can benefit and actively take part in the implementation of the so-called "value chain". The ETOOFS (Expert Team on Operational Ocean Forecasting Systems) Guide on Implementing Operational Ocean Monitoring and Forecasting Systems (Alvarez Fanjul et al., 2022) provides a thorough overview of the need for downstream services as well as examples of advanced systems that include portals for the dissemination of sea state awareness (e.g. https://data.marine.copernicus.eu/, last access: 4 May 2025); oil spill forecasting (e.g. MOTHY (http://www.meteorologie.eu.org/mothy/, last access: 4 May 2025), WITOIL (https://www.witoil.com/, last access: 4 May 2025); MEDSLIK-II (https://www.medslik-ii.org/, last access: 4 May 2025)); port services (e.g. SAMOA (https://www.puertos.es/, last access: 4 May 2025) and Aquasafe (https://hidromod.com/?s=aquasafe, last access: 4 May 2025)); voyage planning (e.g. VISIR (https://www.visir-model.net/, last access: 4 May 2025)); and fishing and aquaculture.

In this chapter, we provide only some examples of existing downstream services for eight of the nine regions identified by the OceanPrediction Decade Collaborative Centre (DCC): the West Pacific and Marginal Seas of South and East Asia, Indian Seas, African Seas, Mediterranean and Black Sea, North East Atlantic, South and Central America, North America, and the Arctic. The Antarctic region is not included in this review of downstream services due to the lack of services provided there. The distribution of the regions is based on both the UNEP (United Nations Environment Programme) and the GOOS Regional Alliances (GRAs), with some clustering.

The regional sections have been prepared by each of the regional teams of the OceanPrediction DCC (https://www.unoceanprediction.org/en/about/community, last access: 4 May 2025), and, though not comprehensive, each provides a flavour of the needs in each region as well as some of the downstream application services developed to meet them and their maturity levels. The downstream applications have been broadly grouped as follows: extremes, hazards and safety; natural resources and energy; shipping, ports and navigation; and climate adaptation. Specific contributions for each grouping may differ per region. Extremes, hazards and safety refers to all extreme events, both offshore (such as marine heat waves) and coastal (such as storm surges); marine pollution (that includes water quality and oil spills); and search-and-rescue (SAR) operations. Natural resources and energy refers to all downstream applications associated with the sustainable exploitation of marine resources (we include aquaculture); renewable energy, tourism and recreation; and conservation efforts. Shipping, ports and navigation includes operational support for research activities (including cruise-track optimization as well as deploying equipment), and climate adaptation focuses on longer-timescale tools that are provided to support coastal and ecosystem resilience. The examples provided are primarily based on public sector forecasting systems and services, with a few exceptions. The OceanPrediction DCC Atlas of Services (https://www.unoceanprediction.org/en/atlas, last access: 4 May 2025), will contain a more complete list of downstream services in each of the regions.

## 2 The West Pacific and Marginal Seas of South and East Asia

In the West Pacific and its marginal sea region, development of operational ocean forecast systems was initiated by governmental operational/research agencies related to meteorology, hydrography and oceanography in several countries including Australia, China, Japan, South Korea, Indonesia and Aotearoa / New Zealand. Several downstream services led by governmental operational agencies have been developed that focus on support of search-and-rescue operations and preparation for marine disasters. Recently, some industrial applications for fishery and shipping operations have been developed based on close collaborations between scientists and targeted users.

As a one-stop shop for the provision of downstream applications with support from the Ocean Decade Collaborative Centre on Ocean–Climate Nexus and Coordination (DCC-OCC) and the Ocean to Climate Seamless Forecasting (OSF) programme, China is developing a COAST Toolkit as a knowledge hub and information platform for decision-makers and scientists to obtain information services for action. The toolkit aims to address the challenge of marine and coastal disaster prevention and resources development based on ocean solutions. There are six main modules included in the COAST Toolkit: Module 1 – Marine disasters prevention and mitigation; Module 2 – Maritime navigation safety, including in the Arctic; Module 3 – Coastal ecosystem health; Module 4 – Integrated coastal zone management; Module 5 – Blue economy support; Module 6 – Ocean literacy. COAST will deliver predictive capacities, services and products for marine and coastal systems. The products will link field data with complex models and applications with visualization.

Examples of various downstream applications in the West Pacific and Marginal Seas of South and East Asia are provided in the sections below.

### 2.1 Extreme, hazards and safety

Aotearoa / New Zealand's Moana Project (https://www.moanaproject.org/, last access: 4 May 2025) has developed an interactive particle tracking tool (https://www.moanaproject.org/particle-tracker, last access: 4 May 2025) on their web portal that allows users to release particles, plankton or larvae into either hindcast or forecast models, based on global or their regionally optimized simulations. This tool supports not only offshore safety operations and oil spill response but also fisheries.

The Ocean and Climate Early Warning Universal System (OCEANUS), developed by the First Institute of Oceanography (FIO) in China, with the support of the Ocean to Climate Seamless Forecasting System (OSF) Ocean Decade programme, is a similar example of a platform that supports various early-warning downstream applications. The OCEANUS platform automatically integrates multi-source observational data, an operational forecast system developed by FIO (the Global Ocean Environment Forecast System; for more information refer to Qiao et al., 2019), automatic post-processing of forecast results, and real-time transmission and release of forecast products. The forecast system supports three downstream applications on the OCEANUS platform: the Global Coral Reef Bleaching Early Warning System, Global Maritime Search and Rescue Forecast System and Global Oil Spill Response System. Detailed information can be found in the OCEANUS brochure at https://osf-un-ocean-decade.com/pdfPreview?id=6401 (last access: 4 May 2025).

The Malaysian Meteorological Department (MMD; also known as Met Malaysia) ocean forecasting system, developed in collaboration with the FIO, provides 5 d forecasts of surface wave heights, wave period, sea level, ocean currents, sea temperature and salinity for the Malaysian and adjacent seas. These forecasts are operationally disseminated through a web portal hosted by the MMD (Fig. 1) and provide early warning to ensure the safety and well-being of marine socio-economic activities in Malaysia through, for example, oil spill and search-and-rescue responses.

Below some examples specific to particular applications within the West Pacific and Marginal Seas of South and East Asia are highlighted.

#### 2.1.1 Search and rescue

The Korea Ocean Observing and Forecasting System (KOOFS) led by the Korea Hydrographic and Oceanography Agency (KHOA) provides forecast information required for SAR operations (Republic of Korea/OceanPredict, 2020). The Japan Coast Guard operates a support system for SAR using an ocean forecasting product provided from the Japan Meteorological Agency (JMA) (Japan Coast Guard, 2025). While also providing ongoing support for SAR, the Australian Bluelink forecast system assisted in the high-profile case of the disappearance of Malaysia Airlines flight MH370 (Schiller et al., 2019).

#### 2.1.2 Oil spills

Oil spill tracking models utilizing ocean forecasting products are also developed in several countries including China, South Korea and Japan. For example, an oil spill tracking model coupled with an ocean circulation–tide–wave coupling model was applied for evaluating potential contamination caused by an accident of an oil tanker Sanchi in 2018 around the East China Sea (Qiao et al., 2019). The Indonesian Agency for Meteorology, Climatology and Geophysics (Badan Meteorologi, Klimatologi, dan Geofisika, BMKG) is operating downscaled model products for forecasting storm surge and coastal inundation hazards around Jakarta and other port cities in Indonesia (Ramdhani, 2019). Coupling of high-resolution coastal ocean current, wave and river flood models is required for forecasting in real-time and evaluating potential inundation locations in the target cites.

#### 2.1.3 Marine heat waves

The Moana Project in Aotearoa / New Zealand aims to improve understanding of ocean circulation, connectivity and marine heat waves to provide information that supports Aotearoa / New Zealand's seafood industry. It provides an operational marine heat wave indicator (https://www.moanaproject.org/marine-heatwave-forecast, last access: 4 May 2025), as well as sea surface temperature anoma-

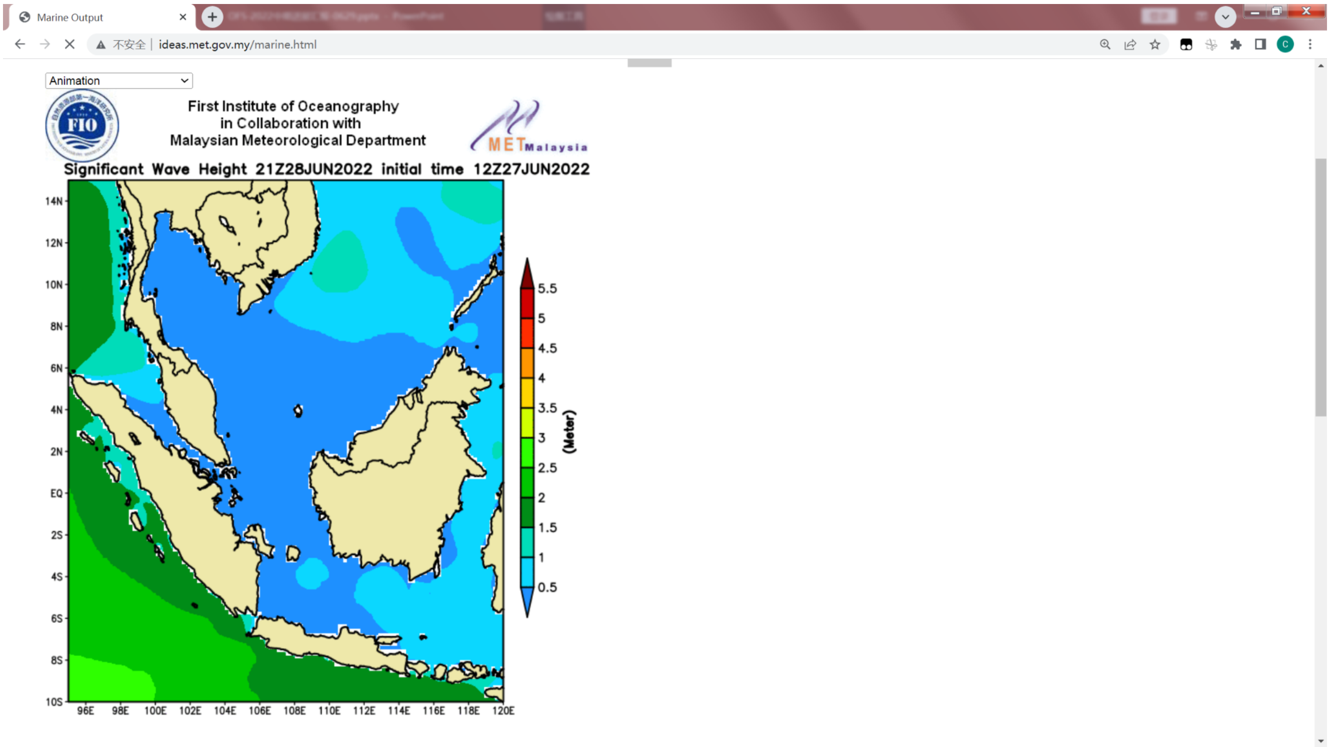


**Figure 1.** A snapshot of the Malaysian Meteorological Department's web portal on which the FIO–MMD ocean forecasting system is disseminated.

lies, based on their regionally optimized operational forecast model.

### 2.2 Natural resources and energy

Decadal timescale reanalysis products of ocean and wave models are used for assessing feasibility of ocean renewable energy development around Japan coastal seas and their adjacent Asian seas (Webb et al., 2020). Reliable estimation of the renewable energy potential associated with waves, ocean currents and thermal energy requires sufficiently long time duration periods for adequately considering the possible time-dependent natural variability. They have evaluated minimum time duration periods of 20 years for wave and 10 years for ocean current and thermal energy conversion around Japan. The high-resolution wave (NOAA WAVEWATCH III) and ocean and tidal current forecast (JAMSTEC JCOPE) models driven by the atmospheric reanalysis forcing were used for calculation of the energy potential reanalysis.

In some cases, ocean forecasting data (JCOPE) have been used for marine environmental assessment for exploration of seafloor resources in the northwestern Pacific such as cobalt-rich ferromanganese crusts (Nagao et al., 2018). Direct velocity measurement using acoustic Doppler current profilers (ADCPs) in deep oceans presents some technical challenges, and combined use of ocean forecasting data and ADCP measurement could be effective for the reliable assessment of ocean current variability around the targeted areas (Nagao et al., 2018).

In Japan, industrial/commercial use of ocean forecasting is being developed for supporting trade ship navigation (Sato and Horiuchi, 2022) and fishery activities (e.g. https://oceaneyes.co.jp/en/home-2, last access: 4 May 2025). An early-warning system of the abrupt occurrences of strong currents damaging set-net fisheries is operated under intensive collaboration between universities and local fishery agencies in Japan (Hirose et al., 2017). Close collaboration among universities, research institutes, instrument companies and fishers demonstrates significant enhancement of marine observation networks through the exchange of ocean forecasting information and in situ observations among them (Nakada et al., 2014; Hirose et al., 2019). In Oceanian seas, Bluelink (https://www.csiro.au/bluelink/, last access: 4 May 2025) forecast products are widely utilized for maritime transport providers, fishing industries and tourism operators.

### 2.3 Shipping, ports and navigation

#### 2.3.1 Defence

The Royal Australian Navy ingests forecast data produced by Bluelink into their System for Acoustic Geo-environmental Exemplification (SAGE) to calculate range predictions (Schiller et al., 2019). These calculate, for a specific ship, the distance they could expect to detect a submarine or be detected by a submarine, based on the current ocean conditions, estimated from the forecasts provided.

#### 2.3.2 Sea level

Sea level is vital for port operations. The Australian Bureau of Meteorology (BOM) provides aggregated sea-level forecasts based on the Bluelink operational systems, superimposed with other factors that influence coastal sea level. Additionally, these forecasts have proven most beneficial when incorporated into existing decision tools that include the BOM river flood warning interface where ocean boundary conditions are improved by the forecasts (Schiller at al., 2019).

### 2.4 Climate adaptation

CSIRO; BOM; and the Australian Government's Department of Climate Change, Energy, the Environment and Water have produced a web portal (https://climatechangeinaustralia.gov.au/en/, last access: 4 May 2025) that provides climate information, projections, tools and data to inform decision-making related to climate change in Australia. The portal incorporates both observational datasets and climate projections.

## 3 Indian Seas

Operational ocean forecast systems and downstream services in the Indian Ocean have several stakeholders, including government agencies, maritime industries, research institutions and the public. The operational oceanographic services for the Indian Seas underwent significant progress during the past 25 years. These functional systems have several components, which include observation networks designed to collect and research teams to analyse and disseminate oceanographic data; assimilate the data to numerical models; and provide forecasts to support decision-making, improve safety and enhance the understanding of the Indian Ocean environment. The Indian Ocean forecasting system, operational at the Indian National Centre for Ocean Information Services (INCOIS) helps several regional small island countries in the Indian Ocean under regional alliances such as Regional Integrated Multi-Hazard Early Warning System for Africa and Asia (RIMES) and the Colombo Security Conclave (CSC). INCOIS serves as the Regional Specialized Meteorological Centre (RSMC) for global numerical ocean and wave prediction for the Indian region as per the WMO mandate. RSMC services are provided to the region through a web portal, which can be accessed at (https://incois.gov.in/oceanservices/rsmc_ocean.jsp, last access: 4 May 2025), with an example of their ocean and wave prediction service provided in Fig. 2. Provided below are some key components and applications of these systems.

### 3.1 Extremes, hazards and safety

#### 3.1.1 Search and Rescue Aid Tool (SARAT)

The Search And Rescue Aid Tool (SARAT; https://sarat.incois.gov.in/sarat/home.jsp, last access: 4 May 2025) is developed for facilitating individuals/vessels in distress in the shortest possible time. This has been initiated and developed under the "Make in India" programme. The tool uses model ensembles that account for uncertainties in the initial location and last known time of the missing object to locate the person or object with high probability – the movement of the lost objects is governed mainly by currents and winds.

#### 3.1.2 Oil spill trajectory prediction

The oil spill prediction system (OOSA; https://incois.gov.in/portal/osf/oosa.jsp, last access: 4 May 2025) operational at INCOIS works based on the GNOME model, which uses ocean currents from an ocean general circulation model and winds from an atmospheric general circulation model to simulate the Lagrangian drift of oil spills, which needs initial location of spill and quantity of the oil and type of oil if available for producing movement of oil under the influence of winds and currents.

#### 3.1.3 Marine heat wave advisory services (MHAS)

Marine heat waves refer to the anomalous (above the 90th percentile) increase in sea surface temperature compared to the historical (past 30 years) values persistent over 5 consecutive days. These heat waves have a profound impact on marine ecology and fisheries and marine biodiversity. In view of the environmental significance of marine heat waves, India started generating marine heat wave advisories and made them available as a service through the web portal (https://incois.gov.in/portal/mhw/index.jsp, last access: 4 May 2025). It also issues special bulletins during excessive and persistent heat waves.

### 3.2 Natural resources and energy

#### 3.2.1 Potential fishing zone (PFZ) advisories

Using satellite-derived sea surface temperature (SST) and chlorophyll and tapping the habitat preference of fishes, advisories to fishers have been provided through a wide range of communication channels such as a web portal (https://incois.gov.in/MarineFisheries/PfzAdvisory, last access: 4 May 2025), Short Message Service (SMS), radio, mobile applications and electronic display boards for the past couple of decades, and there is positive feedback from fishers about this service. As the fisher community are of diverse ethnic background and speak multiple languages, the services are provided as multilingual texts. There are about 700 000 registered users for this service at present.

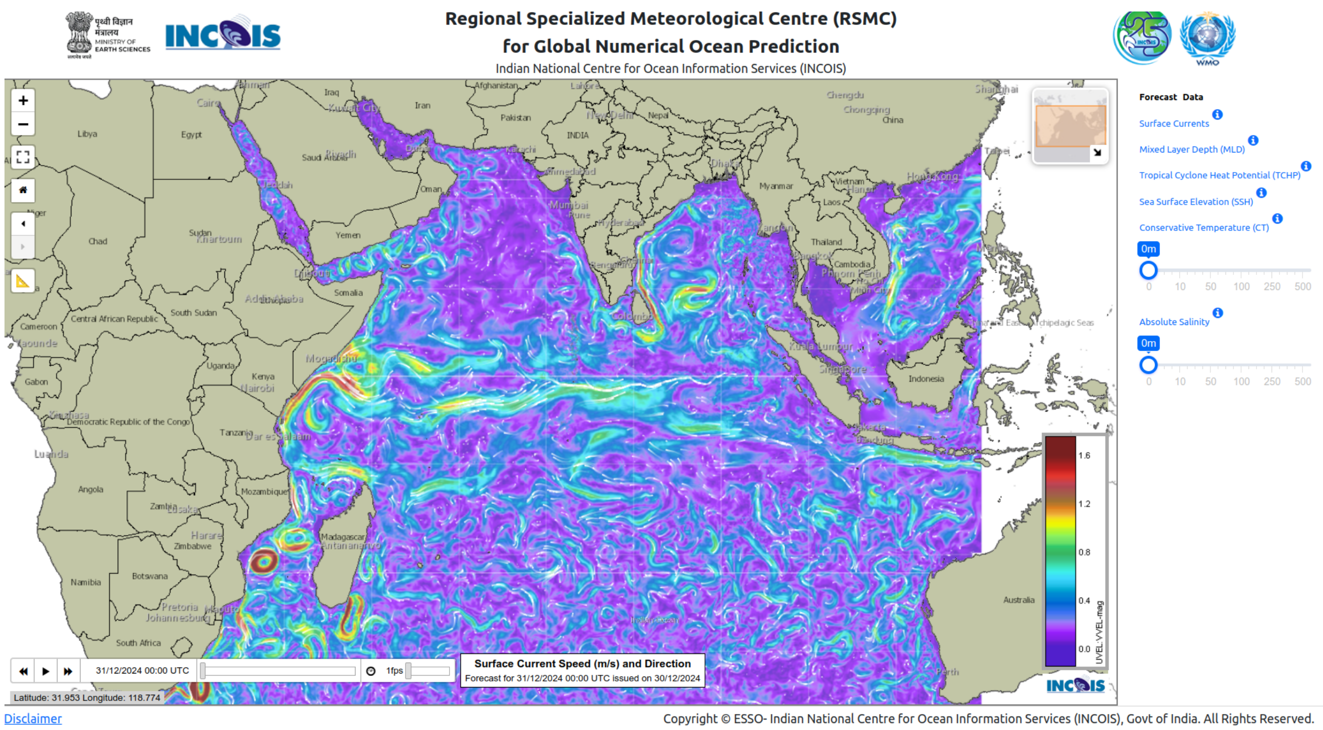


**Figure 2.** Web interface of the RSMC for numerical ocean prediction (left) and the same for wave prediction (right).

### 3.2.2 Coral Bleaching Alert System (CBAS)

Coral reefs play a pivotal role in marine ecosystems and are vital for the habitats of flora and fauna in the ocean. Ecologically, coral reefs are significant as they provide a conducive environment for several marine species and thereby contribute to the biological productivity in the ocean. However, coral reefs are sensitive to SST, and sustained thermal stress can cause severe damage to the coral reefs. They get bleached proportionate to the intensity and duration of the thermal stress. India has developed a satellite-based operational system for assessing the thermal stress on corals from satellite SST corroborated with ground truth through field examination of coral damage. This service is for assessing the degree of damage caused to the coral environments within the Indian Seas and is made available through a web portal (https://incois.gov.in/portal/coralwarning, last access: 4 May 2025).

## 3.3 Shipping, ports and navigation

### Small Vessel Advisory Services (SVAS)

The Small Vessel Advisory and Forecast Services (SVAS; https://incois.gov.in/portal/osf/SVA.jsp, last access: 4 May 2025) system is an innovative impact-based advisory and forecast service system for small vessels operating in the Indian coastal waters. SVAS warns users against potential zones where vessel overturning can take place, 10 d in advance. This warning system is based on a “boat safety index” (BSI) derived from wave model forecast outputs, such as significant wave height, wave steepness, directional spread and the rapid development of wind sea.

## 3.4 Climate adaptation

### Climate indices

Climate indices such as El Niño/La Niña conditions and Indian Ocean Dipole conditions are computed based on model simulations and made available through the web portal (https://incois.gov.in/portal/ElNino, last access: 4 May 2025). The status of the above-mentioned interannual climate modes is regularly updated and provided to the end users alongside the indices for the past 12 months. These indices are widely used by policy-makers and the agricultural sector as they have a significant impact on Indian monsoon and annual rainfall patterns in the region.

# 4 African Seas

While the development of operational ocean forecast systems and downstream services, optimized for African regional seas and coastal regions is limited, it is ongoing (Uba et al., 2020; de Vos et al., 2021; Hart-Davis and Backeberg, 2023), and various strategies exist to support stakeholders. In the simplest example, local met offices use global services to package alerts for subscribed users via text messages

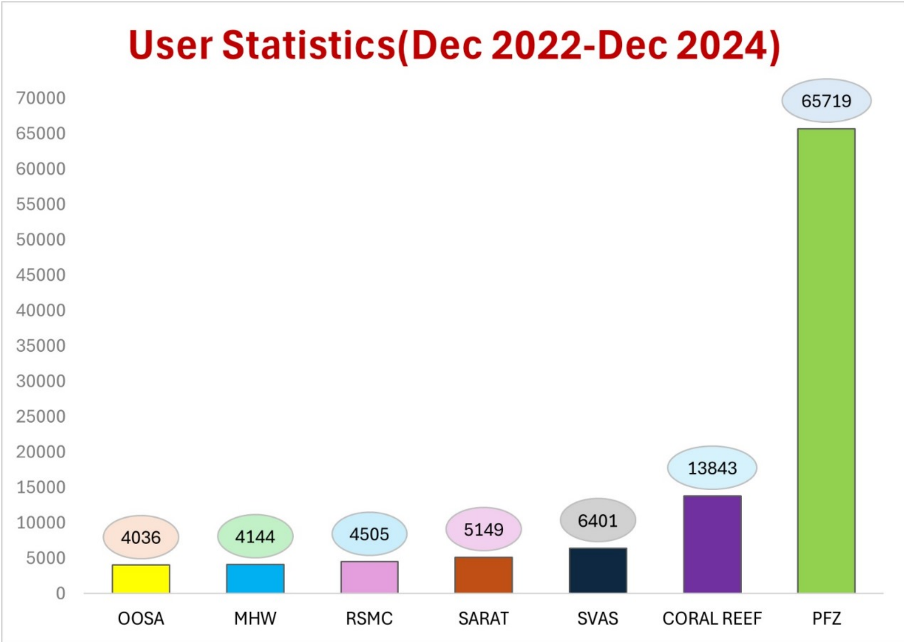


**Figure 3.** User statistics generated from selected services of provided to the Indian Seas region.

or emails, while others add value to global services by customizing solutions for stakeholders. The most advanced services are in the north of the continent, where downstream applications benefit from the advanced Mediterranean Sea operational systems (Cirano et al., 2025 in this report); in the Red Sea area, where an optimized regional system has been developed (Cirano et al., 2025; Hoteit et al., 2021); and in the far south, where a co-designed decision support portal is well established for stakeholders. Examples of approaches to various downstream applications will be provided below.

A more cohesive, regional approach to the provision of operational information to support marine and coastal operations in Africa has been established by GMES (Global Monitoring for Environment and Security; https://au.int/GMESAfrica, last access: 4 May 2025) and Africa via MarCOSIO (Marine and Coastal Operations for Southern Africa and the Indian Ocean; https://marcosio.org/, last access: 4 May 2025) and MarCNoWA (Marine and Coastal Areas Management in North and West Africa; https://gmes.rmc.africa/, last access: 4 May 2025). These platforms currently make use of global services for earth observations as well as marine forecast products that in some cases are optimized for local conditions. Linked to MarCOSIO is the National Oceans and Coastal Information Management System (OCIMS; https://ocims.environment.gov.za/, last access: 4 May 2025), developed by the South African Department of Forestry, Fisheries and the Environment (DFFE) in collaboration with the Council for Scientific and Industrial Research (CSIR). OCIMS provides customized decision support tools that include coastal flood hazard, operations at sea, fisheries and aquaculture, integrated vessel tracking, marine spatial planning, water quality, and marine predators. These tools are co-designed with the key stakeholder groups in annual stakeholder engagement workshops that bring together the developers as well as the end users that include the aquaculture industry, National Sea Rescue Institute (NSRI), marine authorities and the Navy, and municipalities. These tools currently make use of operational satellite products, optimized for the South African coastline, as well as global forecast models that are not locally optimized. Limited area operational forecast models are in development (https://somisana.ac.za, last access: 4 May 2025) and will be integrated into the OCIMS DeSTs within the next year.

### 4.1 Extremes, hazards and safety

#### 4.1.1 Oil spills

In the case of an oil spill in African waters, global services are generally called upon to assist with the mitigation effort. For example, in the case of the devastating oil spill in the Indian Ocean on 25 July 2020, when the MV *Wakashio* bulk carrier ran aground off Mauritius (Seveso et al., 2021), Mercator Ocean International provided Météo-France with ocean current forecasts to feed the MOTHY pollutant drift model, and the CMCC (Euro-Mediterranean Centre on Climate Change) used Copernicus Marine Service near-real-time products like forecasted currents and ECMWF winds to forecast the weathering and transport of the oil slick.

The SOMISANA team in South Africa have developed a pre-emptive approach in which they release a "virtual" oil spill at each of the ship-to-ship refuelling locations within their high-resolution bay-scale models. They use a simple Lagrangian particle tracking approach to allow the hypothetical oil spill to be tracked 5 d into the future. Additionally, their oil spill tracking functionality, developed using the OpenDrift software, allows for seamless tracking between the global and coastal/bay-scale forecast models and can be launched on demand.

The iRED-M1 system (Hoteit et al., 2021), developed at the King Abdullah University of Science and Technology, provides an ocean–wave–atmosphere coupled forecast system with dedicated web servers for interactive visualization, analytics and queries. These forecasts are used mainly for oil-spill trajectories as well as providing assessments on extreme weather and wave conditions.

#### 4.1.2 Storm surge

Storm surge information was highlighted as being important all of the time in eastern African countries due to the frequent flooding events that occur in association with cut-off low events and tropical cyclones and that have serious ecosystem, socio-economic and health impacts (Mather and Stretch, 2012; Ravela et al., 2013; Cambaza et al., 2019; Molua et al., 2020; Singh and Schoenmakers, 2023). In South Africa and Mozambique the meteorological services and a local municipality have developed downscaled storm surge models (Cirano et al., 2025) in order to provide early warnings to coastal stakeholders. These forecasts are provided either on an operational web portal (e.g. https://marine.weathersa.co.za/Forecasts_Surge.html, last access: 4 May 2025) and/or by early warnings that come in the form of emails or text messages to subscribed users that include port authorities, fishing communities, NGOs and consultants.

#### 4.1.3 Search and rescue

The South African OCIMS provides an Operations at Sea decision support tool (https://www.ocims.gov.za/coastops/, last access: 4 May 2025) that operationally disseminates marine weather information that includes NOAA's GFS wind and wave forecasts, historic winds and waves based on the downscaled atmospheric models that are run by the South African Weather Service (SAWS). As an additional tool that has been custom-built for and requires a login from the National Sea Rescue Institute (NSRI), it allows the user to use global wind, wave and current forecasts to optimize search domains.

### 4.2 Natural resources and energy

#### 4.2.1 Fisheries' management

Despite fisheries being consistently identified as the most essential coastal activity requiring operational forecast services throughout the African Seas regions, relatively few downstream applications exist to support the industry. One example is ABALOBI (https://abalobi.org/, last access: 4 May 2025) that is a South African-based enterprise that aims to support the sustainability of small-scale fishing communities through technology. ABALOBI provides a mobile application that is designed for users that span the value chain from small-scale fishers to consumers. The application provides forecast information about marine weather (from the NCEP Global Forecast System) and also notification about red tide events (derived from Copernicus Marine Service satellite information) but also provides various logging and business management tools. ABALOBI supports the traceability of seafood, fully documented fisheries, fair and transparent supply chains, and community cohesion and entrepreneurship (2018–2019 impact report available at https://drive.google.com/file/d/1wbi0PPDOr8oZS_b0LMJs5PFy37tOAiv5/view, last access: 4 May 2025).

The fundamental triad of enrichment, concentration and retention along with the transport of fish eggs and larvae from their spawning to nursery areas is critical for the sustainability of the high productivity that supports the lucrative South African fishing industry. Furthermore, connectivity between marine protected areas is an essential component in the health and longevity of marine ecosystems. To this end, many studies have made use of numerical ocean models to force Lagrangian particle experiments in order to understand these transport and retention processes and their various impacts (Pfaff et al., 2022; Heye, 2021).

#### 4.2.2 Aquaculture

In order to reduce the impact of harmful algal blooms (HABs) on the South African aquaculture industry such as the extreme event that occurred on the southwest of the Western Cape in 2017 and that caused the mortality of $\sim 250$ t of farmed abalone (Groom et al., 2019), OCIMS has incorporated a HAB decision support tool (https://www.ocims.gov.za/hab/app/, last access: 4 May 2025). This operational tool provides a matrix of probability of HABs occurring in key locations along the South African coastline. The spatial and temporal extent of the bloom is captured by remotely sensed chlorophyll data that are provided by the EUMETSAT Data Store (Sentinel-3 OLCI and SLSTR) and the Copernicus Marine Service (Global Ocean Colour chl-$a$), and chl-$a$ estimates are optimized for high biomass bloom water types (Smith et al., 2018).

### 4.3 Shipping, ports and navigation

The South African Weather Service provides regionally optimized wind and wave forecasts to support port operations. The CSIR's Vessel Motion Forecast Tool (Troch et al., 2024) utilizes numerical models to predict long-period wave climates and subsequent moored ship motions, providing port authorities with important information regarding vessel stability. This tool enables port operators to assess the suitability of different vessel sizes at berths for both current and forecasted wave conditions, directly improving operational efficiency and safety. By linking numerical models and providing an intuitive user interface, the tool delivers actionable insights into potential berth-specific issues, allowing for proactive planning and minimization of downtime.

### 4.4 Climate adaptation

Digital Earth Africa (DE Africa; https://www.digitalearthafrica.org/platform-resources/services/coastlines, last access: 4 May 2025) significantly supports climate adaptation along African coastlines through its Coastlines application. This tool leverages satellite imagery and data analysis to monitor coastal erosion, inundation, and shoreline changes, critical factors influenced by climate change. By providing time-series data, DE Africa helps identify vulnerable areas and track the impact of rising sea levels and increased storm surges. While the Coastlines application primarily utilizes satellite data, it can be enhanced by incorporating predictive models. For example, hydrodynamic models forecasting wave action and sea-level rise can be integrated to project future coastal changes. Additionally, climate models that predict changes in rainfall patterns and storm frequency can inform the interpretation of observed coastal shifts, allowing for more robust risk assessments and adaptation planning. This integration of data and models enables informed decision-making for coastal management, infrastructure planning and community resilience in the face of a changing climate.

## 5 Mediterranean and Black Sea

During the last decades, the constant evolution of increasingly accurate operational forecasting systems in particular in the Mediterranean Sea and, to a lower extent, in the Black Sea, from regional to local and coastal scales, providing systematic information of the essential ocean variables, has led to the consolidation and to the development of a wide range of scientific and societal applications in the area.

Mediterranean and Black Sea analysis and forecast operational numerical products, such as the ones delivered through the Copernicus Marine Service (https://marine.copernicus.eu, last access: 4 May 2025) by the MED (https://marine.copernicus.eu/about/producers/med-mfc, last access: 4 May 2025; Coppini et al., 2023) and BLK (https://marine.copernicus.eu/about/producers/bs-mfc, last access: 4 May 2025; Ciliberti et al., 2022) MFCs (Monitoring and Forecasting Centres) are essential to provide a 3-dimensional state of the sea, including currents, temperature, salinity, mixed layer thickness, sea level, wind waves and biogeochemistry to support many downstream applications and activities.

Considering that the two basins are characterized by a large variety of complex physical processes occurring on a wide range of spatiotemporal scales, it is required to develop models that can reproduce specific ocean variables' evolutions and to focus on specific processes representation (from wind-driven and thermohaline circulation to water mass formation, coastal processes such as upwelling and storm surge, and extreme and fast events such as medicanes). Following all these needs, the Mediterranean and Black Sea communities have been implementing models based on different codes and parameterizations, properly designed to solve specific problems.

Several downstream applications developed and implemented in the Mediterranean and Black Sea are presented hereafter, considering climate change studies, oil spill, ship routing, search and rescue, marine litter, ports, water quality, fish and larvae dispersion, and fisheries' and aquaculture management, as well as adaptation and management strategies. Most of the listed applications are described in a recent book from Schroeder and Chiggiato (2022), who edited an introductory guide on the oceanography of the Mediterranean Sea and in the ETOOFS (Expert Team on Operational Ocean Forecasting Systems) Guide by Alvarez Fanjul et al. (2022).

### 5.1 Extremes, hazards and safety

#### 5.1.1 Oil spills

Oil spill models are forced by meteo-oceanographic forecasting products providing ocean currents, wind and waves which should be available on a regular basis. Several oil spill models are operated in the Mediterranean and Black Sea, and specific forecasting systems have also been implemented in areas of oil spill emergencies such as those presented in Cucco et al. (2012). Moreover, oil spill modelling in harbour and port areas has been developed, such as in the Port of Taranto in south Italy (Liubartseva et al., 2021), the Limassol port areas in Cyprus (Zodiatis et al., 2024), the Port of Tarragona in Spain (Morell Villalonga et al., 2020) and the Spanish harbours through the SAMOA project launched by Puertos del Estado (PdE). Additionally, MEDSLIK (Zodiatis et al., 2021) and MEDSLIK-II (De Dominicis et al., 2013), Lagrangian oil spill models for short-term forecasting, were applied in various areas. Several decision support systems (DSSs) dedicated to oil slick emergencies and predictions in the Mediterranean Sea have been developed, such as the French MOTHY (Daniel, 1996) drift system, the Italian WITOIL (Where Is The Oil) multi-model DSS and the MEDESS4MS (Zodiatis et al., 2016; Sorgente et al., 2020). The OILTOX Lagrangian oil spill model adapted for the Black Sea environment for oil spill transport and fate has been implemented in the northwestern shelf of the Black Sea and Dnieper–Bug Estuary (Brovchenko et al., 2003). The POSEIDON Oil Spill fate and trajectory model is based on the PARCEL model (Pollani et al., 2001), which is able to simulate not only the drift of the oil but also the chemical transformations under the specific environmental conditions.

#### 5.1.2 Search and rescue

An advanced web-based and mobile decision support system for search and rescue (SAR) in the Mediterranean has been developed by Coppini et al. (2016). The system simulates drifting objects at sea, using the met-oceanographic data provided by the Copernicus Marine Service as input. The performance of the service is evaluated by comparing simulations to data from the Italian Coast Guard pertaining to actual incidents in the Mediterranean Sea.

At the national and international level, the National Forecasting Centre of Météo-France provides met-oceanographic support and drift forecasts to assist authorities in charge of search-and-rescue operations. The aforementioned MOTHY system can not only resolve search-and-rescue targets, but it also computes the drift of lost cargo containers (Coppini et al., 2022). The system uses the Copernicus Marine Service data among several forcing fields.

The Hellenic Centre for Marine Research (HCMR) has an agreement with the Hellenic Coast Guard for a SAR service in the Greek seas. The application is developed and hosted at the POSEIDON operational system and provides forecasting of drifting objects.

Currently, under the ever-increasing flow of people trying to reach Europe by crossing the Mediterranean Sea, the efficiency of SAR calls for an enhancement. That requires both improved modelling of drifting objects and optimized search assets' allocation.

In the Adriatic basin, the Slovenian Environment Agency provides met-oceanographic support and drift forecasts to assist authorities in charge of search-and-rescue operations (Ličer et al., 2020); the drift forecasts are based on high-resolution wind forecasts and ocean modelling downscaling of Copernicus Marine Service forecasts for the Mediterranean Sea. The system can resolve search-and-rescue targets, oil spills and cargo containers.

#### 5.1.3 Marine litter

Marine plastic pollution, usually from anthropogenic sources, is increasingly recognized as an emerging threat to the Mediterranean environment, biodiversity, human health and well-being (Schroeder and Chiggiato, 2022). Recently, an important shift has been conducted for the Mediterranean Sea from the spatially uniform distributions of plastic sources to a more realistic representation of land-based and offshore inputs (Liubartseva et al., 2018; Macias et al., 2019; Soto-Navarro et al., 2020; Kaandorp et al., 2020; Tsiaras et al., 2021, 2022a) and for the Black Sea (Miladinova et al., 2020; Stanev and Ricker, 2019; Gonzalez-Fernandez et al., 2022) to identify the accumulation and dissipation of floating litter in such semi-enclosed sea basins.

#### 5.1.4 Water quality

The physical–biogeochemical forecasting system for the northern Adriatic Sea developed in the framework of the CADEAU project (Bruschi et al., 2021) is based on a high-resolution (up to around 750 m) implementation of the MITgcm–BFM coupled model (Cossarini et al., 2017) targeting water quality and eutrophication, and it uses the daily MED MFC products for initialization and to constrain the open boundary.

The trophic index (TRIX) eutrophication assessment indicator has been calculated both on in situ data and with a coupled circulation and biogeochemical numerical modelling system. TRIX is defined by four state variables: chlorophyll-*a*, oxygen, dissolved inorganic nitrogen and total phosphorus. As an example, the trophic index differences have been computed to evaluate the trophic state of marine waters along the Emilia-Romagna coastline (Italy) and over the whole Adriatic Sea (Fiori et al., 2016).

A relocatable modelling system for describing and forecasting the microbial contamination that affects the quality of bathing waters was implemented at five coastal areas in the Adriatic Sea, which differ in terms of urban, oceanographic and morphological conditions (Ferrarin et al., 2021). The modelling systems are all based on the hydrodynamic finite element model SHYFEM (Umgiesser et al., 2022). Pollution events are mainly triggered by urban sewer outflows during massive rainy events, with relevant negative consequences on the marine environment and tourism and related activities of coastal towns.

### 5.2 Natural resources and energy

#### 5.2.1 Fish larvae dispersion and fishery and marine aquaculture management

The study of larvae dispersion and regional connectivity and their impact on the structure of species populations and fisheries are generally provided using Lagrangian models (van Sebille et al., 2018; Laurent et al., 2020; Melaku Canu et al., 2020), and in the Mediterranean Sea these have been carried out thanks to the availability of information provided by operational forecasting systems (more information on such applications can be found in Schroeder and Chiggiato, 2022).

Being strongly supported by the policies and initiatives of the European Union, marine aquaculture guarantees food security and reduces the fishing pressure on wild fish stocks. A farm site selection strategy based on an aquaculture suitability index has been developed for the central Mediterranean (Porporato et al., 2020). The index is based on the outputs of eco-physiological models which were forced using time series of sea surface temperature, significant wave height, distance to harbour, current sea uses and cumulative impacts.

Tyrrhenian and Ionian coastal areas are found to be more suitable compared to the northern Adriatic and southern Sicilian ones.

Small pelagic fish play a key role in marine food webs, being the trophic link between plankton and larger fish. Given their pronounced sensitivity to environmental changes, end-to-end (physics–plankton–fish) small pelagic fish two-way coupled models (Gkanasos et al., 2021) are unique tools that can be used to study the impact of climate change and fisheries in a single modelling framework.

Coupled hydrodynamic–biogeochemical models can also be used to evaluate the environmental impact of aquaculture waste and investigate the carrying capacity of coastal marine ecosystems (Tsiaras et al., 2022b; Tsagaraki et al., 2011).

Moreover, dynamic energy budget (DEB) models (Hatzonikolakis et al., 2017), forced with hydrodynamic–biogeochemical model output (temperature, Chl-*a*), can be also implemented to simulate the growth of farmed mussels (*Mytilus galloprovincialis*) and the potential impact of future climate on their habitat suitability.

#### 5.2.2 Adaptation and management strategies to address harmful algal blooms and jellyfish outbreaks

In recent years, eutrophication phenomena, prompted by global warming and population increase, have stimulated the proliferation of potentially harmful algal taxa, resulting in the prevalence of frequent and intense harmful algal blooms (HABs) in coastal areas of the Mediterranean and Black Sea. Drivers of HABs in coastal areas of the eastern Mediterranean were studied by means of a machine learning methodological approach (Tamvakis et al., 2021). Water temperature has been found to have the most powerful effect on genera's presences.

A jellyfish outbreak forecasting system has been developed for the Mediterranean Sea as a preventive and mitigation tool for citizens and coastal stakeholders, aiming to reduce the jellyfish blooms socio-economic impact in coastal areas through a feasible and powerful management strategy (Marambio et al., 2021). The system explores the Copernicus Marine Service output to predict the jellyfish spatio-temporal distributions.

Previously, high-resolution ocean modelling was applied to examine the transport and stranding of the pelagic stinging jellyfish *Pelagia noctiluca* on the Ligurian Sea coast (Berline et al., 2013). Jellyfishes were modelled as Lagrangian particles transported by sea currents with a diel vertical migration. Two environmental factors were found to be critical: the position of the northern current and the wind regime.

### 5.3 Shipping, ports and navigation

#### 5.3.1 Ship routing

The GUTTA-VISIR system is a tactical, global-optimization, single-objective, deterministic model system for ship route planning (Mannarini et al., 2016; Mannarini and Carelli, 2019), which has been implemented in the Mediterranean Sea for several applications (i.e. in the Adriatic Sea, Mannarini et al., 2021) using the analysis and forecast wave and current fields from the MED MFC.

#### 5.3.2 Ports

To respond to the need for information on wind, waves and sea level at the scale of ports and harbour, a Spanish initiative has been developed and operationally implemented called SAMOA-2 (Álvarez Fanjul et al., 2018; Sotillo et al., 2019; García-León et al., 2022) operating in 31 ports. It is an integrated system based on Copernicus Marine data; the service provides daily forecasts of sea-level, circulation, temperature and salinity fields at horizontal resolution that range from 350 m (coastal domains) to 70 m (port domains). Another example implemented along the Spanish coastal waters is provided by PORTUS (https://portus.puertos.es/, last access: 4 May 2025), an early-warning system that employs both the in situ data and the operational forecasts (Álvarez Fanjul et al., 2018).

### 5.4 Climate adaptation

Over the next few decades, marine heat waves (MHWs) are expected to become more intense, longer and more frequent through anthropogenic warming. Combining high-resolution satellite data and a regional reanalysis, Dayan et al. (2023) have studied MHWs to understand how much each Mediterranean country's exclusive economic zone waters may be affected.

As was stated in the second edition of the Copernicus Marine Service Ocean State Report, ocean deoxygenation is found to be one of the most pernicious, yet under-reported, side effects of human-induced climate change. This problem is particularly acute in the Black Sea, where Capet et al. (2016) have found a decline in the Black Sea oxygen inventory. The reason for this is that atmospheric warming reduces the ventilation of the lower oxic layer by lowering cold intermediate layer formation rates.

## 6 North East Atlantic

The structured provision of mature regional core services and coastal operational forecasting systems in the North East Atlantic (Cirano et al., 2025) enabled a significant deployment of downstream operational services addressing a wide variety of sectors (Fig. 4).

A rich portfolio documenting use cases of downstream services uptake can be found for instance in the Copernicus Marine Service User Uptake portal and the ETOOFS Guide (Alvarez Fanjul et al., 2022). In particular, the EuroGOOS coastal working group roadmap for operational coastal services (El Serafy et al., 2023) details components of the coastal services' value chain in Europe and reviews the status, gaps and steps needed to improve these services and the sustainability of their provision. A full review of the downstream services that are presently active or upcoming in the established sectors of the European blue economy is given in El Serafy et al. (2023). Here we highlight a few examples for selected sectors.

## 6.1 Extremes, hazards and safety

### 6.1.1 Oil spills

Coastal areas with industrial ports and harbours are among the locations most at risk from oil spill pollution, which heavily impacts aquatic life and ecology, coastal infrastructures, and the local economy. This underlines the need for timely and accurate coastal services for operations and disaster response. Oil spill models predicting the fate and the transport of the oil slick have been recently enhanced by downscaling from state-of-art regional models (e.g. Copernicus Marine Service) to very high resolution hydrodynamic models for coastal and harbour areas. A coastal service in water monitoring and oil spill pollution is the OKEANOS project (https://parsec-accelerator.eu/portfolio-items/okeanos/, last access: 4 May 2025), a web-based integrated and intuitive service combining open-source satellite observations (i.e. affordable), artificial intelligence and high-resolution ocean modelling (i.e. accurate). Another example of oil spill forecasting is the drift model MOTHY, developed by Météo-France, which uses ocean currents from the Copernicus Marine Global Ocean Forecast model. This system allows predictions of the possible trajectory of oil spills and estimates the resulting impacts several hours or days in advance. MOTHY has been operational since 1994 and is frequently activated for actual spills or search-and-rescue operations.

## 6.2 Natural resources and energy

### 6.2.1 Aquaculture sector

Novel coastal services, including mapping of suitable fishing areas, front detection, marine conditions and scheduler, land pollution, site prospection, spat capture assistance, and contaminant source retrieval, are provided by FORCOAST (https://forcoast.eu/, last access: 4 May 2025) in aquaculture pilot sites, among others, regional waters, the North Sea, the Baltic Sea and the coastal Atlantic Ocean. These services are Copernicus-based services that incorporate Copernicus products, local monitoring data and advanced modelling.

Recent projects that aimed at the co-development with end users and demonstration of harmful algal bloom (HAB) forecasting services as one of the societal needs from the coastal observing and forecasting systems include the FP7 Asimuth (Cusack et al., 2016), H2020 AtlantOS (Cusack et al., 2018) and Interreg Atlantic Area PRIMROSE (https://pml.ac.uk/projects/primrose-predicting-risk-and-impact-of-harmful-eve/, last access: 4 May 2025), all providing near-real-time and forecast information for the aquaculture industry along Europe's Atlantic coast.

Last, but not least, all the data and information produced by operational coastal services may be used in the framework of the Maritime Spatial Planning Directive to identify Allocated Zones for Aquaculture (AZA), following national and international guidelines (e.g. FAO, Macias et al., 2019), as shown by use cases such as AQUAGIS (European Aquaculture Society – ePoster Viewer).

### 6.2.2 Coastal tourism sector

Various coastal services have been developed following inquiries from the coastal tourism sector. A good example is a tailored product based on the North East Atlantic operational forecasting model in Ireland, developed by the Irish Marine Institute (IMI). Surface currents subsets are provided over five geographical areas around the Irish waters and the English Channel and published in a GRIB format via an ftp site (https://sftp.marine.ie/WebClientNew/Login, accessible only to registered users, last access: 4 May 2025), while ensuring low data volume. The service was developed in collaboration with the sailing community that contacted the IMI to request its development and was notably used during the Fastnet sailing race.

Another Irish example serves beachgoers. The Irish Environmental Protection Agency, in collaboration with Local Authorities and the Department of Housing, Planning and Local Government, runs a web page, https://www.beaches.ie (last access: 4 May 2025), where the latest information on water quality and others is presented for 204 beaches in Ireland. Met Eireann (the Irish national meteorological service) and the Marine Institute contribute to the information provided with current weather and weather forecasts and tidal information, respectively.

Among the services that provide the latest water quality information, the service carried out in the framework of the CADEAU project (Bruschi et al., 2021) provides data and information to assess the potential impact of bacterial pollution sources on bathing waters (as defined in the EU Bathing Water Directive) and help bathing waters' managers in identifying potential sources of impact and planning mitigation measures.

National marine forecasting agencies also serve the coastal tourism sector. The Marine Forecasting Centre of Belgium of the Royal Belgian Institute of Natural Sciences (RBINS) is-

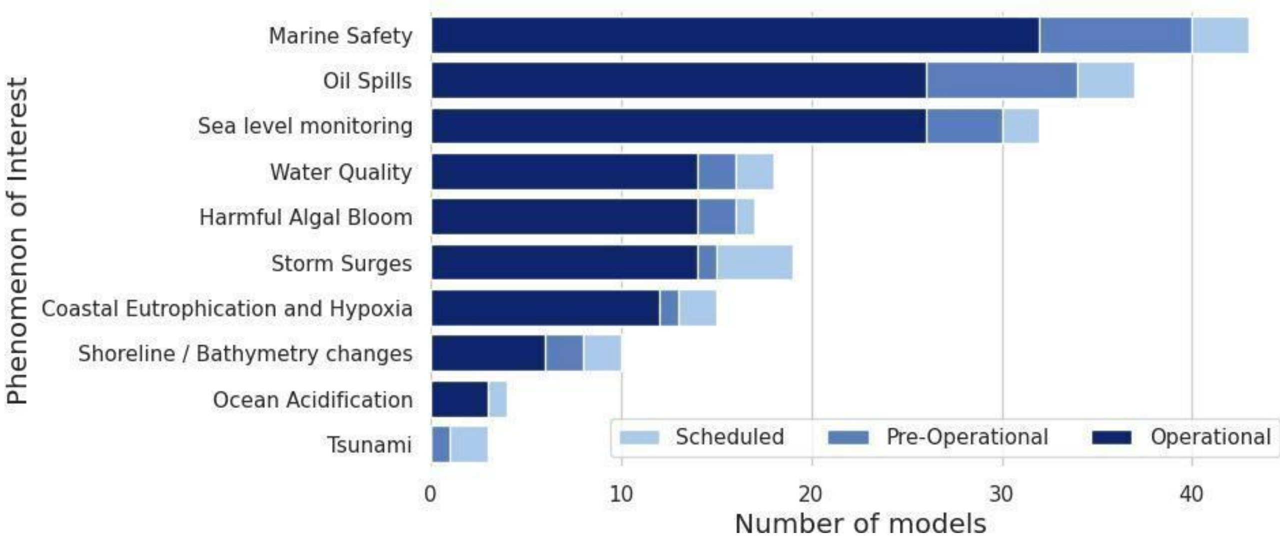


**Figure 4.** Principal characteristics of the Copernicus Marine regional core services for the North East Atlantic region and its relation to its downstream use in sectors.

sues 5 d forecasts of the marine conditions in the North Sea twice a day with a high resolution for the Belgian part of the North Sea. These forecasts are used in numerous applications, among them the tourism and leisure industries. Surfers use the application for mobile devices to schedule their sessions for good waves and current conditions.

### 6.2.3 Renewable energy sector

The renewable energy sector is a prominent player in the blue economy and therefore one of the main potential users of coastal services. Indeed, the EU hosted 70 % of global ocean energy (wave and tidal) installed capacity and 86 % of the world's total installed offshore wind capacity at the end of 2018 (Díaz and Soares, 2020), while jobs in the offshore wind energy sector have multiplied 9-fold in less than 10 years (European Commission, 2020).

Current bottlenecks relating to the large-scale installation of ocean multi-use activities are addressed by the UNITED project (https://www.h2020united.eu/, last access: 4 May 2025), which demonstrates business synergies and benefits of ocean multi-use and provides a roadmap for deployment in future multi-use sites and potential scaling barriers to be addressed through best practices and lessons learnt. Another example of coastal services for the renewable energy sector is Ireland's Marine Renewable Energy Portal (http://www.oceanenergyireland.ie/, last access: 4 May 2025), an online access point for all relevant information and data related to Irish marine renewable energy activity and resources including maps, tools and information for renewable energy site assessment, development and management.

## 6.3 Shipping, ports and navigation

Coastal information services tailored to the needs of the port sector are provided by the HiSea project (https://hiseaproject.com/, last access: 4 May 2025). The services include early-warning service on potential risk factors issuing alerts on storms, harmful algal blooms, faecal contamination and other hazards regarding pollution accidents to identify the appropriate responses. It provides key performance indicators regarding fish growth rates; environmental conditions or the level of vulnerability to storms for vessels; and information for planning operations including accurate and reliable meteorological, hydrodynamic and water quality forecasts. Further examples of platforms and services for ports are SAMOA and AQUASAFE. The SAMOA service from Puertos del Estado aims to provide high-resolution coastal operational prediction systems in domains such as harbours and nearby coastal waters, for different Spanish port authorities (Sotillo et al., 2019). Similarly, the AQUASAFE platform is operational for all Portuguese ports and in the Port of Santos (Brazil). This platform aims to increase efficiency and safety in port operations, by providing access to real-time and forecast information. It is also used to support aquacultures, inland navigation, irrigation and water utilities.

## 6.4 Climate adaptation

Climate adaptation is central to the efforts in the North East Atlantic region, where regional core services and operational forecasting systems play a vital role in responding to the impacts of climate change, such as rising sea levels, extreme weather and changes in marine ecosystems. Key systems like the Copernicus Marine Environment Monitoring Service (CMEMS), the European Centre for Medium-Range Weather

Forecasts (ECMWF) and the UK Met Office's coastal forecasting systems provide essential data on oceanographic and atmospheric conditions, aiding climate resilience in marine sectors like fisheries, shipping and coastal infrastructure. Initiatives such as the Atlantic Action Plan for a sustainable blue economy, the Interreg North Sea Region Programme, and the European Maritime and Fisheries Fund (EMFF) are focused on enhancing climate resilience, offering solutions like adaptive coastal management, improved early-warning systems and sustainable practices.

## 7 South and Central America

The lack of available regional core services and coastal operational forecasting systems in South and Central America (Cirano et al., 2025) makes the development of downstream applications difficult. For instance, very few use case demos are described in the Copernicus Marine Service User Uptake for this region. Normally, downstream applications are only developed in partnership with universities or specialized companies capable of implementing operational systems based on a downscale approach from global models.

Despite the general lack of regional systems for coastal operational forecast systems in South and Central America, smaller-scale services exist and provide useful information for stakeholders. For example, the Baía Digital project (http://www.baia.digital/, last access: 4 May 2025) in Brazil is a portal that integrates various data sources, including regional model forecasts focusing on developing an operational digital platform to provide environmental, social and economic information in the region of Guanabara Bay and its surroundings. The diagnostic and prognostic information generated comes from different sources, such as historical databases, data collection platforms and numerical computational models. Atmospheric and oceanic regional model forecasts represent the marine and atmospheric dynamics of the Guanabara Bay region temporally and spatially. The digital platform has been developed and improved from the interaction between professionals from different areas of science and students from different educational levels, investing in the technical and scientific training of researchers. In addition, extension activities involving students from the school segment will be planned to aim at promoting a scientific culture based on knowledge of Guanabara Bay. The project base is the Laboratory of Computational Methods in Engineering (LAMCE), located in the UFRJ Technological Park, in partnership with other laboratories and teaching and research institutions. The project represents a pioneering effort associated with the regional initiatives of the Atlantic International Research Center (AIR Centre).

In the next sections we showcase a number of bespoke downstream applications based on specific needs.

### 7.1 Extremes, hazards and safety

#### 7.1.1 Oil spills

The Brazilian Oil Research Group (BROIL) was created in response to the oil spill disaster that impacted more than 3000 km along the north-northeastern Brazilian coastline in 2019, with significant environmental, economic and social impacts. BROIL comprises institutions in Brazil (e.g. UFBA, UFPE, UFRJ, INPE and PUC-Rio) and abroad (e.g. OOM, Portugal; IRD/LEGOS, France; HZG, Germany). BROIL works upon three main pillars: (i) detection, through remote sensing techniques; (ii) control, through a set of hydrodynamic and oil spill models; and (iii) remediation, through a set of biota oil-exposure case studies (Franz et al., 2021). Numerical models used to predict oil spill trajectory include the Regional Ocean Modeling System (ROMS) and the Lagrangian model MEDSLIK-II. Recently, a partnership with the Brazilian Sea Observatory will enable the use of forecasts with higher-resolution hydrodynamic models and prediction of the oil spill trajectory automatically through the MOHID modelling system.

The North Coast Project (http://www.projetocostanorte.eco.br/, last access: 4 May 2025) also integrated research groups with different expertise for the development of a method for determining the vulnerability of mangroves to contamination by oil and for producing knowledge about the Brazilian North Coast, in cooperation among ENAUTA; the Nucleus of Studies in Geochemistry and Marine and Coastal Ecology (NEGEMC) of UERJ; the Laboratory of Computational Methods in Engineering (LAMCE) of COPPE/UFRJ; the Laboratory of Research in Marine Environmental Monitoring (LAPMAR) of UFPA; and PROOCEANO, a Brazilian company of oceanographic technology. The largest continuous area of mangrove forests in the world is found on the north coast of Brazil – located between the states of Maranhão and Pará – totalling around 7400 km$^2$, which corresponds to 4.3 % of the entire area of mangrove forests in the world. The main objective of the project was to determine the vulnerability, sensitivity and susceptibility to oil contamination of the mangroves, based on the development of numerical hydrodynamic models with multiple resolution scales and the use of data assimilation techniques to represent large and mesoscale oceanographic phenomena, with seasonal and interannual variability, to small-scale phenomena with daily variability, such as tidal currents in floodplains. The hydrodynamic modelling results were used as input data for the modelling of the transport and dispersion of oil.

#### 7.1.2 Civil protection

The water level increase due to storm surges can be of the same order of magnitude as tide amplitude along the southeastern Brazilian coast (Franz et al., 2016). Following a downscaling approach, water level forecasts are available to this region, aiming to help civil protection actions. Water level forecasts, as well as data from several tide gauges along the Santa Catarina coast, are available for the public in general on the EPAGRI's company website (https://ciram.epagri.sc.gov.br/index.php/maregrafos/, last access: 4 May 2025). The water level forecasts of high-resolution models (e.g. Babitonga Bay) are also available for port operation. The operational models developed by the Brazilian Sea Observatory initiative (Franz et al., 2021) were updated in collaboration with EPAGRI, considering GEOGloWS (https://geoglows.ecmwf.int/, last access: 4 May 2025) flow predictions for major rivers.

#### 7.1.3 Coastal engineering

Coastal models developed by the Centre for Marine Studies (CEM UFPR) within the scope of the Brazilian Sea Observatory initiative, through the application of the MOHID modelling system, were used to support local companies in the design of submarine outfalls and study of the environmental impacts of bridge construction.

### 7.2 Natural resources and energy

#### Aquaculture

Information on water quality in bays and estuaries is essential for planning and managing bivalve mollusc production (e.g. water temperature, microbiological contamination, salinity and nutrients). These parameters are influenced by marine currents, river flows, solar radiation and winds, as well as by urbanization pressure and consequent contamination of water bodies (Cabral et al., 2020). The numerical modelling system MOHID was applied to the main aquaculture production zone of shellfish in Brazil, located in the bay of Ilha de Santa Catarina, with the objective of integrating the range of environmental data in a hydrodynamic and water quality model capable of simulating the variables of greatest interest in the production of bivalve molluscs, thus serving as a powerful management tool (Garbossa et al., 2023; Garbossa et al., 2021; Lapa et al., 2021). The model was recently implemented in operational mode by the company EPAGRI to provide forecasts, nested within a regional model developed in partnership with universities (e.g. UFPR), as a continuation of the Brazilian Sea Observatory initiative (Franz et al., 2021).

### 7.3 Shipping, ports and navigation

#### Ports

Within the objective of increasing navigation security, São Paulo (Brazil) Pilots (*Praticagem de São Paulo* in Portuguese) has been using the AquaSafe platform (https://aquasafe.hidromod.com/landing-page/about, last access: 4 May 2025), developed by the Portuguese company HIDROMOD and locally implemented in partnership with the University of Santa Cecília (Unisanta) (Ribeiro et al., 2016). The data provided by the platform assist in choosing the better entering and leaving periods of the harbour. The AquaSafe platform is connected to a real-time sensor data stream (tide gauge, weather station and ADCPs) from Praticagem's Center for Coordination, Communication and Traffic Operations (C3OT). Furthermore, high-resolution forecast solutions for wave parameters, sea level, wind and other meteo-oceanographic parameters are also available.

### 7.4 Climate adaptation

BASIC Cartagena is an applied research project on Basin Sea Interactions with Communities in the coastal zone of Cartagena (Colombia). Located on the Caribbean coast in the north of Colombia, Cartagena and its surrounding beaches represent the country's principal touristic destination. The first phase of the project started in July 2014 and was completed in June 2017 under the title "Reducing the risk of water pollution in vulnerable coastal communities of Cartagena, Colombia: responding to climate change". The second phase of the project, titled "Building resilience in Cartagena Bay", has been implemented since February 2018. Its general objective is to contribute to the improved environmental governance of Cartagena Bay by providing scientifically based advice toward climate-compatible and sustainable development policies. Studies of fluvial hydrology are dedicated to the research of the Magdalena River basin, with a focus on surface waters that flow from the Dique Canal towards Cartagena Bay. Analysis of the watershed's human development and climatic conditions permits modelling of the watershed's runoff processes. Future scenarios of climate change and human development will be used to generate prognostics of freshwater discharge from the Dique Canal into Cartagena Bay. In the coastal zone, studies focus on the monitoring of water quality and sediment in Cartagena Bay. Analysis of physicochemical and microbiological parameters, as well as contaminants, will permit an impact assessment of human activities and climate variation on the sea, as well as the generation of vulnerability maps. Hydrodynamic modelling will be used for prognostics of the dispersion of fresh water from the Dique Canal into Cartagena Bay under future watershed scenarios.

## 8 North America

North America is a vast continent with lengthy continental coastlines that include densely populated areas with busy harbours and vast remote isolated coastlines. Core ocean forecasting services are anchored by national meteorological centres that increasingly trend towards prediction services of the full earth system. This includes the US National Oceanic and Atmospheric Agency (NOAA) and the Canadian Meteorological and Environmental Prediction Center within the federal department of Environment and Climate

Change Canada (ECCC). Benefiting ocean forecasting services in North America are mature collaborations between government departments, universities and industry including the US Integrated Ocean Observing System (IOOS) (https://ioos.us, last access: 4 May 2025) partnership with 11 regional associations and the CIOOS, the Canadian IOOS (https://cioos.ca, last access: 4 May 2025) networks with 3 regional associations. In Canada, the CONCEPTS initiative coordinates ocean prediction that regroups several federal government departments together including the Department of Fisheries and Oceans Canada (DFO), the Canadian Coast Guard, the Canadian Hydrographic Service, and the Meteorological Service of Canada.

In North America, ocean forecast systems are advanced and relatively abundant. They provide a wide range of downstream applications, some of which are described below.

## 8.1 Extremes, hazards and safety

In the United States, the U.S. Coast Guard (USCG) is the primary federal agency for responding to maritime safety and security (including search and rescue and marine pollution) in navigable waters and deep water ports, although other agencies also play prominent roles, including the Environmental Protection Agency (EPA), NOAA, the Federal Emergency Management Agency (FEMA), and state agencies. The USCG relies on several ocean forecast systems to monitor and predict oceanographic and meteorological conditions critical for navigation, search and rescue, marine pollution, and environmental protection, primarily those run by various NOAA entities (National Weather Service, Ocean Prediction Center, OFS and NCEP). These systems provide data on currents, wave heights, sea surface temperatures and other factors that impact maritime operations.

In Canada, the Canadian Coast Guard (CCG) make use of the Canadian Operational Network of Coupled Environmental Prediction Systems (CONCEPTS) that is collaboratively produced by Environment and Climate Change Canada (ECCC), Fisheries and Oceans Canada (DFO), and the Department of National Defence (DND) to support their offshore operations.

### 8.1.1 Storm surge

While the coast guards in the respective countries are responsible for the dangers associated with storm surges, storm surge warnings are issued by ECCC in Canada and by the National Hurricane Centre (NHC) and the National Weather Service in the United States. The NHC focuses on the broader regional picture and uses both weather forecasts and the SLOSH (Sea, Lake and Overland Surges from Hurricanes; https://vlab.noaa.gov/web/mdl/slosh, last access: 4 May 2025) model with real-time data to issue warnings via graphical maps and advisories through NOAA websites, television and radio broadcasts, mobile alerts, and social media.

In Canada, the ECCC's Meteorological Service of Canada (MSC) monitors and forecasts conditions, based on both global and their own regionally optimized models, that lead to storm surge and coastal flooding. They have recently implemented a comprehensive coastal flooding prediction and alerting programme that provides maps that display an index of the probability of storm surges or coastal flooding occurring.

### 8.1.2 Oil spills

The Emergency Response Division (ERD) of the Office of Response and Restoration (OR&R) within NOAA provides Environmental Sensitivity Index (ESI) maps and data, which are used to identify vulnerable resources and habitats in advance of emergencies so that appropriate response actions can be planned. ERD works with local experts to develop or update ESI maps throughout the country. Another is the CAMEO® software suite (EPA), which helps emergency planners and responders deal with chemical incidents. ADIOS (Automated Data Inquiry for Oil Spills), developed by NOAA, provides rapid analysis of how different oil types weather in various marine conditions. By predicting how oil properties change (e.g. evaporation, dispersion), ADIOS helps responders plan effective cleanup strategies. GNOME (General NOAA Operational Modeling Environment) is a critical software suite developed by NOAA to predict the movement and fate of oil spills in water. It incorporates information from forecast systems, like currents and winds to forecast spill trajectories, while also modelling the weathering processes that alter oil's properties over time. Through its components like WebGNOME, PyGNOME and the ADIOS oil database, GNOME provides mapping and visualization tools, enabling responders to assess situations, plan contingencies and minimize environmental impact. It uses output from various forecast systems produced by the NOAA/NWS's (National Weather Services) Environmental Modeling Center including RTOFS (Real-Time Ocean Forecast System) and GFS (Global Forecast System) and serves as a vital tool for real-time emergency response, contingency planning, and research related to oil spill science.

In Canada, while the CCG is the leading agency for coordinating responses to oil spills, their principle is that the "polluter" pays and should report the spill, take the initial action and fund the cleanup. Industry-funded response organizations, certified by Transport Canada, provide spill response services on behalf of the polluter that would include modelling systems that predict the trajectory and fate of spilled oil.

### 8.1.3 Search and rescue

NOAA's National Environmental, Satellite, Data, and Information Services (NESDIS) Line Office operates the Search And Rescue Satellite Aided Tracking (SARSAT) system to detect and locate people in distress. Mariners, aviators and recreational enthusiasts can all access the satellite system in an emergency using a portable radio transmitter that can send an SOS signal from anywhere on earth, at any time, including in most extreme weather conditions. This is coupled with the Search and Rescue Optimal Planning System (SAROPS) tool, used by the USCG for maritime search planning. SAROPS uses an Environmental Data Server (EDS) that ingests real-time and forecast environmental data (produced by agencies such as NOAA) to predict the drift of a person or object in the water. This is done by simulating thousands of possible drift scenarios providing probability maps that help to focus the search efforts. The success of this tool is strongly dependent on the quality of the forecast models that it ingests.

The Canadian Coast Guard makes use of observations and models produced by Fisheries and Oceans Canada (DFO) and weather and oceanographic forecasts produced by the ECCC in order to optimize their search operations.

#### 8.1.4 Water quality

Several US government agencies are involved in supporting marine water quality. Key agencies include (a) the Environmental Protection Agency (EPA), which sets water quality standards, regulates pollutants, and monitors coastal and marine waters; (b) the National Oceanic and Atmospheric Administration (NOAA), which conducts research on ocean health, manages marine resources and supports programmes like the National Estuarine Research Reserve System; (c) the U.S. Coast Guard (USCG), which monitors and responds to marine pollution incidents and ensures maritime safety; (d) the U.S. Army Corps of Engineers (USACE), which manages coastal projects and assesses impacts on water quality from dredging and construction; (e) the Fish and Wildlife Service (FWS), which protects fish and wildlife habitats and works to restore ecosystems, which directly impacts water quality; and (e), the National Park Service (NPS), which manages marine protected areas and conducts water quality monitoring within national parks.

Ocean forecast systems play a key role in monitoring and managing water quality in North America, particularly in coastal and nearshore areas. Various water quality models are used by the EPA (https://www.epa.gov/beaches/models-predicting-beach-water-quality, last access: 4 May 2025). These incorporate hydrodynamic forecasts that are essential for accurately simulating the transport and mixing of pollutants.

### 8.2 Natural resources and energy

#### 8.2.1 Fisheries

Both the U.S. National Marine Fisheries Service (NMFS) and Fisheries and Oceans Canada (DFO) heavily rely on numerical ocean models to support their operations, particularly for fisheries' management and protected species conservation. The NMFS uses models like HYCOM (Hybrid Coordinate Ocean Model) and RTOFS (Real-Time Ocean Forecast System), while the DFO uses HYCOM as well as regionally tailored models developed by them and in collaboration with ECCC. These models provide crucial data on ocean currents, temperature and salinity, enabling predictions of fish distribution and marine species movements as well as assessments of habitat suitability. This information is then used to set sustainable catch limits, protect endangered species from human activities and forecast environmental impacts, thereby informing critical decisions regarding the management and preservation of marine resources.

The NMFS disseminates information through a variety of channels, including their official website (http://fisheries.noaa.gov/, last access: 4 May 2025), scientific publications and direct communication with stakeholders. They provide online access to oceanographic data, habitat suitability maps and species distribution forecasts, ensuring that researchers, resource managers and the public have access to vital information. NMFS also collaborates with other agencies and organizations to share data and findings, fostering a collaborative approach to marine resource management.

#### 8.2.2 Recreation and tourism

In the United States, NOAA's operational forecast systems (OFSs), as well as the NWS maritime forecasts, cover various regions (including the Great Lakes) and provide information on water levels, current temperature, salinity and winds, essential for safe navigation, recreational boating and fishing. The Regional Ocean Modeling System is used by various institutes to provide high-resolution forecasts for specific regions; for example the Gulf of Maine Operational Forecast System (GoMOFS) uses ROMS to predict ocean conditions to support tourism and marine recreational activities.

In Canada, CONCEPTS and the Regional Ice Ocean Prediction System (RIOPS) are used to support tourism by providing forecasts that support safe navigation, ice prediction and ecosystem modelling. A port ocean prediction system (POPS) is being developed by the DFO for major Canadian ports and waterways that provides high-resolution forecasts that support marine recreation.

The forecast information is provided through a number of different apps; some examples are the NOAA Weather Radar & Live Alerts, PredictWind, Windy, SailFlow, Surfline and MagicSeaweed.

#### 8.2.3 Offshore energy

For the offshore energy sector in North America, ocean forecast systems are essential to ensure the safety and efficiency of operations, particularly for oil, gas and renewable energy projects like offshore wind farms. These systems provide critical information on ocean currents, waves, winds and other environmental conditions. In addition, research centres, like the National Renewable Energy Laboratory (NREL) and Woods Hole Oceanographic Institution, produce specialized models for specific energy projects. Hindcast data help model historical ocean conditions, and operational forecasts aid in planning and real-time decision-making. Companies like Fugro, Woods Hole Group, DNV GL and the RPS Group offer tailored ocean forecasting and meteo-oceanographic services that provide high-resolution, localized ocean and weather forecasts to support the offshore energy industry. These forecasts are often customized for specific platforms, rigs or turbines.

The oil and gas energy industry have specific ocean forecast requirements depending on the application, such as diver operations, uncrewed vehicles operations, rig installation and production. In the Gulf of Mexico, a leading area for exploration and production, the Loop Current eddy (LCE) shedding is a process of great interest, as current speeds of extended or detached LCE's often have current speeds in excess of 2–3 $\mathrm{m\,s^{-1}}$, speeds which often require repositioning of equipment or temporary cessation of operations.

### 8.3 Shipping, ports and navigation

With the advent of new standards for marine navigation, implementations and applications of ocean prediction systems for e-navigation and port management are expanding in North America. In the United States, NOAA's Physical Oceanographic Real-Time System (PORTS) provides real-time water level, current and meteorological information for major US ports and harbours, while the National Operational Coastal Modeling Program (NOCMP) develops and operates a network of Operational Nowcast and Forecast Hydrodynamic Model Systems (OFS) for critical US ports, harbours and coastal waters. These systems provide predictions of water levels, currents and other oceanographic variables, aiding in navigation, harbour management and coastal hazard mitigation. In Canada, CONCEPTS (ECCC/DFO) provides oceanographic forecasts for various regions, including the St. Lawrence Seaway and major Canadian ports, and the DFO is developing a port ocean prediction system (POPS) for major Canadian ports and waterways.

These forecasts are starting to be integrated into various vessel traffic management systems (VTMSs) that are used throughout North America. For example, the Canadian Coast Guard's vessel traffic services (VTS) are increasingly using data from CONCEPTS and other forecast models, and port-specific VTMSs in the United States (e.g. the Port of New York and New Jersey) integrate data from NOAA's operational forecast system.

### 8.4 Climate adaptation

The United States leverages ocean models extensively to bolster climate adaptation strategies for both coastal and ecosystem resilience. A network of federal agencies, including NOAA, EPA, USFWS (U.S. Fish and Wildlife Service), NPS (National Park Service), USACE (Army Corps of Engineers), DOI (Department of the Interior) and FEMA (Federal Emergency Management Agency), utilizes these models to understand and respond to the impacts of climate change on marine environments. NOAA plays a central role, conducting research on ocean temperature, sea-level rise and habitat changes, while also collecting and disseminating crucial data to stakeholders. Models provide critical information on sea-level rise, coastal erosion, extreme weather events and ocean warming, informing the development of resilience strategies and enabling communities, governments and industries to make informed decisions.

Specifically for ecosystem resilience, ocean models support a variety of ecological and biological studies. Agencies like NOAA, through programmes like NMFS and OAR (Office of Oceanic and Atmospheric Research), and USFWS, with its Endangered Species Program and National Wildlife Refuge System, use model outputs to monitor marine biodiversity, track species, understand ecosystem dynamics and manage resources. These models, providing real-time and forecasted data on ocean conditions, help researchers study the effects of climate change, track biological events, and inform conservation and restoration efforts, including those focused on coral reefs and endangered species. Furthermore, for coastal resilience, these models are essential for engineering projects, providing critical predictions of oceanographic and atmospheric conditions that inform the design and maintenance of coastal infrastructure, erosion management and preparedness for extreme events. In particular, the USGS provides a suite of tools for predicting coastal changes, especially during storms. These tools forecast factors like coastal erosion, overwash and inundation, which help engineers evaluate potential changes in shoreline position and design resilient coastal infrastructure. Their Coastal Change Hazards Portal integrates data on sea-level rise, coastal erosion and sediment transport, which are critical for long-term coastal engineering projects.

## 9 Arctic

The Arctic environment is evolving quickly. Short-term models allow users to monitor changes to the landscape, particularly at the ice edge and responses to short-term events (such as storms). This information is valuable for national environment agencies, especially those with Arctic coastlines. As detailed in Cirano et al. (2025), there are a number of short-term (up to 10 d) forecasting systems available in the Arctic. Nine of these are global models, eight are regional and five are coastal. It is important to note that many of the Arctic forecast system outputs are used as inputs to other models. This can be specific modelling in response to an event – for example, oil spill trajectory modelling, as described in Nordam et al. (2019) – or for monitoring the state of a specific parameter that is not present in the main forecasting system, such as the use of TOPAZ4 to force a coastal 800 m resolution ocean model for a weekly monitoring and assessment of the sea louse (https://www.globalseafood.org/advocate/norwegian-researchers-develop-sea-lice-tracking-model/, last access: 4 May 2025). The latter example is currently only applied to the coastline of mainland Norway at present, but as fishing extends further and further north, such forecasts may also become more relevant further into the Arctic.

They are also used to feed into weather forecast models, an Arctic-specific application mirroring the standard process of forcing ocean models with weather forecast outputs that is often used in other regions. This is because ice conditions can have important feedback to the atmosphere, and models developed specifically for ice can represent these conditions well. The NOAA (the US National Ocean and Atmospheric Administration) ice drift is primarily used for this purpose (https://mag.ncep.noaa.gov/docs/NCEP_PDD_MAG.pdf, last access: 4 May 2025) to provide sea ice conditions for the NWS (the US National Weather Service) global atmospheric model; this has been the case since 1998.

In the following subsections, the other main applications of Arctic forecasts are provided, focusing on direct applications of the forecasts themselves. Note that in most cases the downstream applications are suggested by providers but there is little data available in the public domain about user uptake for a given usage.

## 9.1 Extremes, hazards and safety

As more activities happen at the ice edge and in the marginal ice zone, there is an increase in the risk of both harm to humans and negative consequences of their activities, and there have been some incidents in the last decade (for example, https://barentsobserver.com/en/nature/2013/09/tanker-accident-northern-sea-route-09-09, last access: 4 May 2025). Marchenko et al. (2015) note "the main operational risk factors faced include geographical remoteness, climate-change related aspects and weather, electronic communications challenges, sea ice, lack of precise maps or hydrographic and meteorological data". Forecasting models can be used both to reduce risk and to target the response to an incident. For example, the Barents-2.5km model, used by MET Norway, acts as one of the main inputs to further modelling of pollutants (such as drift of oil spills from ships) and iceberg drifting, which are all based on the same type of Lagrangian drift calculations (Sutherland et al., 2022). It is also used in search-and-rescue operations, where information on where a lost person or vessel may drift in the short term is very important.

### Storm surge

Coastal models play an important role in understanding the short-term behaviour of a region. One such example is the storm surge model, which provides both coastal forecasts (useful for those with activities in coastal waters, such as fishing) and a warning system for storm surges along the coast of mainland Norway and Svalbard. Users receive an alert when an extreme weather event is likely; for example, during Storm Elsa in February 2020, it was found to be a useful tool to both monitor the development and send warnings out (Kristensen et al., 2024).

## 9.2 Natural resources and energy

As sea ice declines, more opportunities to exploit natural resources such as oil and gas extraction arise, although the safety of fixed assets and persons will still be at risk of storms, high waves, sea ice and incoming icebergs. To reduce ocean pollution and carbon footprint from transportation of people/resources to and from destinations, as well as minimize risk from ending up in thick ice, companies must choose the best routes for transportation. Short-term forecasts in conjunction with available real-time observations can be very important for this (Grigoryev et al., 2022). While no specific operational downstream applications have been identified in this category for the Arctic, in the sections below the growing needs specific to the region are described.

### 9.2.1 Fisheries

The "Agreement to prevent Unregulated High Seas Fisheries in the central Arctic Ocean" has been in place since 25 June 2021 (https://arctic-council.org/news/introduction-to-international-agreement-to-prevent-unregulated-fishing-in-the-high-seas-of-the-central-arctic-ocean/, last access: 4 May 2025) and aims to ensure that future fishing in the Arctic as sea ice declines can be carried out sustainably.

Short-term forecasts could help to support this agreement as well as to inform users about conditions suited to fish stocks and to reduce the chance of operating in risky conditions which could lead to oil spills. As noted by Neis et al. (2020), "When harvesters adjust their activity or move into new fishing grounds, forecasts become critical tools for anticipating dangerous conditions and 'learning' an unknown environment or working context (e.g. different gear)", which suggests that even if the central Arctic Ocean remains tightly controlled, an increase in fishing activities in the northern peripheral seas as ice declines (Fauchald et al., 2021) may increase the need for forecasts of environmental conditions for a new set of users in the future

### 9.2.2 Tourism

Arctic tourism has been increasing in recent decades (Larsen and Fondahl, 2014), particularly the concept of "last chance tourism" (Eijgelaar et al., 2010). As well as requiring forecasts for navigation in waters, where ships have been built for comfort rather than operational purposes, tourism is often focused on reaching the ice edge or ecosystems to spot wildlife. This can require accurate forecasts of sea ice conditions and the limit of the marginal ice zone, which is a hotspot for biological activity in the Arctic (and attracts the more audacious fishers as a result). Search-and-rescue-based forecasts for such purposes are also relevant as ships aim to get close to the ice rather than avoid it.

### 9.3 Shipping, ports and navigation

Reductions in summer sea ice, and thinner ice, open new routes to traverse the Arctic (for example, the Northeast Passage), providing more efficient routes across the globe, as well as providing opportunities for many of the above users to work further into the Arctic Basin away from the coast. In all the cases currently described, there is an aspect of navigation driving a need for forecasts. One of the main considerations when navigating is sea ice jams and ice accumulation, which can prevent further progress to ships and cause hull damage (for example, the case where two cargo ships were stuck and damaged in Frobisher Bay, https://www.cbc.ca/news/canada/north/ice-damages-hull-of-sealift-ship-near-iqaluit-1.1230034, last access: 4 May 2025). Depending on the ability of the ship (ice-strengthened or icebreaker), different sea ice conditions can be the limit of safe operations. Given the ice can vary quickly, recent efforts have been made to include a dynamical ice edge in fully coupled model for weather prediction (Day et al., 2022) and improve forecasts of the ice edge itself (Posey et al., 2015) A typical use of sea ice short-term forecasts is to assess whether the ice edge is advancing or retreating (which would then feed into decisions related to navigation in the short term, such as whether or not it is safe for a ship to either stay in a given location for deployments or navigate in a certain direction, for example, the use of VENUS for monitoring sea ice in the Bering Strait, Cirano et al., 2025). One of the main limitations of accessing information from a ship is a reliable internet connection, meaning forecasts must be readily available and not hard to download. A number of users still rely on manual ice charts drawn by experts.

Ship operators rely on operational forecast models to adhere to the Polar Code, which is the International Maritime Organization's international code for ships operating in polar waters, in place since 1 January 2017 (https://www.imo.org/en/ourwork/safety/pages/polar-code.aspx, last access: 4 May 2025); it is relevant for navigation (and, as part of this, design and capabilities of ships wishing to work in polar waters) and operational procedures, search and rescue, and protection of ecosystems. Mandatory measures cover safety and pollution prevention, and ships going into the polar regions require a Polar Ship Certificate determining what conditions the ship is suited to (https://www.dnv.com/maritime/polar/requirements.html, last access: 4 May 2025). Forecasts can contribute to helping users abide by the Polar Code, for example by assessing whether ships will be able/authorized to operate in upcoming sea-ice conditions. The definition of "environmental conditions" is evolving in the Polar Code and may in the future include variables that can be skilfully forecast.

Ultimately, all ship-based operations in the Arctic region rely on navigation and sea ice information for navigation, either to avoid or get close to the ice edge, and this is the most mature of the forecast applications. Tools exist to condense or combine multiple forecast outputs and observations to provide near-real-time and forecasted conditions in a user-friendly way. Two such examples are IcySea (https://driftnoise.com/icysea/, last access: 4 May 2025), which uses ice charts with a sea ice drift forecast, and Arctivities (https://arctivities.noveltis.fr/overview/, last access: 4 May 2025), which provides a risk index and anthropic noise levels. Such tools can be used to support maritime users with varying needs.

#### Research support

Forecasts of the Arctic Ocean can be used to inform new developments or deployments of equipment for scientific purposes. One such example is the Sea Ice Drift Forecast Experiment (SIDFEx; https://www.polarprediction.net/key-yopp-activities/sea-ice-prediction-and-verification/sea-ice-drift-forecast-experiment/, last access: 4 May 2025). Two of the main aims of the campaign were to gather information on available sea ice drift forecasts in order to (a) decide on an optimal starting position for the research icebreaker Polarstern to commence a year-long study of conditions while frozen into the sea ice and (b) use the drift forecasts to inform where to order high-resolution satellite images of the local domain around the ship for the coming days as they become available. Using sea ice drift models to selectively download these images saved limited bandwidth and image fees.

Another example of the use of short-term forecasts is the use of the VENUS (VEssel Navigation Unit support System), a forecasting platform which can use a variety of domains to provide forecasts for research ships on demand. This was successfully deployed in a cruise in 2018 (Dethloff et al., 2019). The ice-strengthened ship MIRAI could only go (a) where ice thickness was less than 70 cm and concentration less than 0.1 and (b) where air temperature was greater than −15 °C (Inoue et al., 2019). Scientists were deploying equipment near the marginal ice zone in order to investigate the predictability of conditions during autumn freezing; further, the ship needed to gather as many data as possible while being able to exit through the Bering Strait before ice blocked it for the winter (Dethloff et al., 2019). Using VENUS, which combines forecast from ECMWF, sea ice forecasts from ICE-

POM (University of Tokyo) and passive microwave data, helped to inform these. Such use of forecasts can also feed back into the development – for example, on the MIRAI cruise, the bandwidth was such that it was hard to download data; therefore 2D fields were more valuable (Inoue et al., 2019).

### 9.4 Climate adaptation

The rapidly declining sea ice, environmental changes and potential economic opportunities of the Arctic region have attracted a lot of interest, but with this comes a new state that is still being understood even as it evolves. Large uncertainties in Arctic forecasts somewhat impede their use in climate adaptation, but the strategic and economic interest for the region as well as presence of coastal communities has made it a very active field of research. For example, decadal predictions such as those from the IPCC Sixth Assessment Report (https://www.ipcc.ch/synthesis-report/, last access: 4 May 2025) are used to predict future states, often by selecting some variables in conjunction with past and present in situ and satellite monitoring to make the predictions more robust and downscaled to more local areas. Examples include frequency of marine heat waves (He et al., 2024) and sea-level rise and coastal erosion (Tanguy et al., 2024). In the Barents Sea, climate prediction models have also been used to predict phytoplankton up to 5 years in advance (Fransner et al., 2023) and cod populations under evolving ocean physical properties (Kjesbu et al., 2023). Such studies can provide new understanding, which can contribute to decision-making and planning in vulnerable communities and occupations that are dependent on knowing the physical conditions or biological activity.

Another key tool in developing understanding of the changing Arctic is to use reanalyses or hindcasts to see how the present situation compares to earlier years. Many of the available short-term forecasts in the Arctic (Cirano et al., 2025) have an accompanying reanalysis or hindcast so that past seasonal evolution of relevant conditions. For some maritime users, seasonal predictions can supplement this information to aid voyage planning (Wagner et al., 2020), for both safety and ensuring adherence to the Polar Code (see Sect. 9.3). An additional example is the Disko Bay model, run by the Disko Ice and Ocean service (https://marine.copernicus.eu/services/use-cases/monitoring-ecosystem-within-disko-bay, last access: 4 May 2025), which provides both forecasts and a hindcast of ocean conditions at the high resolution required for Greenlandic fjord environments, using output from a lower-resolution forecasting model as boundary conditions. Outputs from this fjord model have been provided to an ecosystem model; these applications contribute to monitoring efforts to ensure long-term sustainability of the blue economy in Greenland.

## 10 Education, stakeholder engagement and ocean literacy

Education, stakeholder engagement and ocean literacy activities are essential components in supporting the full value chain from data production (operational forecast systems) to the provision of useful downstream applications. These activities are carried out in all regions and at various different stages along the value chain: from education outreach activities with learners and technical workshops to community engagement and co-design workshops with stakeholder groups. They help to ensure that the downstream applications produced have real value and are measurably impactful. Below, we provide some examples of the types of education and engagement activities that take place.

### 10.1 Technical workshops

The International Oceanographic Commission Sub-Commission for the Western Pacific (WESTPAC) develops and strengthens regional and member states' capacity for ocean model development, data assimilation, model validation and development of ocean forecasting systems, through a series of national and regional training, scientific workshops, and professional exchanges among partner institutions (https://ioc-westpac.org/ofs/capacities/, last access: 4 May 2025). The Regional Training and Research Center on Ocean Dynamics and Climate (RTRC-ODC) was officially established at the 8th WESTPAC Intergovernmental Session in 2010. The First Institute of Oceanography, State Oceanic Administration of China, organized the lecture series on ocean models (2011), ocean dynamics (2012), air–sea interaction and modelling (2013), climate models (2014), climate change (2015), ocean dynamics and multi-scale interaction (2016), development of coupled regional ocean models (2017), ocean forecast system (2018), and climate dynamics and air–sea interactions (2019). In the evaluation period of 2015–2019, 191 young scientists from 36 countries joined the lectures (https://ioc-westpac.org/rtrc/odc/, last access: 4 May 2025).

### 10.2 Ocean literacy

With ongoing Arctic Sea ice decline, scientific results from the region are more frequently appearing in national news, and the general public are more aware of the Arctic environment and how it is changing. The freely accessible forecast maps from most services, with an interface that can select given variables and watch as they run forward in time, provide a useful tool to demonstrate how changeable, for example, the ice edge is in response to forcing, even in the short term, which can be used to engage with wider audiences and educate about the Arctic as a dynamic system. For example, Coursera, a website offering a number of free online courses for studying in the evenings, has a course entitled

"Frozen in the Ice: Exploring the Arctic", based out of the University of Boulder, Colorado (https://www.coursera.org/learn/frozen-in-the-ice, last access: 4 May 2025); the course allows participants to act as virtual participants on the MOSAiC Arctic research campaign, and one of the six modules is based around Arctic forecasting. Activities such as this allow the public to get closer to polar research, and many large research campaigns now include outreach as part of their programmes.

### 10.3 Stakeholder engagement and co-design

With NOAA's Office of Response and Restoration, the Emergency Response Division (ERD) develops tools; guidelines; and small, field-oriented job aids to assist preparedness for response communities. In addition, NOAA provides standard techniques for observing oil, assessing shoreline impact, and evaluating and selecting cleanup technologies that have been widely accepted by response agencies.

South Africa's National Oceans and Coastal Information Management System (OCIMS) holds annual stakeholder engagement workshops that facilitate the co-design of the decision support tools. Between the workshops, dialogue between stakeholders and developers is maintained through active WhatsApp groups.

While INCOIS provides extensive training to users for efficient utilization of their forecast products, they have noticed that NGOs, universities, local government departments and localized user community networks are found to be very effective in ensuring that the information reaches the user in time. User uptake is supported by their good relationship with local fishing communities, who are involved with the safe-keeping of their observation platforms in exchange for timely warnings of maritime hazards. This relationship builds awareness as well as trust with coastal communities.

### 10.4 Citizen science

Aotearoa / New Zealand's Moana Project innovatively incorporates citizen science by partnering with commercial fishers to gather essential oceanographic data. Fishing vessels are equipped with the "Mangōpare" sensor system, which automatically collects and transmits subsurface temperature measurements in near-real time as the vessels go about their normal fishing activities. This transforms the fishing fleet into a vast, mobile observation network, expanding data coverage across a wider spatial range than traditional research methods. This mutually beneficial partnership provides scientists with valuable data, while fishers gain access to information that can enhance their own operations. By empowering local communities and increasing data accessibility, Moana fosters collaboration and contributes to a deeper understanding of the marine environment, ultimately supporting sustainable fisheries' management and scientific research.

## 11 Summary

Operational oceanography supports the blue economy, providing the knowledge and tools for us to sustainably use our oceans for economic growth, better livelihoods and job creation. Around the world, scientists and forecasters are developing cutting-edge tools that transform raw ocean data into practical solutions for a variety of challenges. These tools help us understand and protect our marine environments, manage resources, and ensure safety at sea.

This report has provided some examples of downstream applications, based on operational forecast systems, for eight of the nine regional teams identified by the OceanPrediction DCC. It is by no means a comprehensive review, but it does provide an indication of the needs and services in each region as well as the relative maturity level of downstream applications. The OceanPrediction regions with the most established and most numerous operational forecast systems (e.g. the Mediterranean and Black Sea, the North East Atlantic, North America, parts of the West Pacific and Marginal Seas of South and East Asia, and to some extent the Arctic) tend to also have the most mature downstream applications. The forecasting systems of the Indian Seas, South America and Africa can be thought of as "emerging", and by this we mean new, rapidly growing, and often under- or less-resourced. Despite this, the INCOIS system developed for the Indian Seas is a sophisticated system that incorporates real-time observations and provides mature tools for stakeholders that support various offshore activities. Part of their success is related to their close engagement with their stakeholders. The African region is one of the least developed in terms of regionally optimized forecast systems, with only a few developed in various parts of the continent. However, they do have two fairly mature user-support platforms that are based primarily on earth observations and whose tools are co-designed with stakeholders. These dissemination platforms are ready to ingest tools based on regionally optimized forecasts.

In this review, a sample of various downstream applications around the globe reveals that while established and reliable forecast systems are a key factor in their abundance, a good relationship with stakeholders is critical for their uptake.

**Data availability.** No data sets were used in this article.

**Author contributions.** All authors contributed to the content and writing of this manuscript. JV led and collated the various contributions.

**Competing interests.** At least one of the (co-)authors is a member of the editorial board of *State of the Planet*. The peer-review process was guided by an independent editor, and the authors also have no other competing interests to declare.



**Acknowledgements.** The authors would like to gratefully acknowledge the contributions from the Ocean to Climate Seamless Forecasting Decade Programme (OSF).

**Review statement.** This paper was edited by Kirsten Wilmer-Becker and reviewed by two anonymous referees.

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State Planet, 5-opsr, 7, 2025
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# Connecting ocean observations with prediction

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Received: 19 September 2024 – Discussion started: 14 October 2024
Revised: 6 January 2025 – Accepted: 18 January 2025 – Published: 2 June 2025

**Abstract.** Ocean prediction relies on the integration between models and satellite and in situ observations through data assimilation techniques. Nowadays, satellites offer high-resolution observations of essential ocean variables at the surface, widely adopted in combination with precise but sparse in situ measurements that, from the surface to the deep ocean, can constrain large-scale variability in models. Moreover, observations are a valuable source of information for validating and assessing model products, for improving them, and for developing the next generation of machine learning algorithms aimed at enhancing the accuracy and scope of ocean forecasts. The authors discuss the role of observations in operational ocean forecasting systems, describing the state of the art of satellite and in situ observing networks and defining the paths for addressing multi-scale monitoring and forecasting.

## 1 Introduction: the role of observations in ocean prediction

Ocean prediction relies on the integration between models and satellite and in situ observations through data assimilation techniques (Bell et al., 2015). Data assimilation provides a 4D dynamical interpolation of observations by considering the complementarities between the different types of observations. High-spatial-resolution (e.g. from 10 km at global scale to 1 km or less at regional and coastal scales) and high-temporal-resolution (e.g. daily) ocean fields consistent with observations and model dynamics are thus derived and can be used to initialise ocean forecast models. The development of machine learning techniques such as deep neural networks offer different and complementary pathways for ocean prediction. Machine learning techniques analyse and learn from patterns in past data or ocean reanalyses to make ocean predictions from current data. Several studies have already shown the potential of machine-learning-based ocean forecast systems (e.g. Chen et al., 2023).

Whatever the techniques used to produce them, the quality of ocean analyses and forecasts observations at global and regional/coastal scales is directly dependent on the availability of high-quality in situ and satellite observations with a sufficient space and time resolution. These dependencies vary according to ocean dynamics. Data assimilation is, for example, mandatory and quite effective for constraining the mesoscale variability at global and regional scales. At coastal scales, it is more challenging to constrain ocean dynamics where small-scale, high-frequency and non-linear processes play an important role.

Observations are also essential to validate ocean analysis and prediction models (e.g. Gutknecht et al., 2019), to improve ocean models (required for assessment of model performances, for ocean prediction and for digital twins) (e.g. Wang et al., 2021), and for training machine learning algorithms.

For both data assimilation and validation aspects, data must be carefully validated, and information on data errors must be documented. Higher-quality reprocessed data sets are required for reanalyses.

The monitoring of the impact of observations should be part of any ocean prediction activity. This is done through Observing System Evaluations (OSEs) and Observing Sys-

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tem Simulation Experiments (OSSEs) (Fujii et al., 2019; Gasparin et al., 2019). OSEs allow the impact of an existing observing system to be assessed (by withholding observations). OSSEs help in the design of new observing systems, evaluate their different configurations and perform preparatory data assimilation work. Other complementary approaches for quantifying the impact of observations on ocean analysis and forecast systems also exist (Fujii et al., 2019; Drake et al., 2023).

In the following sections we briefly review the role of the different ocean observing systems in ocean prediction at global, regional and coastal scales. Sections 2 and 3 deal, respectively, with satellite and in situ observations.

## 2 Satellite observations

Satellite observations have a major role in and impact on ocean prediction (Le Traon, 2018). Satellites can provide real-time and global observations of key ocean variables at high space and time resolution: sea level and geostrophic currents, sea surface temperature, ocean colour, sea ice, surface wave, and surface winds (Fig. 1). The spatial resolution depends on the nature of the sensor and ranges from a few hundreds of metres (e.g. infrared and ocean colour sensors) to tens of kilometres (e.g. microwave sensors). The time resolution or revisit time ranges from 1 h or less for geostationary satellites up to a few days or longer for polar-orbiting satellites.

Ocean modelling and data assimilation systems have a high dependency on the status of the altimeter constellation (Le Traon et al., 2017). Satellite altimeters provide all-weather observations of sea level, which is an integral of the ocean interior and provides a strong constraint on ocean state estimation at the mesoscale. At least four altimeters are required, and a precise knowledge of the mean dynamic topography (MDT) is also a strong requirement for assimilation into operational ocean forecasting systems (Le Traon et al., 2017; Hamon et al., 2019).

Sea surface temperature (SST) is a key variable for all ocean prediction systems. SST data can be used to correct for errors in forcing fields (heat fluxes, wind) and to constrain the mesoscale variability of the upper ocean. High-resolution SST data from a combination of infrared (polar-orbiting and geostationary) (e.g. S3 SLSTR, VIIRS, GOES, MTG) and microwave sensors (e.g. AMSR-2) are thus essential to constrain ocean prediction systems.

Satellite sea ice concentration and, more recently, sea ice thickness data (SMOS and Cryosat) are routinely assimilated in sea ice models. The assimilation of sea ice drift remains challenging due to the short memory of sea ice drift and sea ice models deficiencies (Sakov et al., 2012). Numerous impact studies have been carried out for sea ice data assimilation, in particular for sea ice thickness products from Cryosat but also for thin ice thickness from SMOS and both satellites together (Xie et al., 2018).

Sea surface salinity (SSS) observations (SMOS, Aquarius, SMAP) from space (Reul et al., 2020) provide valuable information (Martin et al., 2019; Tranchant et al., 2019) for ocean prediction. Satellite SSS data assimilation can now constrain the model forecasts without introducing incoherent information compared to the other assimilated observations.

Satellite significant wave height observations are routinely assimilated in global and regional wave models, and their impact is very well demonstrated. Wave spectra provided by Sentinel-1 SAR instruments and, more recently, with the more precise CFOSAT SWIM instrument can, in addition, significantly improve the quality of wave forecasts (Aouf et al., 2021; Hauser et al., 2023).

Ocean colour missions (e.g. S3 OLCI, VIIRS) provide essential "green ocean" observations for a wide range of applications (e.g. water quality, eutrophication, harmful algal blooms). Higher-resolution and specialised ocean colour products (e.g. case-II water algorithms) are particularly needed for coastal areas. Ocean-colour data are being used to assess the performance of model simulations of chlorophyll-a (Chl-a) fields (Gutknecht et al., 2019) and to improve simulations through data assimilation (Ford et al., 2018; Fennel et al., 2019). However, the assimilation of ocean colour data is arguably less widespread than that of physical variables. The potential for ocean colour data to improve biogeochemical (BGC) models remains significant, though many challenges persist (e.g. error characterisation, observation operators such as bio-optical models and the integration of ocean colour data with in situ measurements like BGC Argo).

While wind observations from multiple scatterometers are essential for improving the forcing fields required for ocean prediction, the primary pathway for utilising scatterometer data is through assimilation in numerical weather prediction (NWP) systems. However, NWP data assimilation systems do not incorporate all the information available from scatterometers, particularly at smaller spatial scales (Belmonte Rivas and Stoffelen, 2019). Therefore, using these observations to directly constrain ocean models may be more beneficial.

## 3 In situ observations

In situ observing systems play a fundamental role to provide measurements of the ocean water column and to complement satellite observations. The combination of high-resolution satellite data with sparse and precise in situ observations of the ocean interior is the only means to provide a high-resolution 3D description and forecast of the ocean state. In situ temperature and salinity data are crucial to constrain large-scale variability in models (Gasparin et al., 2023). In situ observations of high-frequency and high-

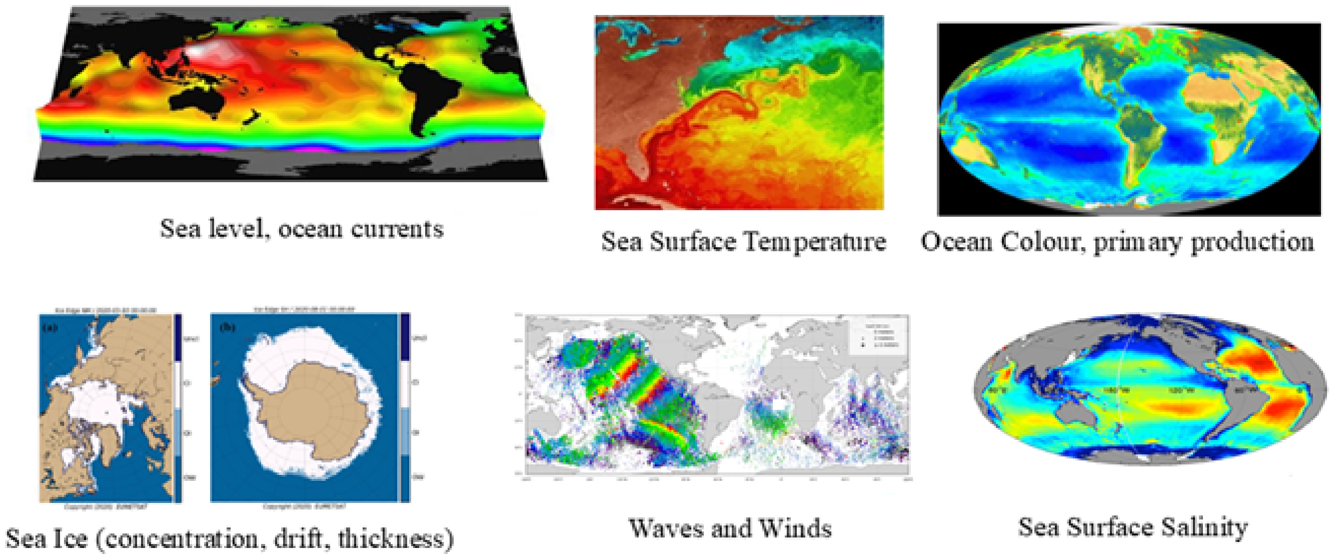


**Figure 1.** The unique contribution of satellite oceanography for ocean prediction.

resolution ocean processes in the coastal zone are also essential to validate coastal ocean prediction systems.

Ocean prediction uses surface observations, vertical profiles and time series coming from different types of instruments (e.g. floats, drifters, moorings, marine mammals, gliders, tide gauges, research vessels, ships of opportunity, FerryBoxes, saildrones, high-frequency (HF) radars) and different parameters (temperature, salinity, currents, sea level, wave, chlorophyll, oxygen, nutrients, pH, fugacity of $CO_2$) (Fig. 2).

Some available observations, such as from surface drifters, thermosalinographs (TSGs), and acoustic Doppler current profilers (ADCPs), are not always assimilated. However, non-assimilated observations are essential for the independent validation of analyses and forecasts, as well as for evaluating model and system improvements.

The global Argo array (Roemmich et al., 2019) plays a fundamental role in ocean prediction (Le Traon, 2013). Impact studies have confirmed and quantified the major impact of Argo on ocean analysis and forecasting systems (e.g. Turpin et al., 2016). The evolution of Argo into OneArgo, which includes deep and BGC components, already shows very promising results to improve ocean prediction systems (Gasparin et al., 2020; Cossarini et al., 2019; Wang et al., 2021; Mignot et al., 2023).

The most important other source of global observations is the surface drifter network, which provides data on surface currents; sea surface temperature; and, for some drifters, sea surface salinity. Additionally, met-ocean and deep-ocean mooring arrays (temperature, salinity, velocity, and biogeochemical parameters) (OceanSITES, including the TAO/PIRATA/TRITON tropical arrays) provide essential data to validate and constrain models. These are complemented by the Voluntary Observing Ship (VOS) network, which provides SST and SSS data as well as surface carbon measurements.

There is a growing need to increase in situ data coverage in shelf and coastal areas. Other data sources, such as HF radars, ferryboxes, gliders, tide gauges and coastal monitoring stations, are regularly used to validate and constrain ocean prediction models. Uncrewed surface vehicles (USVs), like saildrones, are also being used with increasing frequency. The assimilation of HF radar data in regional coastal models is an area of active development (Hernandez-Lasheras et al., 2021; Drake et al., 2023), and the assimilation of glider observations with sufficiently dense spatial and temporal sampling at regional and coastal scales has also proven highly effective (Pasmans et al., 2019; Levin et al., 2021; Drake et al., 2023). The development of low-cost technologies and citizen science can also support expanding coverage, particularly in coastal areas.

## 4 Most important near-future challenges

Ensuring the continuity of existing ocean observing systems is a necessary, but not sufficient, requirement for ocean prediction. Higher spatial and temporal resolution is required to match the increasing model resolution and improve the ability of ocean prediction systems to monitor and forecast smaller scales, including in coastal areas. In this regard, the development of operational swath altimetry (e.g. Morrow et al., 2019; Benkiran et al., 2022), following the outstanding results of the SWOT mission (Fu et al., 2024), is one of the most critical requirements for the evolution of the satellite observing system. For in situ observations, critical gaps remain in coastal areas, shelf seas and polar regions. On a global scale, the lack of biogeochemical observations limits

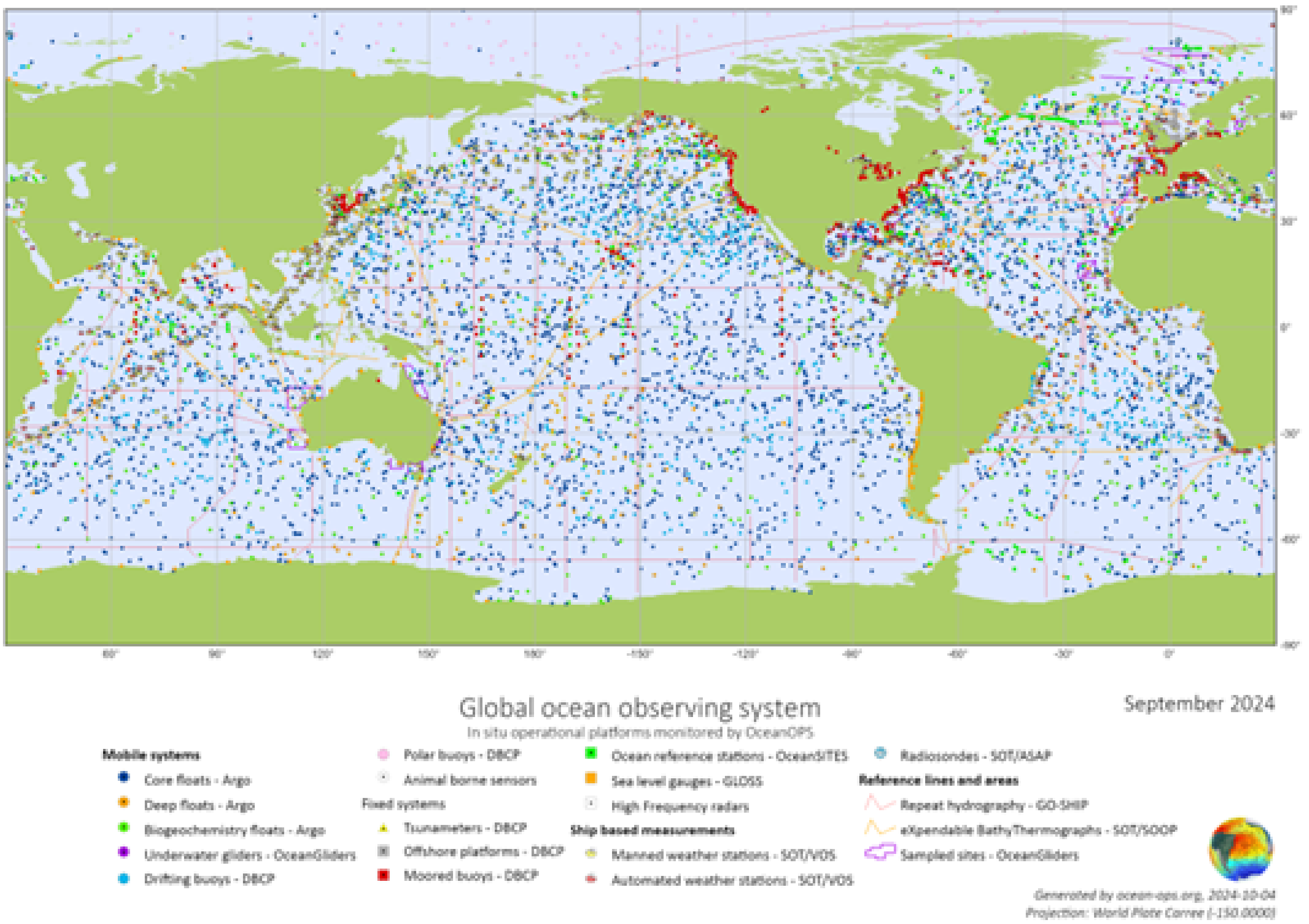


**Figure 2.** In situ networks from the Global Ocean Observing System (GOOS).

our ability to monitor and forecast the "green ocean", making the development of OneArgo a high priority. Data standardisation, quality assurance and quality control are also essential to ensure that ocean prediction systems make the best possible use of observations.

**Data availability.** No data sets were used in this article.

**Author contributions.** PYLT wrote the paper. AN and AMM provided feedback on the paper content.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.



**Review statement.** This paper was edited by Jay Pearlman and reviewed by Peter Oke and one anonymous referee.

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# Merging and serving ocean observations: a description of marine data aggregators

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Received: 13 September 2024 – Discussion started: 27 September 2024
Revised: 17 February 2025 – Accepted: 4 March 2025 – Published: 2 June 2025

**Abstract.** Observations are a fundamental component of ocean predictions: they are critical not only for monitoring the state of the ocean but also for improving forecasting systems and validating model outputs. In this context, it is essential to effectively access, manage, and integrate such information into the ocean value chain. Data providers play a pivotal role in collecting, processing, and analysing these observations, delivering comprehensive data sets that support informed decision-making and enable forecasters to enhance ocean models. This paper discusses several examples of data services, including the Copernicus Marine In Situ Thematic Assembly Centre (Copernicus Marine INS TAC), the European Marine Observation and Data Network (EMODnet), and SeaDataNet, all of which are recognized as key players in the monitoring and management of marine resources. Additionally, the paper provides an outlook on future directions for ocean data integration, emphasizing the opportunities offered by the standardization of data dissemination protocols and the role of cost-effective, citizen-based data collection.

## 1 Introduction

The importance of ocean observation in metocean forecasting is emphasized, as it provides crucial data for understanding oceanic behaviour and coastal areas. The integration of parameters like temperature, salinity, currents, and atmospheric conditions enhances model accuracy, crucial for the effective management of human impacts and resource exploitation. The complex ocean data collection framework involves numerous in situ platforms (Fig. 1), remote sensors, and types of data, necessitating the provision of multidisciplinary, aggregated data sets (Belbéoch et al., 2022).

Marine data aggregators, also referred to as integrators, play a pivotal role in managing, integrating, and advancing the understanding of marine environments. They collect, process, and analyse diverse data types to create comprehensive data sets, contributing to informed decision-making in areas such as fisheries management, offshore energy development, and marine conservation (see e.g. Novellino et al., 2025, in this report). Additionally, these aggregators support the development of technologies for monitoring the marine environment, continually refining data collection processes to enhance accuracy.

Over the past 3 decades, progress in marine data management has been marked by the establishment of international programmes and networks, such as the International Oceanographic Data and Information Exchange (IODE), the Global Ocean Observing System (GOOS), and the Ocean Data Information System (ODIS). These initiatives, including the World Ocean Database, involve collaborative efforts globally, led by organizations such as the Intergovernmental Oceanographic Commission (IOC), the World Meteorological Organization (WMO), the United Nations Environment Programme (UNEP), and the International Council for the Exploration of the Sea (ICES).

Under the GOOS framework (Fig. 2), the Observations Coordination Group (OCG), supported by OceanOPS (the GOOS in situ ocean observations programme support cen-

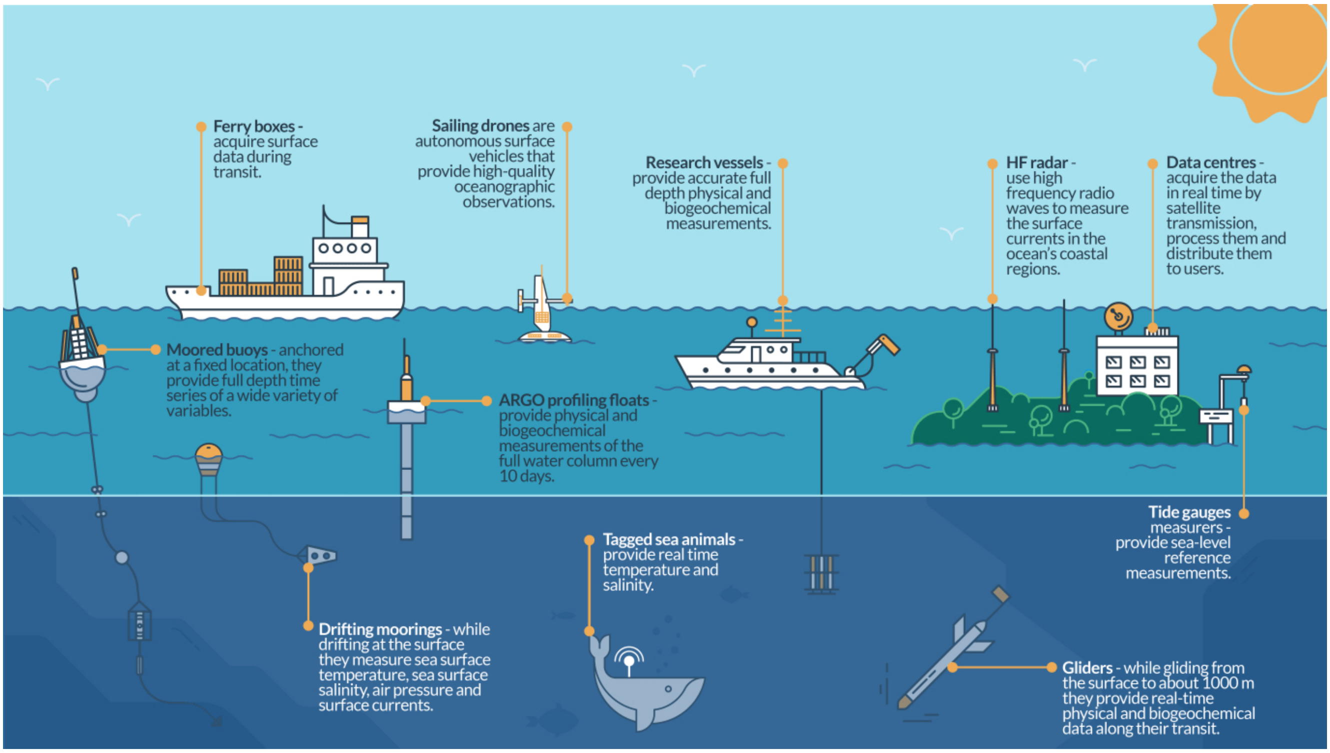


**Figure 1.** In situ platforms for ocean data collection (from https://marine.copernicus.eu/explainers/operational-oceanography/monitoring-forecasting/in-situ, last access: 19 March 2025).

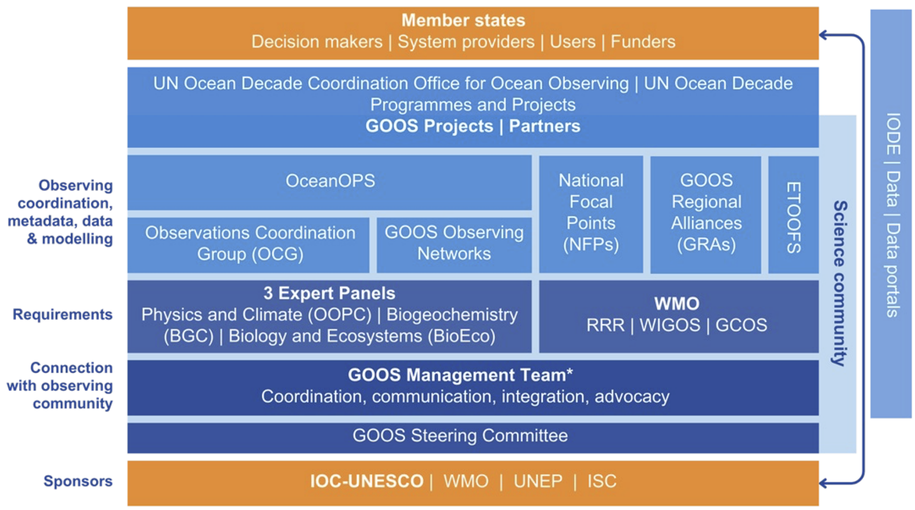


**Figure 2.** GOOS framework (from https://goosocean.org/, last access: 19 March 2025).

tre) and GOOS Regional Alliances (GRAs), coordinates the GOOS observing networks to provide ocean observing information (Moltmann et al., 2019). GRAs integrate national monitoring needs into a regional system, facilitating data assembly and exchange (Corredor, 2018). Data assembly centres (DACs) and global DACs (GDACs) play a critical role in this process by receiving, quality-controlling, and assembling data from various sources. They act as primary access points for this information, adhering to a common data format (netCDF).

Despite these efforts, GOOS networks and data represent only a subset of the overall ocean data framework. While progress has been made in modernizing the WMO data exchange system – transitioning from the Global Telecommunication System (GTS) to WIS 2.0 – by leveraging new web technologies and existing DAC/GDAC infrastructures, full data integration between OCG networks and national/regional initiatives has yet to be achieved.

In this intricate and dispersed framework, integration services play a crucial role in harmonizing metadata, applying standardized data quality checks, and facilitating the integration of diverse data sets and models. GOOS networks, guided by the OCG data strategy (O'Brien et al., 2024), are establishing global data nodes that progressively enhance overall data delivery while maintaining "GOOS quality" within the broader ocean data lake. Furthermore, the adoption of unified controlled vocabularies, common data models, and standardized transport formats ensures the seamless integration of real-time, near-real-time (NRT), and delayed-mode (DM) observations into numerical models.

At the international level, various marine data integrators exist, and Table 1 lists the most active. Some lead the way in adopting new standards and tools, while others take the approach of following them. Europe, along with the US and Australia, is at the forefront of introducing new tools and standards. The following section outlines the European marine data integration landscape, which is shaped by three key initiatives: the Copernicus Marine Service (specifically, the In Situ Thematic Assembly Centre); the European Marine Observation and Data Network (with a focus on physics); and the SeaDataNet network of national oceanographic data centres (NODCs), affiliated with the International Oceanographic Commission.

## 2 European marine data integrators

To exemplify the importance of data integrators, a few relevant examples from Europe are presented.

### 2.1 Copernicus Marine In Situ Thematic Assembly Centre (Copernicus Marine INS TAC)

Within this programme, the Copernicus Marine INS TAC is a distributed service integrating data from different sources for operational needs in oceanography. The Copernicus Marine INS TAC integrates and quality-controls in a homogeneous manner in situ data from data providers in order to fit the needs of internal and external users. It provides access to integrated data sets of core parameters for initialization of, assimilation into, and validation of ocean numerical models, which are used for forecasting, analysis, and re-analysis of ocean physical and biogeochemical conditions. Since the primary objective of Copernicus Marine is to forecast ocean state, the initial focus has been on observations from autonomous observatories at sea (e.g. floats, buoys, gliders, FerryBox systems, drifters, and ships of opportunity). The second objective is to set up a system for re-analysis purposes that requires products integrated over the past 25 to 60 years. The Copernicus Marine INS TAC comprises a global in situ centre and six regional in situ centres: one for each EuroGOOS Regional Operational Oceanographic System (ROOS). The INS TAC was designed to fulfil the Copernicus Marine Service and EuroGOOS ROOS needs. The focus is on essential ocean variables (EOVs) that are presently necessary for Copernicus monitoring and forecasting centres, namely temperature, salinity, sea level, current, waves, chlorophyll/fluorescence, oxygen, and nutrients. Additional atmospheric parameters (such as wind, air temperature, and air pressure) are added by some ROOSs to these regional in situ portals to fulfil additional downstream applications needs.

For near-real-time and delayed-mode products, the Copernicus Marine In Situ Thematic Assembly Centre is connected to the GOOS global networks and each Regional Operational Oceanographic System (ROOS) of EuroGOOS. In the case of DM products, it is also connected to the SeaDataNet Network, which comprises national oceanographic data centres (NODCs). The Copernicus Marine INS TAC integrates data from various observation programmes, including Argo, OceanGliders, the Data Buoy Cooperation Panel (DBCP), OceanSITES, and ship data obtained via NODCs, leveraging the GOOS network observations. Whenever possible, the Copernicus Marine INS TAC adheres to the standards developed within the SeaDataNet framework.

### 2.2 European Marine Observation and Data Network (EMODnet)

The European Marine Observation and Data Network (EMODnet) is the EU infrastructure for in situ marine data. The goal of EMODnet is to provide access to a wide range of standardized and harmonized marine data, making it easier for researchers, policymakers, and the public to access and use marine information. EMODnet focuses on various thematic areas, including bathymetry, geology, physics, chemistry, biology, and human activities in the marine environment (Shepherd, 2018). By pooling and harmonizing data from various sources, EMODnet aims to create a comprehensive and easily accessible marine data infrastructure that supports a wide range of marine and maritime activities (Schaap et al., 2022).

EMODnet Physics (https://emodnet.ec.europa.eu/en/physics, last access: 19 March 2025; Fig. 3) is the domain-specific project (Martín Míguez et al., 2019) that provides in situ ocean physics data and data products built with common standards, free of charge, and without restrictions. These services encompass a wide range of parameters, including temperature, salinity, current profiles, sea level trends, wave height and period, wind speed and direction, water turbidity (light attenuation), underwater noise, river flow, and sea-ice coverage.

EMODnet Physics offers an array of in situ data collections (time series, profiles, and data sets) obtained from various platforms (such as tide gauges, river stations, floats, buoys, gliders, drifters, and ship-based observations). EMODnet Physics does not operate platforms; instead, it

**Table 1.** International marine data integrators (alphabetical order).

| Region | Name | Description | Link |
|---|---|---|---|
| Africa | ODINAFRICA (Ocean Data and Information Network for Africa) | Marine data collection, capacity building, and information sharing across Africa. | http://odinafrica.org/ (last access: 19 March 2025) |
| Arctic Ocean | SAON (Sustaining Arctic Observing Networks) | Enhances and coordinates monitoring efforts in the Arctic region. | https://www.arcticobserving.org/ (last access: 19 March 2025) |
| Australia | IMOS (Integrated Marine Observing System) | Australia's national ocean observing system, providing open-access marine data. | https://portal.aodn.org.au/ (last access: 19 March 2025) |
| India | INCOIS (Indian National Centre for Ocean Information Services) | Provides oceanographic data, forecasts, and early warnings. | https://incois.gov.in/ (last access: 19 March 2025) |
| Japan | JAMSTEC (Japan Agency for Marine-Earth Science and Technology) | Conducts deep-sea research, ocean observations, and marine forecasting. | https://www.jamstec.go.jp/e/ (last access: 26 April 2025) |
| South America | REMARCO (Research Network of Marine-Coastal Stressors in Latin America and the Caribbean) | Latin American and Caribbean initiative for coastal and marine environmental monitoring. | http://remarco.org/ (last access: 19 March 2025) |
| Southern Ocean | SOOS (Southern Ocean Observing System) | A network for sustained ocean observations in the Southern Ocean. | https://www.soos.aq/ (last access: 19 March 2025) |
| United Kingdom | UK-IMON (UK Integrated Marine Observing Network) | The UK's coordinated ocean and coastal observing system, supporting climate monitoring, marine safety, and biodiversity research. | https://noc.ac.uk/ (last access: 19 March 2025) |
| United States (IOOS) | IOOS (Integrated Ocean Observing System) | US national ocean observation network providing real-time and long-term data. | https://ioos.noaa.gov/ (last access: 19 March 2025) |

integrates and federates key data infrastructures and programmes. For example, it is synchronized with Copernicus Marine INS TAC and includes supplementary in situ data from PANGAEA (https://www.pangaea.de/, last access: 19 March 2025), the International Council for the Exploration of the Sea (https://www.ices.dk/data/data-portals/Pages/ocean.aspx, last access: 19 March 2025), the European Multidisciplinary Seafloor and water column Observatory (EMSO) (https://emso.eu/, last access: 19 March 2025), the SeaDataNet network of national oceanographic data centres (NODCs), and other Global Ocean Observing System networks (https://goosocean.org/). The data and data products are accompanied by metadata, offering users comprehensive information regarding the provenance, content, location, time, data sources, and quality-check procedures.

It supports human-based data discovery (https://emodnet.ec.europa.eu/geoviewer/, last access: 19 March 2025) and machine-to-machine interoperability (https://data-erddap.emodnet-physics.eu/erddap/, last access: 19 March 2025) and contributes to enhancing our understanding of the physical aspects of the marine environment. EMODnet Physics supports various applications, including scientific research, coastal management, maritime operations, and policymaking.

## 2.3 SeaDataNet

SeaDataNet (http://www.seadatanet.org, last access: 19 March 2025) is a Pan-European network of professional marine data centres providing data and metadata standards for the marine community and online access to their data holdings of standardized quality (Schaap and Lowry, 2010). Founding partners are the national oceanographic data centres, major marine research institutes, UNESCO-IOC, ICES, and the European Commission Joint Research Centre (EC JRC). Over 3 decades, SeaDataNet has expanded its network of data centres and infrastructure in a long series of EU projects, mostly funded through EU DG RTD. SeaDataNet operates an infrastructure for managing, indexing, and providing access to ocean and marine environmental data sets and data products (e.g. physical, chemical, geological, and biological properties) and for safeguarding the long-term archival and stewardship of these data sets. Data are derived from many different sensors installed on research vessels, satellites, and in situ platforms that are part

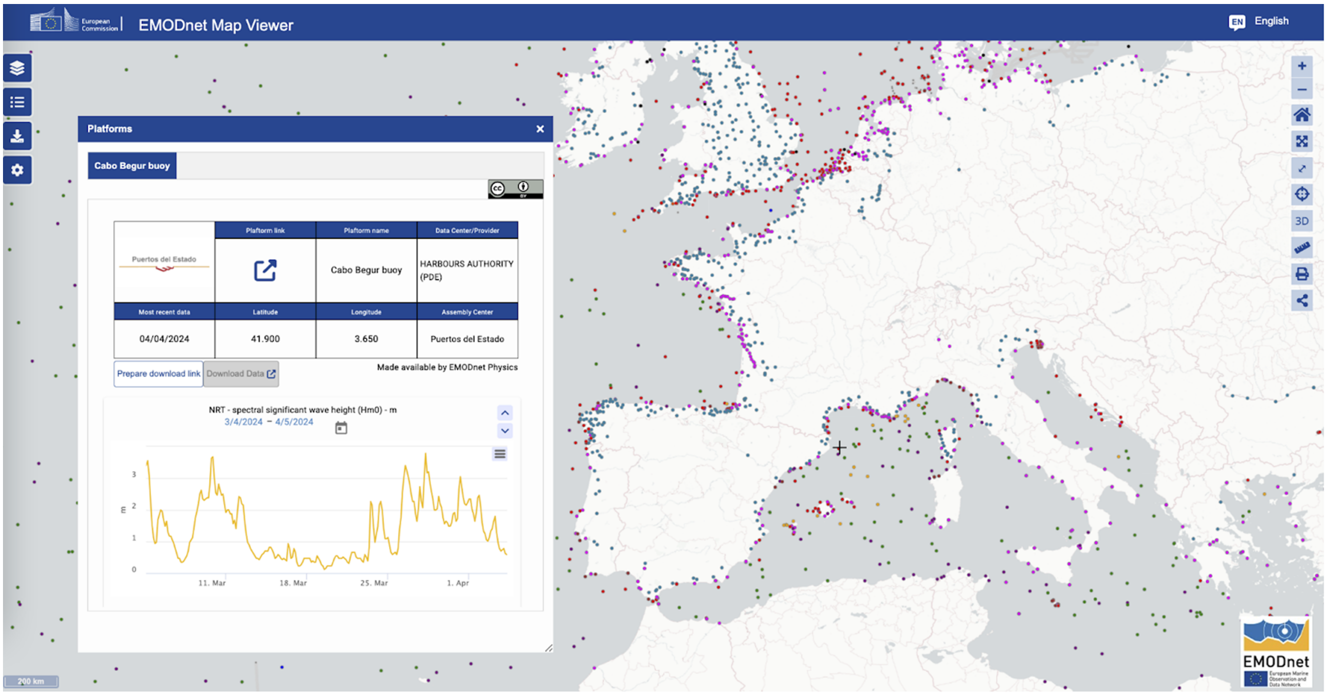


**Figure 3.** In situ data discovery in EMODnet Physics. Wave height chart.

of various ocean and marine observing systems and research programmes. A core SeaDataNet service is the Common Data Index (CDI) data discovery and access service which provides harmonized discovery and access to a large volume of marine and ocean data sets. Currently, more than 110 data centres are connected to the CDI service from 34 countries around European seas, giving access to more than 2.5 million data sets, originating from more than 650 organizations in Europe. This imposes strong requirements towards ensuring quality, elimination of duplicate data, and overall coherence of the integrated data set. This is achieved in SeaDataNet by establishing and maintaining accurate metadata directories and data access services, as well as common standards like vocabularies, metadata formats, data exchange formats, quality-control methods, and quality flags. SeaDataNet data resources are quality-controlled and are major input for developing added-value services and products that serve users from government, research, and industry (Simoncelli et al., 2022).

## 3 Single-source integrators

Besides these key European multi-parameter ocean data integrators, there are a number of initiatives that focus on single platforms or specific ocean variables. These initiatives concentrate on specific aspects of the marine environment, targeting a particular platform or variable for data collection and integration. Examples include projects that solely focus on buoys or floats for collecting oceanic data or on initiatives that specifically address parameters such as sea surface temperature, ocean currents, or marine biodiversity. By specializing in a single platform or variable, they can provide detailed and focused data products and services that cater to specific user needs and applications and provide a simplified source for specific forecasting systems. The following Table 2 summarizes the most used ones.

## 4 Ways forward in ocean data integration

In advancing ocean data integration, several key strategies can push our understanding of marine ecosystems and facilitate more informed decision-making. Shared data repositories and standardized data formats can streamline the integration process, ensuring compatibility and accessibility and, more generically, fair data (Wilkinson et al., 2016). Harnessing the power of emerging technologies, such as artificial intelligence and machine learning, offers opportunities to analyse vast data sets swiftly and extract meaningful insights. Implementing autonomous sensors and advanced monitoring systems enhances real-time data collection, providing a more comprehensive and dynamic picture of oceanic conditions. To follow the evolution of ocean general metocean models in terms of spatial resolution, which, in the future, will reach the kilometric scale at the global level, there is a clear need for more sensors deployed at the global, regional, and local scale. In this framework, the inclusion of cost-effective and

**Table 2.** List of single-data-type sources for the modelling community.

| Data type | Description | Source | Last access |
|---|---|---|---|
| Upper-ocean T&S | Global Temperature and Salinity Profile Programme (GTSPP) | https://www.ncei.noaa.gov/products/global-temperature-and-salinity-profile-programme | September 2024 |
| Surface underway T&S | Global Ocean Surface Underway Data (GOSUD) | https://www.gosud.org/ | March 2025 |
| Underway surface ocean and marine MET data (SAMOS) | Shipboard Automated Meteorological and Oceanographic System (SAMOS) | https://samos.coaps.fsu.edu/html/ | February 2025 |
| Argo profiling float data | Argo global data assembly centres (GDACs) | https://argo.ucsd.edu/data/ | March 2025 |
| Drifters | Global Drifter Program (GDP) Drifter Data Assembly Centre (DAC) | https://www.aoml.noaa.gov/phod/gdp/data.php | March 2025* |
| Meteorological moored buoys | National Meteorological and Hydrological Services (NMHSs) operating the buoys | https://www.ndbc.noaa.gov/ | March 2025 |
| Tsunameters | International Tsunami Information Centre (ITIC) | https://www.tsunami.gov/ | March 2025 |
| Tsunameters | Tsunami Alert Device (JRC) | https://webcritech.jrc.ec.europa.eu/TAD_server/Home | March 2025 |
| Deepwater reference stations | OceanSITES stations | https://dods.ndbc.noaa.gov/oceansites/ | March 2025 |
| Surface marine observational records from ships, buoys, and other platform types | International Comprehensive Ocean-Atmosphere Data Set (ICOADS) | http://icoads.noaa.gov/ | January 2025 |
| Tide gauges | Global Sea Level Observing System (GLOSS) | http://www.gloss-sealevel.org/data/ | March 2025 |
| Tide gauges | IOC Sea Level Station Monitoring Facility | http://www.ioc-sealevelmonitoring.org/list.php | March 2025 |
| Tide gauges | The UHSLC GLOSS Fast-Delivery Centre | https://uhslc.soest.hawaii.edu/data/?fd | March 2025 |
| Gliders | OceanGliders (formerly EGO) | http://www.ego-network.org/dokuwiki/doku.php, https://erddap.ifremer.fr/erddap/tabledap/OceanGlidersGDACTrajectories.html | March 2025 |
| HR SST data from satellites | Group for High-Resolution Sea Surface Temperature (GHRSST) regional data assembly centres | https://www.ghrsst.org/ | March 2025 |
| Bottle data | International Council for the Exploration of the Sea (ICES) | https://data.ices.dk/view-map | December 2023 |
| MEOP-CTD database | Over 600,000 vertical profiles (since 2004) of temperature and salinity collected by sea mammals | https://www.meop.net/database/meop-databases/ | February 2024 |
| CLIVAR and Carbon Hydrographic Data Office (CCHDO) | CCHDO hosts vessel-based CTD and hydrographic data from GO-SHIP, WOCE, CLIVAR, and other repeat hydrography programmes. | https://cchdo.ucsd.edu/ | February 2024 |

* drifter_6hour_qc.

citizen-based data collection is also a key forward-looking step, and long-term initiatives, such EMODnet, may play a crucial role in setting up the data flow capacities for emerging networks not organized under GOOS networks.

Timeliness is also an important parameter to be improved to ensure that data are available at each model run, particularly crucial for coastal applications where ocean dynamics evolve rapidly. Nevertheless, data usability/consumability strongly depends on the data policy licence, and there is an increasing push for adopting the Creative Commons framework and, in particular, the CC-BY licence, where the only limitation is that credit must be given to the creator. Integrating these strategies collectively will not only advance ocean data integration but also contribute to the ongoing evolution of general metocean models, including digital twins of the oceans, and foster a more comprehensive and accessible understanding of the marine environment.

**Data availability.** No data sets were used in this article.

**Author contributions.** AN developed the initial draft, which was reviewed and edited by the co-authors.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** This activity was indirectly supported by the authors' activities under the Copernicus Marine Service and EMODnet programmes and by the following projects: HE OCEAN-ICE (ct. 101060452), HE POLARIN (ct. 101130949), and HE BLUECLOUD2026 (ct. 101094227).

**Financial support.** This research has been supported by the Horizon Europe OCEAN ICE project (grant no. 101060452), Horizon Europe POLARIN project (grant no. 101130949), Horizon Europe BlueCloud 2026 (grant no. 101094227)

**Review statement.** This paper was edited by Kirsten Wilmer-Becker and reviewed by Jon Turton and Mathieu Belbeoch.

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State Planet, 5-opsr, 9, 2025
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# Data assimilation schemes for ocean forecasting: state of the art

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Received: 6 September 2024 – Discussion started: 20 September 2024
Revised: 24 January 2025 – Accepted: 4 February 2025 – Published: 2 June 2025

**Abstract.** Data assimilation (DA) is a process for integrating models and observations into comprehensive and reliable estimates of the ocean state. It is used to produce near-real-time initial conditions (analyses) from which ocean forecasts are produced and to generate reconstructions of the past state of the ocean (reanalyses). Here we provide an overview of the methods currently used in ocean systems for assimilating satellite and in situ observations, together with a brief review of methods being developed which will be implemented in future operational systems, including the use of machine learning (ML) techniques that provide a way to improve their efficiency. A list of data assimilation software used by most of the global and regional operational ocean forecasting systems is provided, together with the availability of each software. A discussion of practical considerations for employing data assimilation software and techniques operationally is also given, including the types of observations which are commonly used, and the implementation choices made by existing operational systems at global and regional scales is summarised.

## 1 Introduction

Accurate estimates of the state of the ocean are required for many purposes. Observations provide direct information about the ocean but are sparse in time and space. Numerical models can give information everywhere and describe the time evolution of the ocean but are prone to error. Data assimilation (DA) is the process by which these two sources of imperfect information are combined, taking into account their errors, in order to produce complete and accurate estimates of the ocean (Moore et al., 2019; Hoteit et al., 2018; Alvarez Fanjul et al., 2022; Stammer et al., 2016; Carrassi et al., 2018). These estimates are used to produce historical reanalyses of the ocean (Storto et al., 2019; Heimbach et al., 2019) and in near real time to initialise forecasts (Moore et al., 2019).

Data assimilation is used in global, regional, and coastal ocean forecasting systems. The characteristics of the models used in each setting can be different, including the resolution, processes represented, and the model components. Global models are usually coupled physical ocean–sea ice models, with a strong move at many operational centres to coupled atmosphere–ocean–sea ice models. Regional and coastal models usually resolve more of the higher-frequency processes which become more important in shallow seas, and they often include coupled physical–biogeochemical components. The observations available for assimilation also often have different characteristics with different technologies needed to measure the ocean closer to the coast. The methods used to initialise forecasts in these different settings have to take into account the characteristics of the model and observations available so that the variability associated with the important processes can be constrained.

Many of the data assimilation methods used in ocean forecasting were originally developed for numerical weather prediction, with the notable exception of the ensemble Kalman filter (KF). The dominant spatial and temporal scales in the ocean are quite different to the atmosphere, though, with the first baroclinic Rossby radius of deformation being a few tens of kilometres at mid-latitudes (see e.g. Chelton et al., 1998) with temporal scales ranging from days to weeks. To resolve the open-ocean mesoscale at mid-latitudes, model resolutions of the order of at least $1/12°$ are required (Hewitt et al., 2016), and the aim of many global ocean data assimilation systems is to initialise the ocean state at these scales. Observations of the surface ocean are available at fairly high resolution from satellites, but observations of the sub-surface ocean are much sparser. Sophisticated methods are therefore required to make the most of the observations to constrain models of the 3D ocean on the desired scales. The integration of high-resolution models along with the high computational processing required for implementing an advanced data assimilation method demands computational resources that are available at only a small number of ocean forecasting centres and research institutions worldwide.

Errors in ocean models arise due to approximations in their numerical formulation, errors in the parameterisation of unresolved physics, and errors in the inputs to the model including the surface atmospheric forcing, river inputs, and the lateral boundary conditions for regional systems. The ocean is a chaotic system, so small differences in the initial state grow over time, especially in strongly eddying regions. All these sources of uncertainty contribute to the model forecast error, estimates of which are needed for data assimilation. Observations also contain errors and measure the ocean on different spatial scales (to each other and to the model). Estimates of the errors in the different observations are therefore also needed, including the component due to the measurement itself and the component due to the difference in the representation of the ocean by the observation and model (Janjić et al., 2018).

Here we provide a summary of the status of ocean data assimilation as part of a special issue introduced by Alvarez Fanjul and Bahurel (2025, in this report). The next section gives a brief overview of data assimilation theory to put into context the various schemes used in operational ocean forecasting centres. The data assimilation software used at many of the operational centres is also described, including community open-source software and other code developed and used at some of the main institutes. An overview of the practical considerations needed to apply data assimilation effectively in an operational setting is given. We then describe the current status of data assimilation as applied in many operational ocean forecasting centres, followed by a summary of future directions.

## 2 Data assimilation methodology

A variety of DA methods are being used or currently tested to develop operational ocean forecasting systems (OOFSs) (Moore et al., 2019). These first followed the 3D formulation of the DA problem (3DDA) in which the ocean state at a given time is estimated based only on the available observations at that time. 3DDA is often cast as a least-squares fitting problem whose solution minimises a composite objective function involving a data misfit term and a regularisation term representing prior knowledge on the ocean state, which is called the background/prior and is usually taken as the most recent ocean forecast. Both terms of the objective function are generally weighted by their respective observations and background error covariances, which can also be imposed following a (stochastic) Bayesian inverse formulation of the 3DDA problem under the assumption of Gaussian observations and background errors (Moore et al., 2019; Hoteit et al., 2018). When the observational operator relating the ocean state to the observations is linear, the 3DDA problem has an analytical solution, known as the best linear unbiased estimator (BLUE); when not, this operator is either linearised to compute the optimal interpolation (OI) solution or the objective function is directly minimised using a gradient-based iterative optimisation algorithm to compute the 3D variational DA (3DVAR) solution.

The solution of the 4D DA problem is more advanced, as it is estimated based on a set of observations that is available over a given period of time (Weaver et al., 2003). It can be computed following a straightforward extension of the 3DVAR problem by formulating an objective function in which the data misfit term constrains the ocean model prediction to the observations in time. When the ocean model and its forcing are considered perfect, only the ocean state at the start of the observation period needs to be estimated. The resulting strongly constrained (by the ocean model equations) 4DVAR solution is then integrated forward with the model beyond the observation period to compute the ocean forecasts. In contrast, the weak constraint 4DVAR problem considers model errors in the ocean model, which can then be estimated as part of the objective function minimisation process. Jointly estimating the ocean initial state and model errors at every time step can quickly become computationally intractable. This was elegantly addressed by moving the optimisation in the observation space, which should be of much smaller dimension in this case, using the dual formulation or Representer method (Bennett, 2005). In between the strong and weak constraint 4DVAR, a large variety of different implementations exist, for instance, estimating the ocean model parameters (e.g. mixing schemes) and inputs (e.g. atmospheric forcing, open boundary conditions, bathymetry) as part of the minimisation process. This has been successfully demonstrated with the MIT general circulation model (MITgcm) (Forget et al., 2015) and the Regional Ocean Modeling System (ROMS) (Moore et al., 2019). In all 4DVAR methods, the computation of the objective function gradients required for the minimisation process can be efficiently implemented through the adjoint model, governed by the adjoint equations to the ocean tangent linear model (Moore et al., 2004; Vidard et al., 2015). Coding and running the adjoint model can be demanding on both human effort and computational resources.

The observational and background error covariances are key in determining the 3D and 4D DA solutions. The first sets the weights of the data misfit terms and their correlations to avoid overfitting the observations while accounting for redundant information (Moore et al., 2019). The second constrains the DA solution by enforcing some dynamical relationships in the initial state and/or smoothness on the estimated inputs and parameters to enable a proper propagation of the observations' information into all ocean model variables (Moore et al., 2019).

The DA methods discussed so far are designed to compute a deterministic estimate of the ocean state (the maximum a posteriori of the Bayesian inversion problem) and therefore do not provide a framework to quantify the uncertainties in the ocean forecasts, the covariance of which could be used as the background for the next DA cycle. This sets the stage to the filtering DA methods which sequentially compute the solution of the Bayesian inversion problem by considering the observations as they become available. The filtering formulation of the DA problem allows model and observational errors and involves computing the probability distribution of the ocean state conditioned on all previous observations. This provides a recursive framework suitable for OOFSs where the model is used for forecasting the ocean state and its error statistics (forecast step), which are then updated with the new incoming observations based on Bayes' rule (analysis step) (Hoteit et al., 2018).

The Bayesian filtering problem can be conceptually solved by the Kalman filter (KF) when the underlying dynamical and observational models are linear and their errors are Gaussian, in which case the forecast and analysis distributions are Gaussian and the analytical form of their mean (state estimate) and covariance is available. Ocean general circulation models are, however, nonlinear, and the discrete dimension of the underlying ocean state can be very large. This motivated the development of a variety of simplified and extended variants of the KF for ocean DA, either by (i) linearising the ocean dynamics and enforcing low-rank error covariance matrices (e.g. singular evolutive extended Kalman (SEEK) filters) or (ii) using the widely celebrated ensemble KF (EnKF) methods (Vetra-Carvalho et al., 2018). EnKF methods use samples to compute statistical approximations of the first two moments of the ocean state forecast and analysis distributions. Given an analysis ensemble, an EnKF integrates its members, eventually with perturbed noise to account for model errors, forward with the ocean model for forecasting, and the resulting forecast ensemble statistics are then updated with the incoming observations using the KF analysis step. The latter is referred to as stochastic when the KF analysis step is applied on each forecast ensemble member using perturbed observations, so that the analysis ensemble covariance matches that of the KF, and deterministic (e.g. ETKF, EAKF, SEIK, DEnKF) when the KF analysis step is directly applied on the mean and covariance of the forecast ensemble, after which a deterministic resampling step is needed to resample a new analysis ensemble (Hoteit et al., 2018).

EnKFs are generally integrated with relatively small ensembles ($\sim 100$ samples) to limit their computational cost, making their sample covariances low-rank and thus necessitating localisation/covariance-tapering techniques to confine the spatial range of their correlations (Hoteit et al., 2018). Limited ensemble size can also result in underestimation of the ensemble variance, leading to the need for ensemble inflation (Evensen et al., 2022). To further reduce the computational requirements, EnKFs are also often implemented with static ensembles, only using the ocean model to compute the forecast starting from the analysis state (ensemble OI (EnOI) methods), or their ensembles augmented with pre-selected static members (hybrid EnOI–EnKF methods) (Counillon et al., 2009). On the other side of the spectrum, more sophisticated filtering methods have also been proposed to move beyond the Gaussian error assumption by employing Monte Carlo approximations of the forecast and analysis distributions, so-called particle filters, or through Gaussian mixture approximations, which, when implemented within an ensemble framework, reduce to some sort of ensemble of EnKFs (Van Leeuwen at al., 2019). These methods are, however, still in testing phases and are yet to be applied in operational settings.

4DVAR and EnKFs were proven to provide viable and robust solutions for many ocean DA applications, and most ocean centres are currently developing their operational systems around these approaches. There are benefits and drawbacks in using an EnKF or a 4DVAR (Lorenc, 2003; Kalnay et al., 2007). EnKFs involve flow-dependent ensemble representation of the background, though rank-deficient. On the downside, the EnKF is generally only efficient for moderate model nonlinearity because of its second-order moments approximation of the error statistics. 4DVAR, on the other hand, should better handle nonlinearities, though the optimisation of its objective function can be a complex task in the presence of strongly nonlinear dynamics (Moore et al., 2019; Hoteit et al., 2018), and can be implemented with a full-rank, albeit static, background error covariance matrix. 4DVAR further requires coding and maintaining the adjoint of the observation and forecasting models, which is quite demanding. The use of automatic differentiation in distributed HPC environments, which is receiving a renaissance in the context of machine learning (ML), may overcome this limitation (Heimbach et al., 2005). Finally, 4DVAR does not lend itself easily to parallelisation, while the important computational cost for computing the forecast ensemble can be drastically mitigated by trivial parallelisation.

There have been various attempts to merge the 4DVAR and EnKF approaches in order to combine their strengths, which introduced a new family of hybrid ensemble-variational (EnVAR) methods. This includes (i) consideration of an ensemble of DA (EnDA) methods to obtain flow-dependent error representations, (ii) the iterative ensemble Kalman filters (iEnKFs) and smoothers (iEnKSs) which use a forecast ensemble to describe the background statistics and apply a nonlinear optimisation to the 4DVAR objective function in the ensemble space (Sakov et al., 2012a), and (iii) the class of 4D ensemble-variational (4DEnVAR) methods which also performs a set of 4DVAR optimisations in the subspace spanned by the ensemble using a set of perturbed observations (Liu et al., 2008). Different 4DEnVAR versions have been proposed (Bannister, 2017), employing hybrid background covariances, adjoint model or finite differences to compute the gradients, and different types of perturbations.

Recently, machine learning (ML) techniques have also been considered to enhance the efficiency of the DA methods, in terms of both capacity and computations (Cheng et al., 2023). ML techniques harness the potential of neural networks (NNs) to approximate highly nonlinear functions, which may enable the development of computationally less demanding forecasting models (Barthélémy et al., 2022), and backward models for efficient data fitting. NNs were also proposed as end-to-end replacement of the analysis steps (Beauchamp et al., 2023) and to parameterise and account for model errors (Farchi et al., 2021).

## 3 Data assimilation software

Data assimilation software packages come in all sizes and flavours. A first distinction needs to be made between educational packages that can be used for methodological developments and operational codes designed for high-performance computers. We will only consider the latter category in this section. A second distinction can be made between software packages aimed at 4DVAR methods and those that take the EnKF as their target algorithm. These two types of software differ in their complexity and size and therefore adopt different development strategies. There are thus several small-sized EnKF packages and a few more ambitious 4DVAR packages on the market. The latter may also include the EnKF as a small addition to their ensemble-variational toolbox. Some of the packages (DART, PDAF, JEDI) have users in other research fields beyond ocean forecasting. See Table 1 for a list of commonly used DA software in ocean prediction systems.

The software packages listed in Table 1 have mainly been used on high-performance computers (HPCs), and some of them have been used on personal computers. The NEMOVAR and MITgcm 4DVAR codes and the NEDAS ensemble code are actively being developed for use on GPU-based systems. However, all the DA software packages listed above have been around long enough to be ported several times to different HPC architectures with different compilers and can be qualified as portable.

## 4 Practical implementations in operational systems

Several factors dictate the practical implementation of ocean DA systems within an operational environment. The primary controlling factors in any operational environment typically relate to (i) scheduling of the DA analysis and forecast phases with respect to the competing demands of other essential activities (e.g. numerical weather prediction, hydrological forecasts) and (ii) the release of analysis–forecast products in a timely manner so that they are of maximum benefit to the users. These overarching criteria therefore, in turn, dictate the configuration of the forecast model and the data assimilation approach that may be used.

In the case of ensemble approaches, such as the EnKF or EnVar, there may be a trade-off between model resolution and the ensemble size in that computation time increases with resolution. Thus, with limited resources, fewer ensemble members can be run within the constraints imposed by items (i) and (ii). An advantage of ensemble approaches is that each ensemble member can be computed independently, meaning that, in very large HPC environments, many ensemble members can be run simultaneously. Here again, though, there can be a trade-off between resolution and ensemble size. While most ocean models scale reasonably well on parallel computing architectures, wall-clock time typically does not scale linearly with the number of cores. Hence, there is a point of diminishing returns whereby it may be better to allocate fewer cores to the business of computing ensemble members at the expense of a longer wall-clock time for each member, rather than dedicating a very large number of cores to a single task.

Unlike ensemble methods, the traditional approaches to variational data assimilation, namely 3DVAR and 4DVAR, are strictly sequential and cannot be parallelised in time. In other words, the inner- and outer-loop iterations of the cost function minimisation algorithm must be performed sequentially. The sequential iterative nature of variational approaches therefore imposes a heavy computational burden on the data assimilation phase of the analysis–forecast cycle, especially in the case of 4DVAR. This burden is alleviated in some 4DVAR systems by performing the inner-loop minimisation steps at lower model resolution – for example, a reduction in the horizontal resolution by a factor of 2 typically yields a reduction in wall-clock time by a factor of 8 assuming that the inner-loop time step can also be halved. Performing the inner loops at lower arithmetic precision (i.e. 32-bit arithmetic versus 64-bit arithmetic) can lead to further cost savings. In 4DVAR, the inner-loop iterations involve integrations of the tangent linear (TL) and adjoint (AD) versions of the forecast model. Further reductions in computational

**Table 1.** Data assimilation software packages.

| Software name | Target algorithm(s) | Programming language | Development community | Code availability |
|---|---|---|---|---|
| JEDI | Variational DA | C++ | JCSDA, NOAA, NASA, US Navy and Air Force, Met Office | Open source. https://github.com/JCSDA (last access: 25 March 2025) |
| MITgcm | Variational DA | Fortran. A version in Julia is under development. | ECCO consortium, GECCO, MIT, Uni Texas | Open source. https://mitgcm.readthedocs.io/ (last access: 25 March 2025) |
| NEMOVAR | Variational DA | Fortran | CERFACS, ECMWF, Met Office, INRIA | Not open source |
| OceanVar | Variational DA | Fortran | CMCC, CNR | Not open source |
| ROMS | Variational DA | Fortran | ROMS community | Open source. https://www.myroms.org/ (last access: 25 March 2025) |
| DART | Ensemble DA | Fortran | NCAR | Open source. https://dart.ucar.edu (last access: 25 March 2025) |
| EnKF | Ensemble DA | Fortran | NERSC | Open source. https://github.com/nansencenter/enkf-topaz (last access: 25 March 2025) |
| EnKF-C | Ensemble DA | C | Bureau of Meteorology | Open source. https://github.com/sakov/enkf-c (last access: 25 March 2025) |
| NEDAS | Ensemble DA | Python, parallel | NERSC | Open source. https://github.com/nansencenter/NEDAS (last access: 25 March 2025) |
| OAK | Sequential DA | Fortran | U. Liège | Open source. https://github.com/gher-uliege/OAK (last access: 25 March 2025) |
| OpenDA | Ensemble DA | Java | TU Delft | Open source. https://www.openda.org (last access: 25 March 2025) |
| PDAF | Ensemble DA | Fortran | AWI | Open source. https://pdaf.awi.de (last access: 25 March 2025) |
| SAM2 | SEEK filter | Fortran | Mercator Ocean International, ECCC | Not open source |
| Sequoia | Sequential DA | Fortran | OMP/LEGOS | Available on request. https://sirocco.obs-mip.fr/ (last access: 25 March 2025) |

cost can therefore also be achieved by reducing the complexity of the TL and AD models. Time-parallel formulations of 4DVAR based on a saddle-point algorithm also yield substantial computational savings (Fisher and Gurol, 2017; Moore et al., 2023).

The assimilation strategy employed also depends on the types of observations that are to be assimilated and their distribution in time. In the case of a Kalman filter, while each observation can be assimilated sequentially at the associated observation time, this may not be an efficient strategy, since this might require overly frequent stopping and restarting of the filter computations. Thus, it is often preferable to group together observations that are closely spaced in time and treat them as though they were available at the same time. This approach underpins the strategy of first guess at appropriate time (FGAT), which is commonly employed in conjunction with both ensemble approaches and 3DVAR. Such approaches necessitate the choice of a time window over which the observations will be aggregated for assimilation. In between times, the forecast model is run to yield the first guess or background for the next data assimilation cycle, so the time window of aggregation also dictates how frequently the analysis–forecast cycle can be performed. For an EnKF, it is sufficient to store observation equivalents from each model ensemble member to calculate asynchronous cross-covariances (Sakov et al., 2010). In the case of 4DVAR, observations are typically assimilated at the actual time of observation. This involves integrations of the TL and AD models forward and backward in time. Since these are based on a linearised version of the forecast model, the validity of the linear assumption through time is an important consideration. In particular, linear instabilities can develop if appropriate care is not exercised. Therefore, while a long time window in 4DVAR may be preferable so that the analysis is informed by more observations, this must be balanced by the validity of the linear assumptions employed in the TL and AD models and the added computational burden of the longer assimilation window.

## 5 Ocean observations

While there is a common subset of observations from the global ocean observing system (GOOS) that are assimilated into ocean models, additional sources of data may be available for assimilation into regional ocean models that are not appropriate for global models. The GOOS and different types of observations available are discussed in the ETOOFS guide (Alvarez Fanjul et al., 2022). The mainstay of the GOOS is remote sensing observations of sea surface temperature (SST), sea surface height (SSH), sea surface salinity (SSS), and sea ice concentration. This is supported by the Argo network of profiling floats that provide vertical sections of temperature and salinity (and in some cases biogeochemical variables) mostly over the upper 2000 m of the water column, although deep Argo floats below 2000 m are now also being deployed. In the tropical oceans, the observing system is augmented by networks of buoys that provide profiles of temperature (and in some cases salinity and currents) to depths of $\sim 500$ m. Observations from tagged marine mammals also provide useful information in some regions of the world ocean. In coastal regions, other data sources are often available that cannot be readily assimilated into global models because of the disparity in horizontal resolution. These include data from gliders and other autonomous underwater vehicles (AUVs), estimates of surface currents from high-frequency (HF) radars, other tagged marine mammals, moorings, drifters, and (in some locations) dedicated coastal arrays.

All observations, regardless of their origin, must be subject to strict quality control (QC) standards before they can be assimilated into a model (Good et al., 2023). All operational centres employ sophisticated QC systems for flagging and rejecting erroneous observations and those of poor quality. In addition, the large volume of remote sensing observations from Earth-orbiting satellites must generally be thinned in space and time. There are three main reasons for this: firstly, remote sensing observations contain a great deal of redundancy which can be reduced by judicious thinning; secondly, the sheer volume of remote sensing observations can quickly overwhelm a data assimilation system if not appropriately thinned (particularly in light of the high redundancy); and, lastly, accounting for correlated observation errors in data assimilation systems is technically challenging, so thinning the observations is one approach for reducing the degree of correlation. Another important aspect of operational data assimilation systems is the formation of so-called “super-observations”. This refers to the procedure for combining multiple observations of the same type that fall within a model grid cell at the same observation time into a single datum (a super-observation). This usually entails some simple averaging or aggregation procedure and is necessary in order to improve the numerical conditioning of the data assimilation inverse problem.

The use of observations in data assimilation requires information about their uncertainties. The observation uncertainty consists of a component due to the instrument error and a component related to the different representation of the ocean by the observations and the model (for example, representing different spatial scales and/or timescales; Janjić et al., 2018). Some observation types (e.g. satellite SST) are provided together with information about the expected uncertainty in each measurement, and this information can be used directly in the data assimilation. For other observation types, estimates of the uncertainty have to be obtained from the literature. An example list of instrumental uncertainties for different observation types assimilated in a global ocean forecasting system is provided in Table 1 of Lea et al. (2022).

Since the observations are the only, albeit far from complete, measure of the true state of the ocean, they often form the basis for metrics that are used to monitor the performance of data assimilation systems. The statistics of the observation minus background (OmB) and observation minus analysis (OmA) provide information about the fit of the model to observations before and after the observations have been assimilated. The statistics of OmB and OmA provide an important diagnostic check on prior assumptions made about the background error and observation error covariances (Desroziers et al., 2005). Inconsistencies between the actual and expected error statistics can be used to retune the data assimilation system, regardless of the data assimilation methodology employed. In variational data assimilation systems, continuous monitoring of the cost function and cost function gradient also provide useful diagnostics of system performance. The impact of different components of the observing system can also be quantified and monitored in various ways. This is commonly done in terms of the impact on the skill of forecasts that are initialised from the data assimilation analyses. By continuously monitoring the impact of each component of the observing system on forecast skill, data streams that consistently degrade the forecast skill can be flagged (and removed) and the degradation of any data stream over time can be identified.

## 6 Current status of data assimilation in operational forecasting systems

An overview of operational ocean data assimilation systems and their characteristics is provided in Fig. 1 for global systems and Fig. 2 for regional and coastal systems. Not all operational systems are covered here, but the figures provide information about the main choices which have been made by some of the existing operational centres producing near-real-time forecasts in the configuration of their data assimilation schemes. The information represents the current operational status, but all centres are continually developing and improving their systems, and many have research configurations which are more sophisticated than those presented.

In general, the global systems use somewhat simpler DA algorithms (though they are still complex in their implementation of those algorithms) than the regional and coastal systems, the exception being the BoM system which uses a hybrid EnKF with 48 dynamic members and 144 stationary low-mode members (Brassington et al., 2023). Many global forecasting groups use a 3DVAR-FGAT algorithm (Barbosa Aguiar et al., 2024; Zuo et al., 2019; Cummings and Smedstad, 2013; Storto et al., 2016; Ravichandran et al., 2013), with some groups using a SEEK filter or an LESTKF with a static ensemble (Lellouche et al., 2018; Smith et al., 2016; Li et al., 2021). The reason these algorithms are generally simpler is largely due to the large number of grid points, especially in the higher-resolution global systems, which restricts the options for more expensive algorithms when timely delivery of forecasts is the main goal. Some groups are testing more sophisticated schemes in research mode, though, including those which make use of ensembles; e.g. MOI are testing LETKF, the Met Office and ECMWF are testing hybrid 3DEnVAR schemes (Lea et al., 2022; Chrust et al., 2024), and JMA are implementing 4DVAR (Fujii et al., 2023). The observations assimilated in these systems are fairly consistent across the different systems, with the main difference being whether the systems include sea ice or atmosphere components. Some of the DA systems are focused purely on the ocean, many include a sea ice component, and some now run with a coupled atmospheric component, though these systems all still use so-called "weakly" coupled DA where the DA in the atmospheric and ocean/sea ice components is run separately, despite using coupled models (see, for example, Guiavarc'h et al., 2019, and de Rosnay et al., 2022). There is a large range of time windows used by the different systems, with the most common time window being 1 d. A short 6 h window is used in the Met Office coupled DA system (to match the time window in the atmospheric DA; Guiavarc'h et al., 2019), and longer time windows of 5–7 d are used by some systems.

There is a wider range of DA algorithms employed in regional and coastal forecasting systems from EnOI/static SEEK filters (Carvalho et al., 2019; Ji et al., 2017; Smith et al., 2021; Escudier et al., 2022) and 3DVAR-FGAT schemes (Rahaman et al., 2018; King and Martin, 2021; Coppini et al., 2023) through to the more sophisticated EnKF (Sakov et al., 2012b; Röhrs et al., 2023), LESTKF (Brüning et al., 2021), and 4DVAR algorithms (Moore et al., 2023; Iversen et al., 2023; Hirose et al., 2019; Lee et al., 2018). Many of these regional systems also include biogeochemical DA (see Fennel et al., 2022, for a recent review), and some include coupled sea ice DA (e.g. Sakov et al., 2012b). The range of observations assimilated is also quite varied, with some systems only assimilating SST data, while others include the full range of available observations, including HF radar, gliders, and biogeochemical data from satellites and in situ platforms.

## 7 Future directions

Operational ocean forecasting systems are under constant development, including the data assimilation component. There is a continued push towards higher resolution at many centres and an increase in the use of ensembles both for improved data assimilation and for providing forecast uncertainty information to users. These directions both require significant additional computational resources, so improving the computational efficiency of data assimilation software, particularly on new computer architectures like GPUs, is important to allow more flexibility in the choice of algorithms and resolutions used. While there is evidence that increasing ensemble size provides greater improvements in forecast skill once the important processes are resolved, rather than further increasing model resolution (Thoppil et al., 2021), there is also continued research in improving assimilation methodology to allow sub-mesoscale processes to be constrained where there are sufficient observations (Ying, 2019; Jacobs et al., 2023). New observing systems are being developed and launched, particularly wide-swath altimeter missions such as SWOT (Morrow et al., 2019), which allow improved constraints on mesoscale ocean forecasts (King et al., 2024; Liu et al., 2024; Benkiran et al., 2024). Treatment of spatially correlated observation errors is important to allow the most information to be extracted from such data, and various groups are developing methods to represent these in data as-

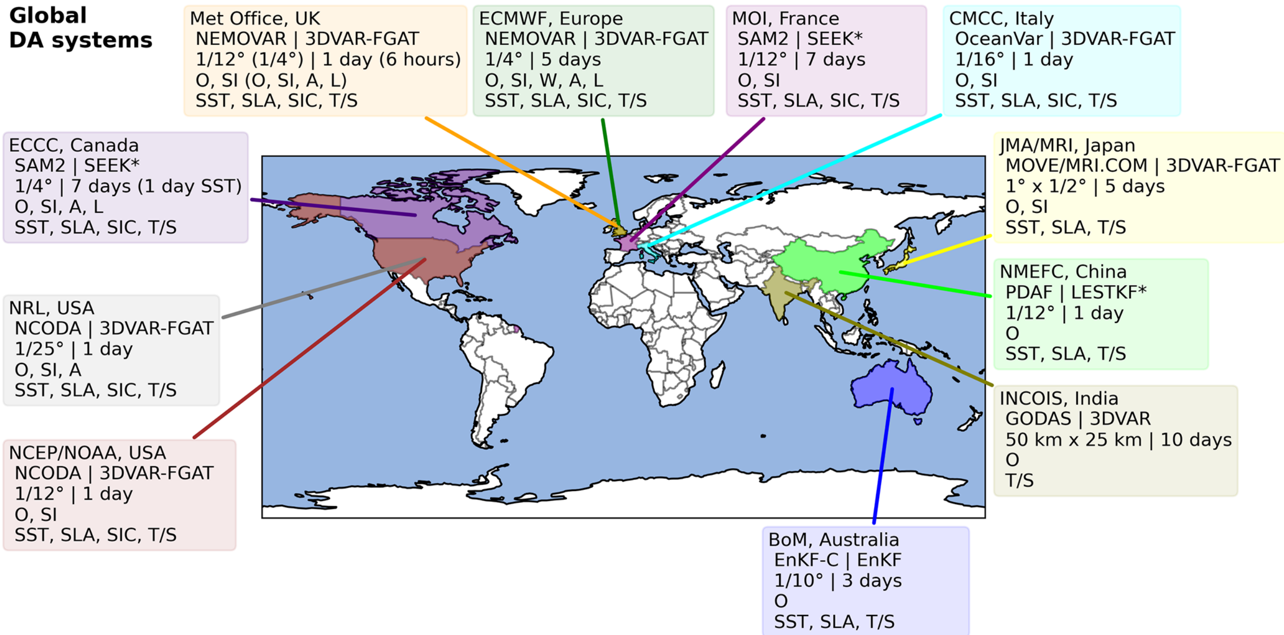


**Figure 1.** Operational global ocean data assimilation systems. For each institute, the following are listed: the DA algorithm (* indicates the fixed-basis version of the algorithm) and software, DA resolution and time window, Earth system components (O: physical ocean; SI: sea ice; A: atmosphere; W: surface waves; BGC: ocean biogeochemistry; L: land), and observations assimilated (SST: sea surface temperature; SLA: sea level anomaly; SIC: sea ice concentration; SID: sea ice drift; T/S: profiles of temperature and salinity; OC: satellite ocean colour; BGC: biogeochemical profile data; HFR: HF radar).

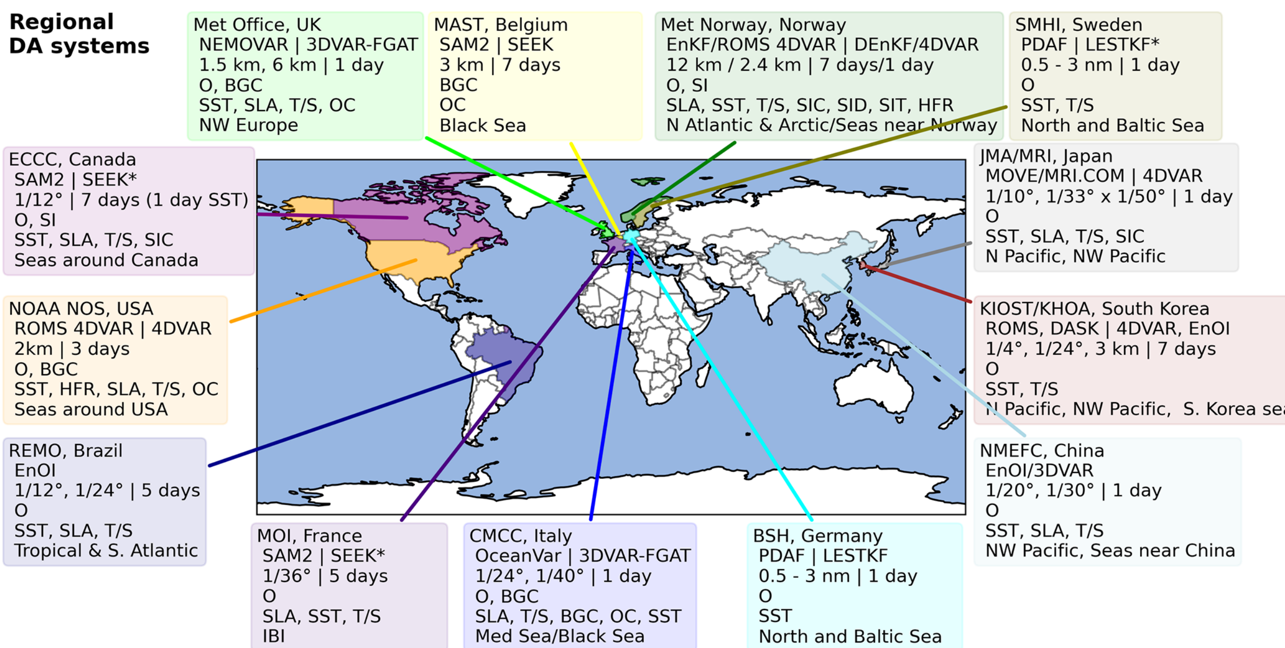


**Figure 2.** Operational regional and coastal ocean data assimilation systems. See description for Fig. 1.

similation systems (e.g. Guillet et al., 2019; Yaremchuk et al., 2024). Coupled ocean–atmosphere data assimilation is also an evolving area (de Rosnay et al., 2022), with the development of more strongly coupled data assimilation algorithms requiring the use of consistent software across the different Earth system components. The use of machine learning in the ocean forecasting process is also developing quickly, with various applications in the context of data assimilation being tested and implemented (Heimbach et al., 2025, in this report).

**Code and data availability.** No data or codes were used to produce the article, but a list of data assimilation software packages is provided in Table 1, together with their availability.

**Author contributions.** All authors contributed to the writing and review of the article. MJM organised the article and led the writing of Sects. 1, 6, and 7. IH led the writing of Sect. 2. LB led the writing of Sect. 3. AMM led the writing of Sects. 4 and 5.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** The authors would like to thank the compilation team of the OceanPrediction Decade Collaborative Centre who organised this special issue. We would also like to thank the reviewers for their suggestions to improve the article.

**Review statement.** This paper was edited by Stefania Angela Ciliberti and reviewed by G. C. Smith and one anonymous referee.

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# Numerical models for simulating ocean physics

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Received: 2 October 2024 – Discussion started: 7 October 2024
Revised: 13 December 2024 – Accepted: 13 December 2024 – Published: 2 June 2025

**Abstract.** We describe, at an elementary level, the spatially varying properties of the ocean that physical ocean models represent, the principles they use to evolve these properties with time, the physical phenomena that they simulate, and some of the roles these phenomena play within the Earth system. We describe at an intermediate level the governing equations the models use and the grids that they typically use and, at a more advanced technical level, the methods and approximations that the models use and the difficulties that limit their accuracy or reliability. We also briefly describe the wider context and future prospects for the development of these models.

## 1 Introduction

The models of ocean physics described in this paper use physical principles to simulate how the three-dimensional structures of the ocean's temperature, salinity, and currents evolve in time. Section 2 describes the models at an introductory level. It first outlines the spatially varying quantities they predict and the physical principles they use. It then describes the circulations the models simulate and some of the reasons why these circulations are important in the Earth system. Section 3 describes the models at an intermediate level, outlining their governing equations, some approximations used to improve their efficiency, and the grids they typically employ. Section 4 outlines at a more technical level the main approximations the models typically use and the steps in the discretization of their equations, drawing attention to some of the difficulties which limit their accuracy or reliability. Section 5 discusses wider and future perspectives.

Chassignet et al. (2019) provide an alternative non-technical introduction to ocean modelling. McWilliams (1996) and Fox-Kemper et al. (2019) provide more detailed reviews, and Griffies (2004) is still a helpful primer on the basic techniques. Aspects of the design, testing, documentation, and support for an ocean model code that are crucial for it to be suitable for use in operational predictions or climate simulations are covered in Wan et al. (2025, in this report). Porter and Heimbach (2025, in this report) discuss the adaptations of ocean models required for them to perform efficiently on modern high-performance computers (HPCs).

## 2 An overview of the models and what they simulate

### 2.1 The quantities simulated and the principles used

The temperature structure of the ocean at a given time in a physical ocean model is represented by a three-dimensional (3D) grid of temperature values. The three dimensions of the grid correspond to the three dimensions of space. One of the dimensions is aligned with the local vertical and the other two with locally horizontal directions. The set of temperature values on the grid is referred to as the temperature field. The salinity structure is similarly represented by a 3D grid of salinity values, referred to as the salinity field. The currents in the two locally horizontal directions are represented by two fields and the locally vertical current by a third field. The fluid's density and pressure are also represented by fields. In total, conceptually there are seven 3D fields (the temperature, salinity, density, and pressure as well as three velocity fields) and the physical ocean model simulates how these fields will evolve in time. Given all these fields at time $t$, the model predicts how they will all evolve over the next few minutes or hours – that is, over a time step $\Delta t$ – and hence their values at time $t + \Delta t$. Model predictions to days, months, or years ahead are generated by performing a large number of time steps.

The equations used by physical ocean models are based on the following physical principles:

- conservation of momentum (Newton's laws of motion) for each direction in space;
- conservation of the mass of water and salt;
- conservation of energy (the first law of thermodynamics); and
- the thermodynamics determining the density at a point from the temperature, salinity, and pressure (the equation of state).

Together with information about the momentum, heat, and fresh water exchanged with the atmosphere and sea ice at the ocean surface and with the solid Earth at the bottom of the ocean (the boundary conditions), these seven sets of constraints are sufficient to determine how the seven fields will evolve from given initial values at every point of the seven fields (the initial conditions). In practice, the details of how the equations are used to provide computationally efficient, stable, and accurate solutions are quite intricate. The accuracy of the model predictions is primarily limited by the representation of the ocean structure by the values on a grid whose resolution is limited by computational power. Motions at scales comparable to or smaller than the grid are not resolved. The effects of these subgrid-scale (SGS) motions on the resolved scales are calculated by parameterization schemes. Although these are based on physical principles and detailed studies, their accuracy and reliability are inevitably limited. This is one of the main areas where further research has potential to improve the model simulations.

### 2.2 The circulations simulated and their impacts

The circulations and physical phenomena that these ocean models are typically used to simulate are principally the following:

- the near-surface boundary layer where there is strong turbulent mixing driven by surface winds and heating or cooling (Large et al., 1994);
- gyre circulations associated with the region, called the thermocline, where the vertical density gradient is strongest – large-scale displacements in the thermocline are primarily driven by Ekman pumping: in the subtropical gyres, the thermocline is bowl-shaped and in the sub-polar gyres it is dome-shaped (Chap. 20 of Vallis, 2017);
- meridional overturning circulations (MOCs) associated with heat loss and stirring of mixed layers at high latitudes and wind-driven upwelling and heat uptake in the Southern Ocean and near the Equator (Srokosz et al., 2021);
- western boundary currents (WBCs) – the depth-mean WBCs are associated with the wind-driven gyre circulations (Pedlosky, 1982, Chap. 5) and oppositely directed surface and deep WBCs (Hogg, 2001) with MOCs;
- mesoscale circulations (with horizontal scales $<100$ km) associated with instabilities of the boundary currents and gyre circulations (Robinson, 1983); and
- sub-mesoscale motions (with horizontal scales $<10$ km) that are strongest in the near-surface boundary layer (Taylor and Thompson, 2023).

These circulations and phenomena play important roles in the Earth system. For example, the western boundary currents are responsible for very large meridional transports of heat and geographically varying air–sea fluxes which contribute to the shape of atmospheric circulations, interannual variations in the slope of the thermocline along the Equator in the Pacific Ocean are an essential component of the El Niño–Southern Oscillation (ENSO) phenomenon, the advection of heat by large-scale ocean currents towards ice shelves has a significant impact on their heat balance and evolution (Stewart et al., 2018), and biogeochemical cycles are typically sensitive to the vertical advection of nutrients (Williams and Follows, 2011).

The ocean models can be configured as a component of a coupled system, with models of other components such as the atmosphere, sea ice, surface waves, or biogeochemistry, or as a stand-alone system with suitable datasets providing surface forcing. They can be configured to cover the entire global ocean, or to cover just a limited region with lateral boundary conditions (that are often taken from a model of a larger region). Their initial conditions can be specified by climatologies based on historical measurements or regularly updated by assimilating the latest measurements as in operational forecast systems (Martin et al., 2025, in this report). The model coupling, domain, resolution, and initial conditions should be chosen to suit the purpose of the modelling and are constrained by the computational resources available.

## 3 A simple description of ocean models

### 3.1 Governing equations

There are many good books on the basics of fluid dynamics. Fluid dynamics is usually formulated using the concepts of vector calculus. Appendix A gives a brief introduction to vector calculus and its application to fluid dynamics, including simplified derivations of Eqs. (1)–(3) below.

Tracers are defined to be properties that fluid parcels retain unchanged with time. Using $\mathcal{T}$ to denote a tracer, $\boldsymbol{u}$ the velocity field, and $\mathrm{D}/\mathrm{D}t$ the Lagrangian time derivative (following the motion),

$$\mathrm{D}\mathcal{T}/\mathrm{D}t = \partial\mathcal{T}/\partial t + \boldsymbol{u}.\nabla\mathcal{T} = 0. \tag{1}$$

The fraction of the mass of water in a fluid parcel due to saline components, $S$, is a tracer and evolves according to the prognostic equation (Eq. 1). Conservation of mass requires that the rate of decrease of mass inside an infinitesimal volume be equal to the fluxes out of its faces and hence that the density, $\rho$, satisfies

$$\frac{\partial\rho}{\partial t} + \nabla.(\rho\boldsymbol{u}) = 0. \tag{2}$$

Combining Eqs. (1) and (2) one obtains an alternative flux form for the evolution of tracers,

$$\frac{\partial(\rho\mathcal{T})}{\partial t} + \nabla.(\rho\boldsymbol{u}\mathcal{T}) = 0. \tag{3}$$

The thermodynamics of seawater is rather complex. Vallis (2017) Sections 1.5–1.7 give a helpful introduction to it. The macroscopic motions models represent are taken to be in thermodynamic equilibrium and reversible (e.g. not to include mixing). The internal energy of a fluid parcel (following its motion) is then only changed by the heat ($Q$) input into it and the work done on it by pressure forces on it reducing its volume (work done equals force times distance travelled). A potential temperature, $\theta$, can be defined that is equal to the temperature the fluid parcel would have if reversibly moved without input of heat (adiabatically) to a reference height (such as the surface or 2000 m). The potential temperature evolves according to

$$c_\mathrm{p}\frac{\mathrm{D}\theta}{\mathrm{D}t} = \frac{\theta}{T}Q, \tag{4}$$

where $c_\mathrm{p}$ is the heat capacity of the seawater at constant pressure and $T$ is temperature. Ocean models generally use $\theta$ as a prognostic variable. This requires that $T$ and $\rho$ be calculated from the pressure $p$, $\theta$, and $S$ using the equation of state for seawater.

The acceleration of fluid particles is determined from Newton's second law of motion: $\boldsymbol{F} = m\boldsymbol{a}_\mathrm{I}$. The acceleration $\boldsymbol{a}_\mathrm{I}$ in an inertial frame of reference must take into account that the Earth is rotating and that the fluid velocity $\boldsymbol{u}$ is the velocity relative to this rotating frame of motion. Representing the rotation by the vector $\boldsymbol{\Omega}$ which is aligned with the axis of rotation and equal to the rate of rotation, Vallis (2017) Section 2.1 nicely shows that

$$\boldsymbol{a}_\mathrm{I} = \frac{\mathrm{D}\boldsymbol{u}}{\mathrm{D}t} + 2\boldsymbol{\Omega}\times\boldsymbol{u} + \boldsymbol{\Omega}\times(\boldsymbol{\Omega}\times\boldsymbol{r}). \tag{5}$$

A perfect fluid does not resist shearing motions (Batchelor, 1967). Then the force exerted on an infinitesimal element of the surface area of a fluid parcel by the fluid outside is inward and in the direction normal to the surface. So with this force $\boldsymbol{F} = -p\hat{\boldsymbol{n}}$, where $\hat{\boldsymbol{n}}$ is the outward-pointing normal vector of unit length and by an argument similar to that in Eq. (A7), one finds that the pressure force on a volume $\delta V$ is given by $-\delta V\,\nabla p$. The force due to gravity on this cell is downward and equal to its mass $\rho\delta V$ times $g$. Putting these expressions together for a perfect fluid we infer that

$$\rho\left[\frac{\mathrm{D}\boldsymbol{u}}{\mathrm{D}t} + 2\boldsymbol{\Omega}\times\boldsymbol{u} + \boldsymbol{\Omega}\times(\boldsymbol{\Omega}\times\boldsymbol{r})\right] = -\nabla p - \rho g\hat{\boldsymbol{k}}, \tag{6}$$

where $\hat{\boldsymbol{k}}$ is the local unit vector pointing upward.

In fluids, energy input at one scale does not stay at that scale; some "propagates" to larger scales and some to smaller scales. The smaller scales are visible in tracer fields where one sees tongues of tracers drawn out into filaments that become interleaved. The cascade of energy to small scales results in dissipation of energy and vorticity. In the oceans most mixing occurs on isopycnal (constant density) surfaces. Models are formulated to mix tracers preferentially along isopycnal surfaces (Redi, 1982) and aim to constrain the diapycnal mixing to realistic levels. The mesoscale motions in the boundary currents usually derive their energy by extracting potential energy from the sloping isopycnals associated with the currents. Models which only partially resolve mesoscale motions usually include formulations for additional velocities which flatten these sloping isopycnals (Gent and McWilliams, 1990). The momentum equations also include terms which drain kinetic energy. These are usually designed to be strongly scale-selective (e.g. biharmonic) in order to drain energy preferentially from the grid scale. It is important to restrict the grid-scale velocities to levels that do not result in excessive diapycnal mixing of tracers (Ilicak et al., 2012).

### 3.2 Principles of efficiency, accuracy, and stability

Ocean models should be designed to accurately represent the motions of interest and to be as efficient in their calculations as possible. It is also highly desirable that they possess analogues of important conservation properties, such as conservation of energy and momentum, and that they have operators that mimic the properties of div, grad, and curl for some of the fields.

It is also essential that the model integrations are stable. The prognostic equations are of the form $\partial P/\partial t = R$. When calculating $P$ at time step $t_n+1$ nearly all the terms in $R$ need to be written in terms of quantities at step $t_n$ or earlier steps such as $t_n - 1$. If the time step is too large one of these terms will cause exponential growth of near-grid-scale fluctuations in $P$. The Courant–Friedrichs–Lewy (CFL) criterion, which requires $c\Delta t < \Delta x$, where $c$ is a speed (such as $|\boldsymbol{u}|$ or the phase speed of a gravity wave), $\Delta t$ is the time step, and $\Delta x$ is the grid spacing, is of this form (Durran, 1999). If the terms in $R$ that are directly related to $P$ are specified using $P$ at time step $t_n + 1$, a resulting formulation whose time step is not restricted can usually be found. Such implicit schemes usually require the solution of a matrix equation. If the matrix involves the whole 2D or 3D domain its solution is usually costly. Vertical mixing is a fast process (mixing across many grid cells typically happens in one time step) and implicit schemes result in 1D tridiagonal matrix equations that can be solved robustly and efficiently, so most ocean models use implicit schemes for vertical mixing.

### 3.3 Approximations that improve efficiency

Sound waves in the ocean travel at about $1500\,\mathrm{m\,s^{-1}}$ and sea level variations associated with depth-independent motions travel at about $200\,\mathrm{m\,s^{-1}}$. Other motions associated with internal waves (gravity waves, Kelvin and Rossby waves) and the currents themselves propagate signals at no more than about $3\,\mathrm{m\,s^{-1}}$. Ocean models usually employ approximations that make their solution more efficient by eliminating sound waves and enabling special treatment of the depth-independent motions. The Boussinesq approximation takes the ocean density to be treated as a constant except in the gravitational force $-\rho g\hat{\boldsymbol{k}}$. The conservation of mass (Eq. 2) then reduces to $\nabla \cdot \boldsymbol{u} = 0$, which says that the fluid is incompressible and the evolution of tracers simplifies to $\partial \mathcal{T}/\partial t + \nabla \cdot (\boldsymbol{u}\mathcal{T}) = 0$. The deliberate omission of $\partial \rho/\partial t$ from Eq. (2) eliminates sound waves from the model's solutions. The external mode, which is almost depth-independent, is usually calculated separately as a depth-independent mode. It is usually calculated using variables that depend only on the "horizontal" coordinates using time steps that are about 60 times smaller than those used for the 3D calculations.

Another approximation that is commonly used is to neglect the vertical velocities in the vertical component of the momentum equation. This hydrostatic approximation is valid for motions with horizontal scales that are much larger than their vertical scales. The vertical pressure gradient is then diagnostic (rather than prognostic) and typically satisfies $\partial p/\partial z = -\rho g$.

### 3.4 Model grid cells

Finite-difference schemes take cell values to be point values and calculate derivatives explicitly. The advection of tracers might be calculated using Eq. (1). Finite-volume schemes calculate the fluxes and forces across cell faces and treat cell values as grid cell means. They conserve volume, heat, and momentum and usually aim to conserve energy. Most ocean models are formulated using finite-volume schemes, at least for tracers.

Most ocean models use curvilinear orthogonal coordinates in the horizontal (on spheroidal surfaces) but an increasing number use triangular or hexagonal grids (Ringler et al., 2010; Korn et al., 2022). Panels (a) and (b) of Fig. 1 illustrate the two most common choices for the placement of variables in grid cells, the Arakawa B- and C-grids, respectively (Arakawa, 1988). Both grids store the tracers and the pressure at the centre of each cell. The B-grid stores both components of the velocities at each of the corners of the cell, whilst the C-grid (Fig. 1b) stores them at the centres of the faces to which they are normal and hence at different points. Particularly when the Boussinesq approximation is made, the C-grid is ideal for the evolution of tracers, conservation of volume, and calculation of $\partial p/\partial x$ at the $u$ points and $\partial p/\partial y$ at the $v$ points. The B-grid is ideal for the calculation of the Coriolis terms, whereas the simplest expression for $v$ at the $u$ point on the C-grid involves a four-point average of $v$ at the surrounding grid points. On the B-grid the horizontal divergence and vorticity are naturally centred at the tracer points, whilst on the C-grid they are centred at the tracer points and the cell corners, respectively (Fig. 1c).

The choice of vertical coordinate is particularly important in an ocean model. A model level may have a constant height ($z$ coordinates), have constant potential density (isopycnal coordinates), or vary in proportion to the local depth (terrain-following coordinates). In principle the vertical coordinate could aim to transition from $z$ coordinates near the sea surface to isopycnal coordinates in the interior and terrain coordinates near the bottom. These coordinates are discussed further in the next section. We note that the axes used by the momentum equations are not altered by these schemes. It is just the coordinates, not the axes, that are transformed.

Most of the terms in ocean models, including the boundary conditions, are only calculated to second-order accuracy. This means that if the model were used to simulate an idealized case in which the motions are reasonably well-resolved, the errors in the solution should be reduced by a factor of 4 as the grid spacing is reduced by a factor of 2. To second-order accuracy, a grid cell mean value is equal to the point value at its centre. So in some models it is not entirely clear what the grid cell values are intended to represent. It has been found to be advantageous to calculate the advection terms (usually the fluxes through the cell faces) to higher-order accuracy and to limit the values of the fluxes to avoid extending the range of tracer values (Durran, 1999; Fox-Kemper et al., 2019). Higher-order schemes for the calculation of pressure forces are also advantageous for terrain-following coordinates.

## 4 Methods and approximations employed in ocean models

### 4.1 Variables and equations used

The ocean models used in physical ocean prediction systems evolve 3D fields of the active tracers and the three components of velocity (see Section 5.5.1. of Alvarez Fanjul et al., 2022). They also evolve either a 2D surface pressure (or surface height) field or a 3D pressure field. The active tracers used depend on the formulation of the equation of state. When it is EOS80 (Fofonoff and Millard, 1983) the active tracers are potential temperature and practical salinity, whilst

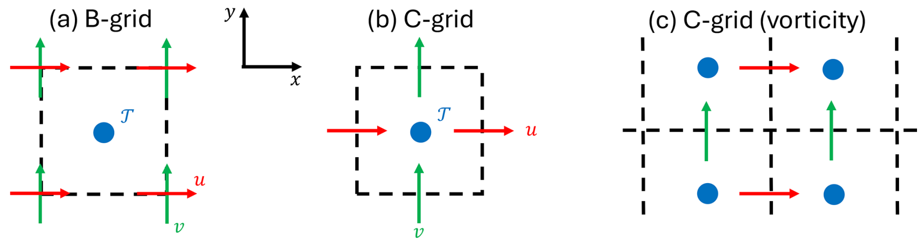


**Figure 1.** The horizontal placement of variables on **(a)** the B-grid and **(b)** the C-grid. Tracers, $\mathcal{T}$, and velocities $u$ and $v$ in the $x$ and $y$ directions are located at the points marked by blue dots and red and green arrows, respectively. Panel **(c)** shows that on the C-grid the vorticity is naturally centred at the corners of the tracer grid.

when it is TEOS10 (IOC et al., 2010) they are conservative temperature and absolute salinity. The evolution of these fields is determined by some form of the so-called primitive equations (Griffies and Adcroft, 2008). The approximations that are usually made are generally well-described in Section 5.4 of Alvarez Fanjul et al. (2022). We note, however, that the centripetal acceleration is not included in the equations because they have been transformed so that the spheroid coincident with the Earth's bulge follows a spherical surface (Vallis, 2017). It is of course assumed (the turbulent closure hypothesis) that the effect of small-scale motions on large-scale motions can be represented (that is parameterized) in terms of the large-scale motions. None of the Boussinesq, hydrostatic, incompressible, or additional Coriolis term approximations are mandatory, but maintaining consistent, well-behaved equations requires care. Some alternative forms of the primitive equations which enjoy good conservation properties are derived in White et al. (2005). Compressible equations support rapidly travelling sound waves, which (can be artificially slowed but) make a competitively efficient solution difficult.

### 4.2 Numerical discretization

Ocean models normally use a smoothly varying horizontal grid consisting of triangular or quadrilateral elements (Section 5.4.2. of Alvarez Fanjul et al., 2022). Where the grid lines on the quadrilateral grids intersect, they are usually orthogonal (hence called curvilinear orthogonal). The grids are chosen to have rather uniform resolution (cubed sphere grid; Ronchi et al., 1996) or to be isotropic (same resolution locally in the two directions) with grid spacing decreasing away from the Equator and the poles of the grid placed over land (Madec and Imbard, 1996). Triangular elements have the obvious advantage that they can be chosen to follow coastlines more accurately. With triangular elements, reduced grid spacing is often employed for selected regions within one smoothly varying grid. With quadrilateral elements, reduced grid spacing is usually achieved by using separate "child" grids that are nested within the "parent" grid with one-way nesting (the child takes boundary values from the parent – Staniforth, 1997) or two-way nesting (the parent also takes values from the child – Debreu and Blayo, 2008).

Finite-difference and finite-volume methods are usually employed with the quadrilateral grids. Finite-volume models evolve their fields by calculating the fluxes across their cell faces (the difference between the two is not significant for terms that are calculated only to second-order accuracy). Models using triangular elements use either finite-element or finite-volume techniques (Danilov, 2010; FESOM has transitioned from finite element to finite volume).

The main choices for the staggering of variables on orthogonal grids are the B-grid and C-grid (Arakawa, 1988). The dispersion properties of gravity waves on the C-grid are better (worse) than the B-grid when the grid resolves (does not resolve) the Rossby radius. Stationary chequer-board modes for the pressure field on the B-grid and the velocity field on the C-grid can be associated with undesirable grid-scale "noise". The dispersion properties of gravity waves on triangular grids are more problematic, though some finite-element pairs (Le Roux et al., 1998) perform relatively well. There has been significant recent progress in the development of C-grid-like formulations for triangular grids (and their hexagonal dual grids) with good mimetic properties (Ringler et al., 2010; Cotter and Shipton, 2012).

The choice of vertical "grid" is well-known to have far-reaching consequences for ocean models. Lorenz grid staggering is commonly used despite its computational mode and susceptibility to spurious shortwave instabilities (Arakawa and Moorthi, 1988; Bell and White, 2017). Ideally, the vertical grid would have fine vertical spacing near the surface so that the mixed layer can be well-represented. Also, the surfaces on which the vertical coordinate takes constant values would follow isopycnals at mid-depths (so that advective velocities and spurious numerical time-mean advective diapycnal transports are minimized) and would follow the bathymetry at the ocean bottom so that flow down slopes (with the associated vortex stretching) is well-represented. Techniques to use coordinates that treat some parts of the motions using Eulerian methods and others using Lagrangian approaches with re-mapping are described in Petersen et al. (2015), Griffies et al. (2020), and Hofmeister et al. (2010).

The generation of an appropriate vertical grid for ocean models is an active area of research.

Most terms in ocean models are calculated using second-order-accurate formulae. The advection of tracers should, however, be calculated using schemes of higher-order accuracy (typically third or fourth order) which also take care to retain the upper and lower bounds of the advected quantities. There is a very extensive body of literature on this subject (Durran, 1999; Brasseur and Jacob, 2017) and it is generally agreed that the advecting velocity field should be constrained to be sufficiently smooth (e.g. Ilicak et al., 2012). The effective resolution of the model also depends on how scale-selective the dissipation of variance is near the grid scale (Soufflet et al., 2016).

Specific terms in the equations of motion present different challenges depending on the grid that has been chosen. For terrain-following coordinates, calculation of the horizontal pressure gradient to higher order (Shchepetkin and McWilliams, 2003) and of the diffusion along isopycnal surfaces (Lemarié et al., 2011) is beneficial, and some smoothing of the bathymetry is necessary. The formulation of the governing equations for the cells that are only partially filled by water is an active area of research (Adcroft, 2013; Debreu et al., 2020). For C-grid models, calculation of the Coriolis term should ensure conservation of energy, and some care is needed to avoid unintended transfer of energy to the grid scale (Hollingsworth et al., 1983; Bell et al., 2017; Ducousso et al., 2017).

The strengths and weaknesses of various time-stepping schemes used in ocean models are reviewed in Lemarié et al. (2015). Various approaches have been taken to the time stepping of the external (barotropic) mode (Shchepetkin and McWilliams, 2003; Demange et al., 2019).

### 4.3 Parameterization of unresolved processes

The parameterization of unresolved processes is of primary importance: Fox-Kemper et al. (2019) provide a useful review. The classic parameterizations of isopycnal diffusion (Redi, 1982; Visbeck et al., 1997) and of the slumping of isotherms by baroclinic instabilities (Gent and McWilliams, 1990) work well in climate models with order 1° grid spacing. The latter needs to be developed further for models of higher resolution using ideas such as Bachman (2017) and Mak et al. (2018). It is increasingly clear that sub-mesoscale motions within the ocean surface boundary layer cause heat to flux vertically (Fox-Kemper et al., 2011) and generate filamentary structure. The interaction of these motions with standard parameterizations of turbulence (Umlauf and Burchard, 2005) and Langmuir turbulence (Reichl et al., 2016) is an active area of research, as is the parameterization of internal dissipation by internal gravity waves generated by tidal displacements over steep bathymetry (de Lavergne et al., 2020). Machine learning (ML) methods are being applied to the parameterization of subgrid-scale motions (Zanna and Bolton, 2020; Ross et al., 2023) and are likely to play important roles in future ocean models.

## 5 Wider and future perspectives

Modern ocean models use large HPC resources and open-source codes supported by communities of scientists and software engineers. They support public safety and protection of the environment by contributing to short-range weather predictions (including forecasts of hurricanes), seasonal forecasts of El Niño, and information about climate change. In order to properly appreciate their roles one needs to see them as one component within the much wider range of scientific activities required to provide this support. Innovations in remote sensing and in situ measurement technology and their internationally coordinated and sustainable implementation are fundamental to these endeavours. The development of seasonal predictions in the late 1980s and early 1990s, for example, was closely tied to the development of the TOGA TAO array (Smith, 2001). The doubling of the number of transistors in a CPU every 2 years from 1970–2020 (Porter and Heimbach, 2025), and the emergence of accurate near-real-time satellite altimetry and the ARGO system of drifters around the turn of the century, enabled near-global assimilation and prediction of the strongest mesoscale ocean motions to first become a reality around 2015 (Bell et al., 2015). What will be the major societal drivers and what are the best opportunities for scientific improvement in the next 10–20 years? We do not have a crystal ball but we can offer some suggestions.

As mentioned at the end of the last section, ML methods have recently emerged as a new set of tools that can be used in many ways to improve Earth system models (Eyring et al., 2024). Depending on the directions explored, the ocean model codes may need to be rewritten as differentiable functions to exploit ML methods fully (Silvestri et al., 2024). Ocean reanalyses based on measurements from 1980 onwards are gradually being improved and together with atmospheric reanalyses will provide an essential resource for inputs to ML and the assessment and improvement of coupled ocean–atmosphere models. The international coordination established under CMIP (Coupled Model Intercomparison Project, https://www.wcrp-climate.org/wgcm-cmip, last access: 17 February 2025) should enable much richer sets of experiments to be conducted and more diverse ensembles of ocean and Earth system models to be explored than would otherwise be possible. There is also scope for more traditional improvements to ocean models, such as improved methodologies and choices for vertical coordinates, parameterization of vertical mixing, specification of surface exchanges (Yu, 2019; Storto et al., 2024), the use of finer horizontal resolution in selected regions, and more efficient generation of ensembles of simulations. Coupled simulations of ENSO still have significant deficiencies and simulations of the future Atlantic MOC are not as reliable as they need to be. In summary, it is reasonable to be optimistic that successful progress with significant societal impacts can be made over the next 10–20 years.

## Appendix A: An introduction to vector calculus for fluid dynamics

Fluid dynamics is concerned with properties like temperature and salinity that vary spatially and evolve with time. Such properties are referred to as fields. Just as $y(x)$ represents any curve $y$ that is a function of $x$ in ordinary calculus, $F(x, y, z, t)$ represents any field that depends on $x$, $y$, $z$, and $t$. In ordinary calculus we have $\delta y \cong y(x+\delta x) - y(x)$ and consider $\delta y/\delta x$ in the limit as $\delta x$ becomes very small. For "smooth" enough functions there is a limiting value $\mathrm{d}y/\mathrm{d}x$. In vector calculus we consider how $F$ varies with each of its coordinates whilst keeping the other coordinates fixed. Varying $x$ and considering the limit when $\delta x$ becomes very small we write

$$\frac{\partial F}{\partial x} = \left.\frac{\partial F}{\partial x}\right|_{y,z,t} = \frac{F(x+\delta x, y, z, t) - F(x, y, z, t)}{\delta x}$$
$$\text{in the limit as } \delta x \to 0. \tag{A1}$$

$\partial F/\partial x$ is termed the partial derivative of $F$ with respect to $x$. The variables that are held constant can be explicitly declared as shown. For brevity they are often omitted, in which case they are implicit. An extremely useful expression analogous to $\delta y \cong y(x+\delta x) - y(x)$ is

$$\delta F \cong \frac{\partial F}{\partial x}\delta x + \frac{\partial F}{\partial y}\delta y + \frac{\partial F}{\partial z}\delta z + \frac{\partial F}{\partial t}\delta t. \tag{A2}$$

For the sake of simplicity we limit ourselves hereafter to rectilinear Cartesian coordinates in which the axes are orthogonal straight lines, the coordinates of a point $\boldsymbol{r}$ are denoted by $(x, y, z)$, the distance from the origin, $d$, is given by the Pythagorean theorem ($d^2 = x^2 + y^2 + z^2$), and $z$ points upward. We explain later that the equations can be derived for a more general set of locally orthogonal coordinates.

Consider first a curve $\boldsymbol{r}(s)$ between two points, $\boldsymbol{r}_0 = \boldsymbol{r}(s_0)$ and $\boldsymbol{r}_1 = \boldsymbol{r}(s_1)$, as illustrated in Fig. A1a. Integrating Eq. (A2) along the curve (with $\delta t = 0$) one sees that

$$F(\boldsymbol{r}_1) - F(\boldsymbol{r}_0) = \int_{s_0}^{s_1} \left(\frac{\partial F}{\partial x}\frac{\mathrm{d}x}{\mathrm{d}s} + \frac{\partial F}{\partial y}\frac{\mathrm{d}y}{\mathrm{d}s} + \frac{\partial F}{\partial z}\frac{\mathrm{d}z}{\mathrm{d}s}\right)\mathrm{d}s. \tag{A3}$$

Writing $\nabla F = (\partial F/\partial x, \partial F/\partial y, \partial F/\partial z)$ and $\mathrm{d}\boldsymbol{r}/\mathrm{d}s = (\mathrm{d}x/\mathrm{d}s, \mathrm{d}y/\mathrm{d}s, \mathrm{d}z/\mathrm{d}s)$, Eq. (3) can be re-expressed as

$$F(\boldsymbol{r}_1) - F(\boldsymbol{r}_0) = \int_{s_0}^{s_1} \nabla F.\frac{\mathrm{d}\boldsymbol{r}}{\mathrm{d}s}\mathrm{d}s = \int_{r_0}^{r_1} \nabla F.\mathrm{d}\boldsymbol{r}. \tag{A4}$$

Equation (A4) is the defining property of $\nabla F$, which is termed the gradient of $F$ or "grad $F$" for short. If one integrates around any path which closes on itself, i.e. $\boldsymbol{r}_1 = \boldsymbol{r}_0$, one sees that the left-hand side of Eq. (A4) is equal to zero. Hence the integral of $\nabla F$ around any closed curve is zero.

The rate of change with time of a field $F$ following a fluid particle moving at velocity $\boldsymbol{u} = (u, v, w)$ can also be inferred from Eq. (A2) by dividing it by $\delta t$. Following the fluid parcel, $\delta x \cong u\delta t$, $\delta y \cong v\delta t$, and $\delta z \cong w\delta t$. So

$$\frac{\mathrm{D}F}{\mathrm{D}t} = \frac{\partial F}{\partial t} + u\frac{\partial F}{\partial x} + v\frac{\partial F}{\partial y} + w\frac{\partial F}{\partial z} = \frac{\partial F}{\partial t} + \boldsymbol{u}.\nabla F. \tag{A5}$$

Here we have used the standard notation $\mathrm{D}F/\mathrm{D}t$ to denote the rate of change of $F$ with respect to time following a fluid parcel, which is often called the Lagrangian derivative. Tracers are defined to be properties that fluid parcels retain unchanged with time. Using $\mathcal{T}$ to denote a tracer we see that

$$\mathrm{D}\mathcal{T}/\mathrm{D}t = \frac{\partial \mathcal{T}}{\partial t} + u\frac{\partial \mathcal{T}}{\partial x} + v\frac{\partial \mathcal{T}}{\partial y} + w\frac{\partial \mathcal{T}}{\partial z} = 0. \tag{A6}$$

An equation expressing conservation of mass can be derived by considering the "notional" cuboid cell illustrated in Fig. A1b. The density of a fluid, $\rho$, is defined to be its mass per unit volume. The volume of the cell in Fig. A1b equals $\delta V = \delta x\delta y\delta z$. The fluxes of mass through the two side faces perpendicular to the $x$ axis are $U(x, y, z)\delta y\delta z$ and $U(x+\delta x, y, z)\delta y\delta z$, where $U = \rho u$. So in the limit as the cell volume becomes very small the mass flux out of the cell from these two faces equals

$$\left[U(x+\delta x, y, z) - U(x, y, z)\right]\delta y\delta z \cong \frac{\partial U}{\partial x}\delta x\delta y\delta z. \tag{A7}$$

Conservation of mass requires that the increase in mass inside the cuboid plus the fluxes out of the three pairs of side faces equal zero. Using expressions corresponding to Eq. (A7) and dividing by $\delta V$ one obtains

$$\frac{\partial \rho}{\partial t} + \frac{\partial(\rho u)}{\partial x} + \frac{\partial(\rho v)}{\partial y} + \frac{\partial(\rho w)}{\partial z} = \frac{\partial \rho}{\partial t} + \boldsymbol{\nabla}.(\rho\boldsymbol{u}) = 0. \tag{A8}$$

The operator $\boldsymbol{\nabla}.$ introduced in Eq. (A8) is called the divergence. At any point it is defined to be the outward flux per unit volume through a surface enclosing that point. Gauss's theorem shows that for smooth fields the divergence does not depend on the shape of the volume (e.g. it is the same for infinitesimal spheres and cuboids). Combining Eqs. (A6) and (A8) one obtains the flux form for the conservation of tracers,

$$\frac{\partial(\rho\mathcal{T})}{\partial t} + \frac{\partial(\rho u\mathcal{T})}{\partial x} + \frac{\partial(\rho v\mathcal{T})}{\partial y} + \frac{\partial(\rho w\mathcal{T})}{\partial z} = \frac{\partial(\rho\mathcal{T})}{\partial t}$$
$$+ \nabla.(\rho\boldsymbol{u}\mathcal{T}) = 0. \tag{A9}$$

There is one other vector quantity that is particularly important in fluid dynamics: the curl of the velocity field, $\boldsymbol{\nabla} \times \boldsymbol{u}$, which is termed the vorticity. The component of the vorticity perpendicular to the infinitesimal square shown in Fig. A1c is calculated by considering the line integral of

$\boldsymbol{u} \cdot d\boldsymbol{r}$ anticlockwise around its sides. Similarly to Eq. (A7), $\left[v\left(x+\delta x, y\right)-v\left(x, y\right)\right]\delta y \cong \frac{\partial v}{\partial x}\delta x \delta y$ and

$$\oint \boldsymbol{u}.d\boldsymbol{r} = \iint \left(\frac{\partial v}{\partial x} - \frac{\partial u}{\partial y}\right)\mathrm{d}x\mathrm{d}y = \iint \nabla \times \boldsymbol{u}.\mathrm{d}\boldsymbol{S}. \qquad \text{(A10)}$$

Here $\mathrm{d}\boldsymbol{S}$ is the vector perpendicular to the area enclosed by the line integral whose length is equal to that area. Stokes' theorem shows that the vorticity does not depend on the shape of the area used to calculate it (e.g. it is the same for infinitesimal circles and squares). The vorticity of the fluid is particularly important because of Kelvin's theorem, which states that under certain conditions following a fluid parcel the vorticity does not change with time (i.e. it is conserved). Ertel's theorem on conservation of potential vorticity is based on Kelvin's theorem (Pedlosky, 1982 Chap. 2).

Expressions for the gradient, divergence, and curl of vector fields and relations between them can be derived for generalized curvilinear orthogonal coordinate systems (see Lorrain and Corson, 1970, for a well-illustrated introduction and Appendix A of Batchelor, 1967, for a concise summary). Latitude and longitude coordinates for the sphere are one example of such coordinate systems.

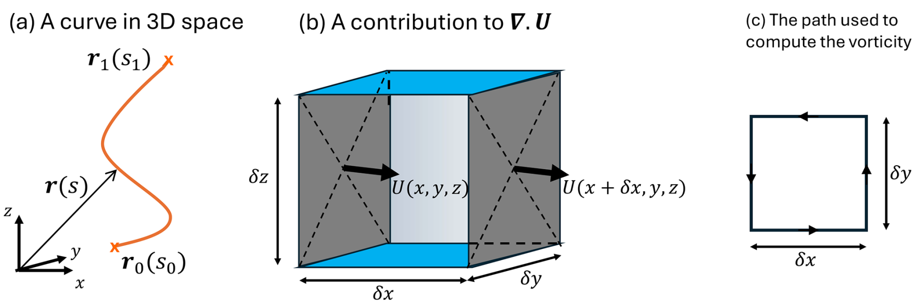


**Figure A1.** **(a)** Illustration of a curve $\boldsymbol{r}(s)$ in 3D space obtained by varying the scalar parameter $s$ from $s_0$ to $s_1$. **(b)** Illustration of the contribution to the mass flux divergence for a cell of volume $\delta x \delta y \delta z$ from the fluxes through the faces perpendicular to the $x$ axis. **(c)** The anticlockwise path around the sides of the infinitesimal cell with sides of length $\delta x$ and $\delta y$ used to calculate the area integral within the cell of the normal component of vorticity.

**Data availability.** No datasets were used in this article.

**Author contributions.** MJB wrote most of the text of all the sections. SC wrote the first draft of Sect. 2. AS reviewed and made improvements to all the sections.

**Competing interests.** At least one of the (co-)authors is a member of the editorial board of *State of the Planet*. The peer-review process was guided by an independent editor, and the authors also have no other competing interests to declare.

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**Acknowledgements.** We gratefully acknowledge advice and insights from many colleagues over many years.

**Financial support.** This research has been supported by the Met Office Hadley Centre Climate Programme.

**Review statement.** This paper was edited by Enrique Álvarez Fanjul and reviewed by two anonymous referees.

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State Planet, 5-opsr, 11, 2025
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STATE OF THE PLANET



# Numerical models for monitoring and forecasting sea level: a short description of present status

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Received: 13 September 2024 – Discussion started: 26 September 2024
Revised: 19 January 2025 – Accepted: 2 February 2025 – Published: 2 June 2025

**Abstract.** Forecasting the sea level is crucial for supporting coastal management through early warning systems and for adopting adaptation strategies to climate change impacts. Such objectives can be achieved by using advanced numerical models, which are based on shallow-water equations used to simulate storm surge generation and propagation due to atmospheric pressure and winds, or with ocean general circulation and baroclinic models. We provide here an overview on models commonly used for sea level forecasting that can be based on storm surge models or ocean circulation ones and is integrated on structured or unstructured grids, including an outlook on new approaches based on ensemble methods.

## 1 Introduction

The low-elevation coastal zone, defined as the contiguous and hydrologically connected zone of land along the coast with an elevation above sea level of less than 10 m, covers only 2 % of the world's land area, but close to 10 % of the world population lives there (Neumann et al., 2015). Due to the large economic value of coastal zones, economic losses due to coastal flood risks induced by rising sea levels and extreme sea levels at the coast are huge (Abadie et al., 2020). Sea level rise and extremes can also exacerbate coastal erosion, saltwater intrusion, and the degradation of coastal ecosystems.

A wealth of factors is influencing sea level changes at the coast (Woodworth et al., 2019). Extreme sea levels are due to the combination of different drivers: astronomical tides, storm surges, wind wave setup and swash, and mean sea level changes. Mean sea level changes are themselves induced by ocean circulation redistributing mass, heat, and salt in the ocean and by the transfer of water mass from land to the ocean (from mountain glaciers, ice sheets, and terrestrial water level storage changes). Mean sea level changes, including long-term trends, have been accurately monitored over the quasi-global ocean through satellite altimetry (Legeais et al., 2021). Sea levels at the coast, on the other hand, have been monitored thanks to tide gauges (TGs), whose data have been compiled in different datasets (e.g. Global Extreme Sea Level Analysis (GESLA3), Permanent Service for Mean Sea Level (PSMSL), Copernicus Marine Service). Tides, storm surges, and wind waves can also change in response to climate change (Haigh et al., 2020; Kirezci et al., 2020; Morim et al., 2019)

Numerical ocean models can be used to provide both consistent retrospective datasets of sea level changes over the global, regional, or coastal ocean and forecasts of sea level change (Melet et al., 2021). Both can be used to support adaptation to sea level rise (Alvarez Fanjul et al., 2022). Due to sea level rise, the frequency of extreme sea levels at the coast will increase (Kirezci et al., 2020), and associated impacts on population and economic damages will, too, without further adaptation (Fig. 1). Short-term (a few days) sea level forecasts provided by ocean forecasting systems are necessary information to feed early warning systems (EWSs) for coastal floods. EWSs are integrated systems allowing a real-time monitoring of potential natural hazards, issuing warnings when a natural hazard is measured or forecasted, and informing stakeholders (e.g. civil protection agencies, re-

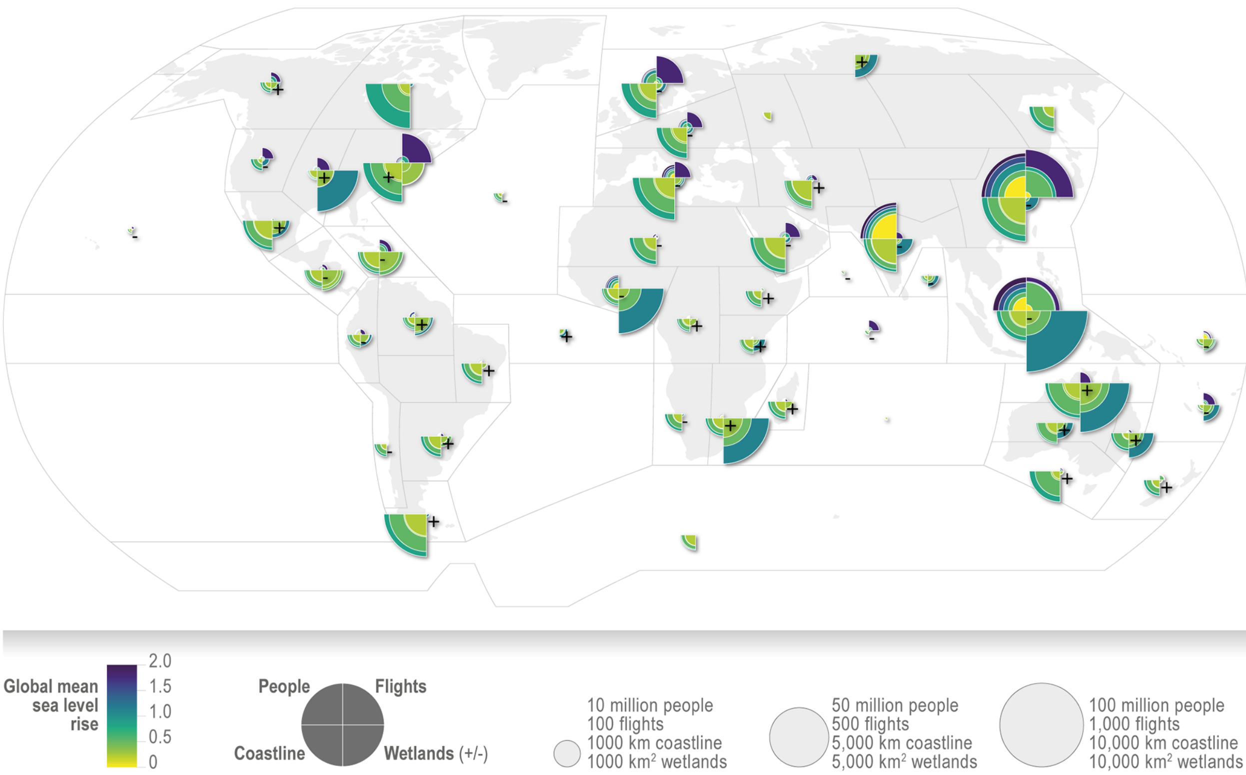


**Figure 1.** Map of risks for cities and settlements by the sea according to IPCC regions, extracted from IPCC AR6 (Glavovic et al., 2022). The map shows risks to people (number of people at risk from a 100-year coastal flood event; Haasnoot et al., 2021), risks of loss of coastal land (length of coast with more than 100 m retreat; Vousdoukas et al., 2020), risks to the built environment (airports at risk indicated by expected annual number of flights disrupted by coastal flooding; Yesudian and Dawson, 2021), and risks to wetlands (± indicates positive or negative area change; Schuerch et al., 2018). Risks are reported against the global mean sea level (GMSL) rise relative to 2020 (in metres), depending on data availability.

gional and local authorities, ports, environmental agencies) as part of an integrated risk assessment cycle to mitigate risks. EWSs were found to be an efficient adaptation measure by providing more than a 10-fold return on investment (Global Commission on Adaptation, 2019).

Monitoring of sea level change over past decades provides the historical baseline for quantifying sea level rise and extremes and their return periods, along with synoptic sea level variability in a broader sense. Ocean (wave) reanalyses combine ocean (wave) model dynamics with in situ and satellite observations through data assimilation. As such, reanalyses provide a consistent view of the ocean in space and time and across variables, accounting for observation information and dynamics. The reliability of ocean reanalyses has increased over the last decade (Forget et al., 2015; Lellouche et al., 2021; Storto et al., 2019; Zuo et al., 2019).

## 2 Numerical models for forecasting sea level

Numerical modelling systems are the backbone of ocean and wave hindcasts (modelling past evolutions over the last decades), reanalyses (hindcasts constrained by observations through routine assimilation of in situ and space observations), and forecasts (over a few days to weeks). Such models are solving the equations governing ocean and wave dynamics and are often constrained by observations through assimilation of in situ and satellite observations (Alvarez Fanjul et al., 2022). They provide a synoptic spatial and temporal monitoring of the ocean.

Regarding sea level forecasts, both storm surge models based on shallow-water equations (Fujiang et al., 2022) and ocean general circulation models (OGCMs) based on primitive equations (Ciliberti et al., 2022) are used. In terms of model grids, both structured and unstructured grids can also be used. Other details on model equations, discretization methods, grid types, coordinates, data assimilation techniques, and inventory of operational systems are available in Alvarez Fanjul et al. (2022).

Wind waves also contribute to mean and extreme sea levels through wave setup and to the fluctuation of the water line at the coast through wave runup (Dodet et al., 2019). Wind wave sea level contributions are estimated from wave models (Aouf et al., 2022). In addition, non-linear interactions between mean sea level, tides, storm surges, and waves act on the total sea level at the coast (Chaigneau et al., 2023; Idier et al., 2019).

The accuracy of numerical models in forecasting sea levels is limited by several factors (e.g. discussion in Irazoqui Apecechea et al., 2023), such as the accuracy of the atmospheric forcing forecasts (especially so for the storm surge and wave components of total sea level changes at the coast), the tidal forcings for regional to coastal systems, the representation of bathymetry, the lack of representation of nonlinear interactions between sea level components (mean-sea level-tides-surges-wave), and the limitations of the ocean and wave models themselves (e.g. model numerics, resolution, lack of some coastal processes such as wetting and drying, the river–estuary–ocean continuum).

## 2.1 Storm surge models

Storm surge models, also called hydrodynamic models here, are usually based on shallow-water equations. They are the most common tools to simulate the generation and propagation of storm surges due to atmospheric surface pressure and winds, thereby providing water levels and velocities (e.g. SELFE, SCHISM, POM, Delft3D, ADCIRC, GTSM, MIKE21, TuFlow, ROMS, FVCOM, SHYFEM) (Fujiang et al., 2022; Ciliberti et al., 2022). They can also incorporate astronomical tides. In these models, shallow-water equations are often discretized based on unstructured meshes with either finite-volume methods or finite-element methods. Unstructured grids allow seamless modelling from the open ocean to the coastal ocean using a spatially variable resolution with finer resolution in the coastal zones (Fig. 2), which enhances the simulation of coastal processes (e.g. Federico et al., 2017; Ferrarin et al., 2018; Toomey et al., 2022; Zhang et al., 2016). Mostly used in their 2D, barotropic version, such models are computationally fast and can be used over continent-wide regions or the global ocean to produce hindcasts (Fernández-Montblanc et al., 2020, 2019) reaching up to 1.25 km resolution at the coast (Muis et al., 2020) and operational forecasts (NOAA, 2023) and to produce tidal atlases (Lyard et al., 2021). However, barotropic hydrodynamic models do not simulate changes in mean sea level due to baroclinic effects, although this contribution can be substantial even for extreme sea levels, such as in micro-tidal or non-stormy regions.

There are also 3D baroclinic hydrodynamic models, which are able to solve additional physical processes, such as the gradients of seawater-density-induced changes in mean sea level (e.g. steric sea level), and lead to more accurate sea level measurements with even greater impacts on currents (Ye et al., 2020). Adding baroclinicity in a global barotropic operational model can lead to significant improvements in predictions of extreme water levels (Wang et al., 2022).

In storm surge models, the calibration of bottom friction is especially important. Such systems can assimilate different sources of observations notably to provide more accurate initial conditions for their forecasts and increase forecast skills over short lead times. Observations assimilated in storm surge models include sea surface height from tide gauges, for higher frequency and coastal processes, and/or from satellite altimetry, for longer-period processes. Operational storm surge forecasting systems have been implemented in many countries, based on different types of storm surge models (Fujiang et al., 2022).

## 2.2 Ocean general circulation models

The 3D baroclinic ocean general circulation models, based on primitive equations (Ciliberti et al., 2022), are widely used in operational oceanography (e.g. NEMO, HYCOM, ROMS, MOM, MITgcm, CROCO, FVCOM, SHYFEM, SCHISM, FESOM, MPAS) for ocean circulation forecasting systems, also providing a valuable solution for forecasting sea level changes (Irazoqui Apecechea et al., 2023; Melet et al., 2021). More complex and expensive than storm surge models previously described, they can simulate mean sea level changes due to ocean circulations, along with tides and storm surges when forced by surface atmospheric pressure and wind, coherently with other ocean state variables (e.g. 3D temperature, salinity, ocean currents). Operational systems also usually assimilate observations. Of particular importance for the representation of sea level changes are the assimilation of satellite altimetry data, to directly constrain total sea level; in situ profiles of temperature and salinity, to constrain the steric and dynamic component of sea level; and satellite gravimetry data, to constrain the mass component of global mean sea level (GMSL) rise. The assimilation of satellite altimetry exerts a major constraint on such forecasting systems to increase their skills (Hamon et al., 2019; Le Traon et al., 2017).

Due to the Boussinesq approximation in primitive-equation models, the global mean (or spatial average in an area-limited regional model) steric sea level change cannot be explicitly simulated. However, this time-dependent scalar can be diagnosed from the temperature and salinity fields (Griffies and Greatbatch, 2012) and added to simulated sea level changes. Spatial gradients of steric sea level changes are directly simulated in primitive-equation models through changes in temperature and salinity inducing differences in density and circulation changes. Another limitation stems from the use of a constant, uniform gravity field and the approximation of spherical geopotential surfaces. This approximation does not allow us to represent the changes in the Earth's gravity and rotation or solid-Earth deformation (the so-called GRD effects; Gregory et al., 2019; Mitrovica et al., 2011) due to the transfer of water from land to the ocean (e.g. melting mountain glaciers, mass loss of ice sheets, changes in land water storage), which contribute to regional departures from the global mean sea level rise.

As hydrodynamical models, operational OGCMs can be used to forecast sea level changes from global scales (E.U. Copernicus Marine Service Information, 2024) to coastal

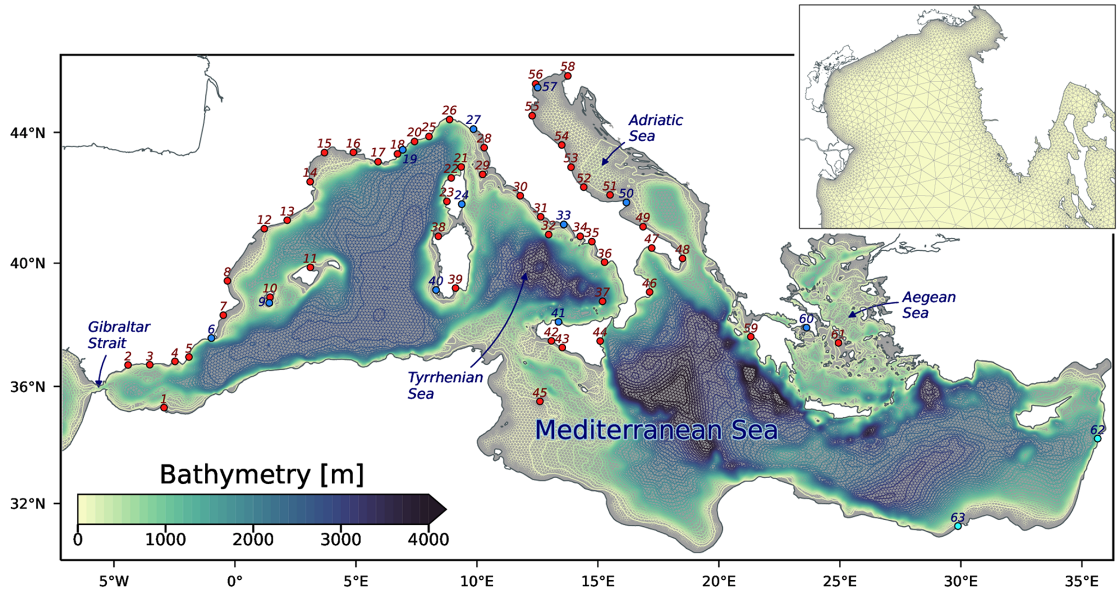


**Figure 2.** An example of an unstructured barotropic ocean model and bathymetry (here, from the System of HydrodYnamic Finite Element Modules (SHYFEM); Bajo et al., 2023). The inset is a zoom of the grid in the northern Adriatic Sea. The blue and red dots mark the locations of tide gauges.

scales (Fig. 3). For instance, the skills of the regional operational ocean forecasting systems (OOFSs) of the Copernicus Marine Service covering European seas to forecast sea level extremes were evaluated (Irazoqui Apecechea et al., 2023), showing satisfactory performance, with an underprediction of peak magnitudes of both extreme sea levels and their surge components. For these OOFSs, forecast skills are stable for the first 3 d of the forecasts but decrease at forecast lead times of 4 d and longer, demonstrating the suitability of the systems for early warning applications. The possible sea level processes included in these regional models must be taken into consideration when comparing/validating with local tide gauge data. This may require additional pre-processing of tide gauge data to deal with higher-frequency sea level oscillations often recorded at very local scales and contributing to local extremes. Adding sea ice effects in a global operational model was shown to improve total water level forecasts (Wang and Bernier, 2023).

Regional or global operational ocean forecasting systems can also be used to downscale sea level changes at more coastal scales for local applications. Regional ocean models can have higher resolutions than global ocean models (e.g. ranging from 2 to 12 km for European seas in the Copernicus Marine Service for operational forecasting systems as of July 2023) and benefit from ocean models adapted to the regional dynamics and from the representation of additional processes.

Global and regional reanalysis can be used to provide a baseline over the past decades of sea level changes, when tide gauges are sparsely located along coastlines. Reanalyses benefiting from data assimilation capture the spatial variability in altimetry-derived sea level trends (Lellouche et al., 2021). Since altimetric observations capture sea level trends due to land ice mass loss and land water storage changes, in addition to trends due to sterodynamic sea level changes (Gregory et al., 2019), a processing of the altimetric data to be assimilated in OGCMs or a processing of the sea level represented in the model needs to be performed. For instance, in the global ocean high-resolution reanalysis provided by the Copernicus Marine Service (GLORYS12; Lellouche et al., 2021), a global mean sea level trend is added at each time step to the modelled dynamic sea level, prior to data assimilation. This added GMSL signal is composed of the diagnosed global mean steric sea level change and of a barystatic (land-ice-related as in Gregory et al., 2019) sea level trend.

## 2.3 Ensemble forecasting

Deterministic solutions provided by numerical models can be complemented by multi-model systems, stochastic approaches, and ensemble estimates. Ensemble forecasting allows us to account for different sources of uncertainties that arise from errors in e.g. the initial or boundary conditions, the atmospheric forcing or forcing functions, the physics or parameterization of the numerical model, the bathymetry, and the spatial- or temporal-resolution limitations. Forecast skills tend to decrease with increasing forecast lead times, as errors grow. It is therefore possible to provide probabilistic forecasts that better support coastal decision-makers by adding a confidence interval to the forecasted variable. This can be achieved in different ways (Alvarez Fanjul et al., 2022), both

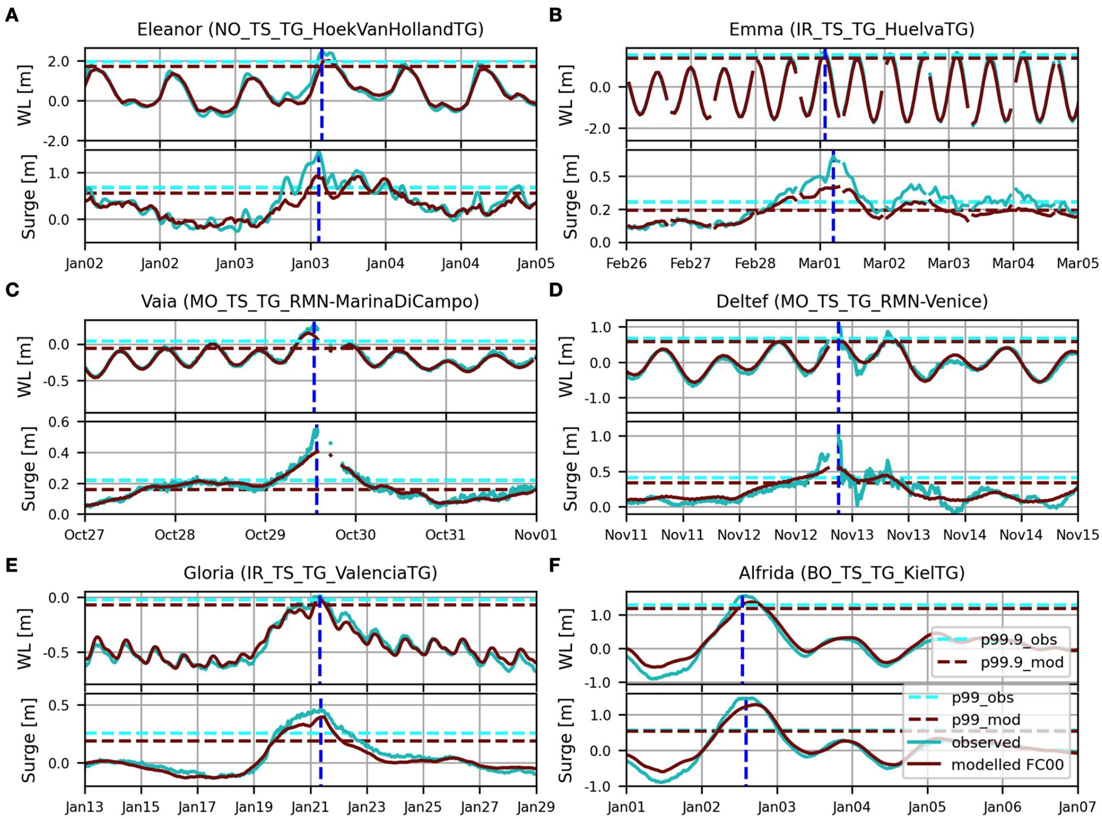


**Figure 3.** Simulated (in dark red) and tide gauge (TG) (in blue) sea levels (including mean sea level, tides, surge) and surges observed during a selection of extreme events in Europe. **(a)** Hoek Van Holland TG (Eleanor, 2018), **(b)** Huelva TG (Emma, 2018), **(c)** Marina Di Campo TG (Vaia, 2018), **(d)** Venice TG (Detlef, 2019), **(e)** Valencia TG (Gloria, 2020), **(f)** Kiel TG (Alfrida, 2019). Water level and surge percentile thresholds for the model and observations are shown in the corresponding colours as horizontal dashed lines. The vertical blue line denotes the observed peak time for the plotted component. Extracted from Irazoqui Apecechea et al. (2023).

for hindcasts and short-term forecasts, taking into account (or not) observational data to determine model performance and decrease model errors.

A first immediate approach is considering existing operational forecasts over an overlapping area to build a multi-model system. This is possible today thanks to the number of general ocean circulation operational systems with a reliable coastal sea level solution, such as those of the Copernicus Marine Service (global and regional marine forecasting systems (MFCs)). The good performance of these models for coastal sea level (Irazoqui Apecechea et al., 2023) can complement the solution provided by storm surge forecasting systems run at national level. This is the approach followed by Ports of Spain, which combines its 2D barotropic storm surge forecasting system (Nivmar; Alvarez-Fanjul et al., 2001) with the different MFCs covering the Spanish coast since 2012 (Pérez-Gómez et al., 2021). Today, the system, named ENSURF, combines Nivmar with two regional MFCs, IBI-MFC (Aznar et al., 2016) and MedFS (Clementi et al., 2021). It makes use of the Bayesian model averaging (BMA) statistical technique (Beckers et al., 2008) for validation of the different models with tide gauge data in near-real time and provides the outperforming mean and spread of sea level forecasts at the Spanish ports (Fujiang et al., 2022).

Thanks to the increased computational resources, storm surge ensemble forecasts can rely today on a larger number of members. A more recent multi-model and higher-resolution approach is in place today for the Adriatic Sea, combining up to 19 sea level and wave models as described in Ferrarin et al. (2020). Very often, the storm surge ensemble members are obtained by forcing the same model with an ensemble of meteorological forecasts providing different wind and sea level pressure fields, which account for most of the uncertainty during a storm. In this case, the model uncertainty will reflect the one of the meteorological forcing. As an example, the ECMWF ensemble (Molteni et al., 1996) is used for storm surge operational forecasts in the North Sea (Flowerdew et al., 2010, 2013). This approach was also applied for sea level forecasting in Venice by Mel and Lionello (2014).

Machine learning techniques can also be used to improve model performance locally and account for high-frequency sea level oscillations. This is the approach followed by Rus et al. (2023) in the northern Adriatic, where traditional ensemble forecasting is replaced by computationally efficient machine-learning-based ensemble models, trained with tide gauge data to improve the probabilistic forecast and account for seiches at a single location.

## 3 Conclusions

Sea level forecasting is especially important at the coasts due to impacts on population and assets. Many operational systems are already in place, based on different model types, assimilating different observations (Capet et al., 2020; Fujiang et al., 2022; Ciliberti et al., 2022). Storm surge numerical modelling started in the 1950s, and operational oceanography with OGCMs combined with data assimilation largely developed in the 1980s and 1990s with the availability of satellite observations and increase in computational capacities. Despite decades of developments of such modelling systems and satisfactory forecast skills at short lead time, forecasting sea level changes at the coast at spatiotemporal scales relevant for decision-making remains challenging. This is notably due to the wealth of processes driving sea level changes at the coast (Woodworth et al., 2019) and to the short scales of coastal zone dynamics.

**Data availability.** No data sets were used in this article.

**Author contributions.** AM led the writing of the article. All authors participated in the review and revision of the article.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** The authors thank the reviewers for their constructive criticism and are grateful to Stefania Ciliberti and Enrique Alvarez Fanjul for their unwavering support.

**Financial support.** Angelique Melet was supported by grants of the European Union's H2020 programme (project ECFAS, grant no. 101004211, and CoCliCo, grant no. 101003598).

**Review statement.** This paper was edited by Jay Pearlman and reviewed by Georg Umgiesser and one anonymous referee.

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STATE OF THE PLANET



# Numerical models for monitoring and forecasting ocean biogeochemistry: a short description of present status

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Received: 14 August 2024 – Discussion started: 23 September 2024
Revised: 7 February 2025 – Accepted: 21 February 2025 – Published: 2 June 2025

**Abstract.** The ability to model biogeochemical features in the ocean is a key factor in predicting the health of the ocean: it involves the representation of processes and cycles of chemical elements (such as carbon, nutrients, and oxygen) and the dynamics of living organisms such as phytoplankton, zooplankton, and bacteria. This paper gives an overview of the main modelling aspects aimed at describing the low trophic levels of marine ecosystems and shows how they can be coupled with advection and diffusion models. The complexity of biogeochemical models can vary considerably depending on the topics of interest, assumed hypotheses, and simplifications of the numerical parameterizations. The paper also discusses the uncertainties in the numerical solution due to the lack of knowledge about the parameterizations, the initial and boundary conditions, the lack of a robust observation network, and the high computational cost of running such models.

## 1 Introduction

Marine biogeochemistry refers to the cycling of chemical elements (e.g. carbon, nutrients, oxygen) resulting from physical transport, chemical reactions, and uptake and processing by living organisms (e.g. phytoplankton, zooplankton, bacteria). Biogeochemical models describe the low trophic levels of marine ecosystems and are usually coupled with advection and diffusion models. Operational biogeochemical models have generally been developed by incorporating biogeochemical models developed for research and process-based studies into existing physical forecasting systems (Gehlen et al., 2015) and are used to assess (i) past and current marine ecosystem states and trends and (ii) short-term (days to weeks) or seasonal (months) forecasts (Le Traon et al., 2019; Fennel et al., 2019). When observations are assimilated, simulations of a past period are called reanalysis, while unconstrained simulations of a past period are called hindcast. When the simulations are carried forward to the present, they are referred to as nowcasts (Fennel et al., 2023). By providing timely information for the current state and a consistent reconstruction of the past, biogeochemical operational models can support ocean carbon sequestration and storage estimations, monitoring effects of acidification and deoxygenation; marine spatial planning; and, as input for habitat and food web modelling, marine biodiversity conservation and fisheries management.

Biogeochemical models can have a wide range of complexity, from a single nutrient and simple parameterizations of processes to fully explicit representations of several nutrients, trophic levels, and functional groups. They can also include carbonate systems, pollutants (e.g. Hg, persistent organic pollutants (POPs)), and other features, depending on the specific goals and domains for which they were developed. This chapter provides a brief introduction to biogeochemical modelling in the context of operational oceanography, and more detailed descriptions and discussions can be found in the following articles (Gutknecht et al., 2022; Fennel et al., 2022; Ford et al., 2018). The focus is on the levels of model complexity in existing biogeochemical prediction systems, with examples taken mainly from the Copernicus Marine Service (Le Traon et al., 2019).

## 2 Biogeochemical models in oceanography

### 2.1 Formulations, processes, and elements of biogeochemical models

In general, biogeochemical models solve a system of partial differential equations. Eq. (1) describes the rate of change of a set of state variables $C$ representing biogeochemical tracers: dissolved inorganic substances (e.g. nutrients), living organic compartments (e.g. primary producers and secondary consumers), and non-living organic dissolved and particulate matter (Gutknecht et al., 2022; Fennel et al., 2022). The first three terms on the right-hand side of Eq. (1) represent the physical terms, advection (first term) and diffusion (second (horizontal) and third (vertical) terms) of biogeochemical tracers, where $K_\mathrm{H}$ and $K_\mathrm{V}$ are the horizontal and vertical diffusivities, respectively, which act on different spatial scales. The remaining terms describe the sinking processes that affect biological particles (fourth term) and biogeochemical reactions (fifth term).

$$\frac{\partial C}{\partial t} = -v \cdot \nabla(C) + \nabla_\mathrm{H}(K_\mathrm{H}\nabla_\mathrm{H}(C)) + \frac{\partial}{\partial z}\left(K_\mathrm{V}\frac{\partial C}{\partial z}\right) + w_\mathrm{sink}\frac{\partial C}{\partial z} + R_\mathrm{bio}(T, \mathrm{light}, \rho, C) \quad (1)$$

The last term, $R_\mathrm{bio}$, represents the local source-minus-sink terms for the biogeochemical tracers and is typically based on the principle of conservation of mass to simulate the cycling of chemical elements through various marine compartments. Biogeochemical models (Eq. 1) are generally discretized on a grid covering a spatial region of interest, and they are solved numerically by using appropriate initial and boundary conditions for each of the tracers. The physical parts of Eq. (1) can be solved directly by the advection–diffusion component of ocean dynamic models (i.e. on-line coupling). Alternatively, the output of the ocean dynamics model is used to force the biogeochemistry off-line (Heinze and Gehlen, 2013). Different schemes can be used to couple the physical and biogeochemical processes to optimize accuracy and computational cost (Bruggeman and Bolding, 2014; Cossarini et al., 2017). Operational biogeochemical models also include data assimilation schemes (Brasseur et al., 2009; Fennel et al., 2019), with satellite observations being the most commonly used due to their spatial coverage and time availability, even in near-real time. Ocean colour chlorophyll is the variable most typically assimilated in biogeochemical models (Nerger and Gregg, 2008; Ciavatta et al., 2011; Fontana et al., 2013; Teruzzi et al., 2014; Ciavatta et al., 2016), but other remote sensing variables have also been tested: diffuse attenuation coefficient (Ciavatta et al., 2014), phytoplankton functional type (PFT) chlorophyll (Ciavatta et al., 2018; Skákala et al., 2018; Pradhan et al., 2020), and inherent optical properties (Jones et al., 2016). While ocean colour provides unique information about the surface of the ocean, the transfer of surface information to deeper layers usually requires approximations. The emergence of autonomous underwater sensors (biogeochemical gliders and Argo floats) has opened the possibility to better constrain biogeochemical dynamics below the water surface (Verdy and Mazloff, 2017; Cossarini et al., 2019; Teruzzi et al., 2021; Skákala et al., 2021). Oxygen, chlorophyll, and nitrate profiles are currently used in forecast systems for assimilation (Amadio et al., 2024) but also for parameter tuning (Wang et al., 2020; Yumruktepe et al., 2023; Falls et al., 2022), validation of operational systems (Salon et al., 2019; Mignot et al., 2023), and adaptive monitoring of phytoplankton blooms (Ford et al., 2022).

Unlike physical models based on Navier–Stokes equations (Bell et al., 2025, in this report), there are no fundamental laws and principles for the biogeochemical term ($R_\mathrm{bio}$). Rather, equations describing biogeochemical processes rely on empirical relationships based on laboratory experiments (e.g. nutrient limitation experiments, grazing dilution experiments), biological theories, and ecological principles based also on biogeographic relationships.

The NPZD approach, which stands for nutrient–phytoplankton–zooplankton–detritus (Fasham et al., 1990), is the basis of most marine biogeochemical models. In its simplest form, the cycling of a single nutrient (e.g. nitrogen) is represented by four marine compartments: inorganic nutrients, living organic matter (phytoplankton and zooplankton), and non-living organic matter (detritus). The nutrient fluxes between the compartments are the uptake of the nutrient as a function of phytoplankton growth, the mortality and grazing of phytoplankton and zooplankton, and the remineralization of the detritus compartment. In the original Fasham model (Fasham et al., 1990), the nutrient inorganic pool (nitrogen) is divided into ammonium and nitrate, and the remineralization process includes bacteria and dissolved organic nitrogen, increasing the number of state variables from four to seven and nearly doubling the number of processes described.

A schematic representation of the cycles of multiple chemical elements (e.g. nutrients) among living and non-living compartments, together with some additional features presented below, is shown in Fig. 1.

Increasing model complexity (e.g. greater number of state variables and processes) enables the expansion of the model objectives and the range of applications, but it is accompanied by larger uncertainties in the parameterization and higher computational costs. There is no general consensus on the level of complexity of biogeochemical models and the priority for new components to be added. This often depends on the specific objectives for which a model is being built. In recent years, the complexity of biogeochemical models used in operational oceanography has increased, as have their applications. These span multiple objectives: monitoring ocean state and variability, assessing ocean health (acidification, eu-

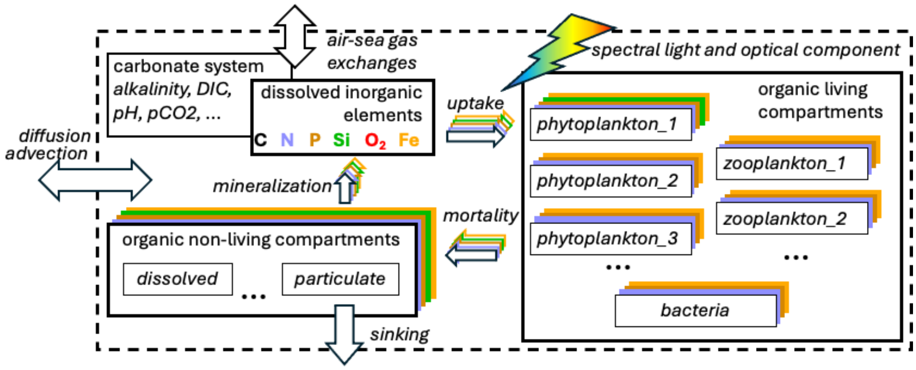


**Figure 1.** Simplified scheme of compartments (boxes) and processes (arrows) representing the cycles of multiple chemical elements typically included in a biogeochemical model. The ellipses indicate the increase in the number of compartments and variables (e.g. multiple plankton functional types, multiple size compartments of non-living organic matter, and additional variables resolved by the carbonate system).

trophication, deoxygenation), supporting resource management, and studying pollutant impacts.

The number of chemical elements is often increased, typically including carbon, other macronutrients (such as phosphorus and silicon), and micronutrients (e.g. iron). The increase in model complexity allows modellers to represent a wider range of chemical and biological processes, such as nitrification, denitrification, calcification, competition for the limiting nutrients, and dimethylsulfide (DMS) dynamics. Another typical tracer included in biogeochemical models is oxygen because of its importance for ocean health (e.g. deoxygenation; Schmidtko et al., 2017; Grégoire et al., 2021; Bopp et al., 2013) and the effects of low oxygen concentrations (hypoxia) in changing ecosystem functions (Baird et al., 2004).

Fixed or variable nutrient stoichiometry can then be formulated within the simulated organisms, e.g. phytoplankton. Typical values of fixed nutrient ratios are $138[O_2] : 106[C] : 16[N] : 15[Si] : 1[P] : 0.1–0.001[Fe]$ (Redfield, 1934; Lenton and Watson, 2000). When models include variable stoichiometry (e.g. Vichi et al., 2017; Tagliabue et al., 2011), multiple state variables are required to represent the living organic compartments, and a formulation of intracellular ratios can be used to simulate the multiple nutrient limitation of phytoplankton growth (Klausmeier et al., 2004). Primary production, the basis of the marine food web, is the chemical synthesis of organic compounds from dissolved carbon dioxide through chlorophyll-mediated photosynthesis. When chlorophyll is explicitly included in models, photosynthesis and acclimation to light can be dynamically simulated to balance the growth rate and the variable chlorophyll–carbon ratio as a function of light, nutrient limitation, and temperature (Geider et al., 1997).

The complexity of biogeochemical models can be measured by the number of plankton functional types (PFTs) used to simulate the trophic food web. The autotrophic community can be conceptually grouped considering various ecological functions (e.g. silicifiers, calcifiers, nitrogen fixers, and dimethylsulfide (DMS) producers); cell size (e.g. pico-, nano-, and microphytoplankton); and specific physiological traits, such as optical absorption, light use, growth rate, and affinity for nutrients (Hood et al., 2006). To improve the representation of the dynamics of phytoplankton functional groups, biogeochemical models can include a spectral radiative component which resolves solar radiation penetration in the water column (Dutkiewicz et al., 2009; Skákala et al., 2020; Álvarez et al., 2022). The zooplankton community can be subdivided by size (nano-, micro-, meso-, or macroplankton) and grazing strategy (herbivorous versus carnivorous). Additionally, a rigid partition between autotrophs and heterotrophs is not exhaustive, and the food web can incorporate mixotrophs to account for organisms that obtain energy through both photosynthesis and consumption of others (Flynn et al., 2013; Mitra et al., 2014).

Biogeochemical models can target biodiversity (Litchman and Klausmeier, 2008) if the number of functional plankton groups is large enough to deterministically represent niches based on certain factors (e.g. adaptation to the light spectrum; Álvarez et al., 2022) or by including tens or hundreds of PFTs with randomly prescribed parameters so that the fittest groups can prevail in the resulting ecosystem (Follows et al., 2007).

Assessing ocean carbon uptake and the associated ocean acidification requires modelling of the marine carbonate system: the two prognostic variables are typically dissolved inorganic carbon and alkalinity, and carbonate chemistry is solved to determine water acidity and to calculate the air–sea CO2 gas exchange (Zeebe and Wolf-Gladrow, 2001; Artioli et al., 2012; Cossarini et al., 2015a).

The microbial loop describes the role of bacteria in decomposing organic matter that is converted back to nutrients. It also includes the channelling of energy and matter to higher trophic levels (HTLs) by microzooplankton, which can be an important pathway in oligotrophic conditions (Legendre and Rassoulzadegan, 1995; Hood et al., 2006). In addition, models can describe the dynamics of multiple pools of dissolved organic matter (e.g. labile, semilabile, and refractory) characterized by turnover timescales ranging from days to years (Anderson et al., 2015; Glibert and Mitra, 2022). In coastal- and shallow-water applications, a benthic model allows us to represent the mutual interaction and nutrient, carbon, and oxygen exchanges between the water column and the sediment (Soetaert et al., 2000).

Biogeochemical models can be linked or coupled to higher-trophic-level or ecosystem models (Libralato, 2025, in this report). This requires parameterization or explicit representation of the link of phytoplankton productivity and zooplankton mortality with higher-trophic-level (HTL) compartments, such as nekton and fishes, and possibly the feedbacks from HTLs to biogeochemical processes (e.g. Travers et al., 2009).

Although not yet ready to be integrated into an operational prediction system, additional – and useful to society – components of biogeochemical models could include the fate, dynamics, and transport of metals and POPs (Melaku Canu et al., 2015; Wagner et al., 2019, Bieser et al., 2023), including bioaccumulation in low-trophic-level compartments and cumulative impacts on marine species and ecosystems (Rosati et al., 2022; Zhang et al., 2020).

## 2.2 Main models used in operational systems

Unlike ocean dynamics, where a limited number of numerical models are used in operational applications (e.g. NEMO, ROMS, MITGCM; see Alvarez-Fanjul et al., 2022), there is a long list of biogeochemical models that have varying levels of complexity in response to specific regions and topics of interest for which they were developed. As part of the UN Decade of Ocean Science for Sustainable Development programme, the Decade Collaborative Centre for Ocean Prediction (Alvarez-Fanjul et al., 2024) is promoting the Atlas of Operational Systems, which also describes their biogeochemical component (https://www.unoceanprediction.org/en/homepage, last access: 18 April 2025). Some of the biogeochemical models used in operational prediction systems are briefly presented below, roughly ordered by increasing complexity:

- *HadOCC* (Palmer and Totterdell, 2001). A model of low complexity (10 variables) with a single phytoplankton and single zooplankton, with fixed stoichiometry used to produce global reanalysis of the carbon cycle (Ford and Barciela, 2017).

- *SCOBI*. Used for reanalysis of nutrient cycling in the Baltic Sea (Liu et al., 2017), it has fixed nutrient stoichiometry in three phytoplankton and one zooplankton and includes anaerobic processes and a sediment module for oxygen and nutrient dynamics (Eilola et al., 2009).

- *NEMURO* (Kishi et al., 2007). A relatively simple low-trophic-level model of the Pacific Ocean (11 state variables), based on N dynamics with two phytoplankton and two zooplankton, that has been coupled with an HLT model (e.g. bioenergetic fish model; Kishi et al., 2011).

- *ECB* (Feng et al., 2015). Developed to study eutrophication in the Chesapeake Bay, it consists of 11 variables (C and N cycles) with one single phytoplankton and one single zooplankton and processes applicable for estuarine ecosystems, such as inorganic suspended solid dynamics and the impact on light attenuation (Feng et al., 2015; Irby and Friedrichs, 2019; Irby et al., 2018).

- *GulfMexico*. Developed to investigate eutrophication and acidification in the Gulf of Mexico, it is a model of intermediate complexity (15 variables) that simulates N, P, $O_2$, and C dynamics with a single phytoplankton and single zooplankton group, a sediment-water flux parameterization, and the carbonate system (Fennel et al., 2011; Laurent et al., 2017).

- *PISCES*. A model of intermediate complexity (24 state variables) with five nutrients, fixed stoichiometry, and two phytoplankton and two zooplankton size classes, it includes carbonate system and dissolved oxygen dynamics (Aumont et al., 2015). It is currently used in regional (northeastern Atlantic; Gutknecht et al., 2019) and global operational systems (Mignot et al., 2023). A version with variable stoichiometry (PISCES-QUOTA) also exists and is used for climate scenario studies (Kwiatkowski et al., 2018).

- *ECOSMO* (Daewel and Schrum, 2013). Its operational version in use for the Northern Atlantic and Arctic oceans (Yumruktepe et al., 2022) has two phytoplankton, two zooplankton, multiple nutrients (N, P, and Si), and a fixed molar Redfield ratio but variable chlorophyll-to-carbon dynamics, and it includes a nutrient sediment layer.

- *ERGOM*. Used in the Baltic Sea operational system, it is a model of intermediate complexity (25 variables) with three phytoplankton and two zooplankton groups, and it includes processes related to hypoxia and anoxia, a carbonate system, and a radiative model with dynamics for coloured dissolved organic matter (Neumann, 2000; Neumann et al., 2015).

- *BAMHBI*. Developed for the Black Sea, which is characterized by an anoxic deep layer, the model includes 33 pelagic state variables, with multiple nutrients and eight plankton functional types, and explicitly describes processes in the anoxic layer. It also includes dynamics of the sedimentary stocks of organic C, N, P, and biogenic

Si (Grégoire et al., 2008; Grégoire and Soetaert, 2010; Capet et al., 2016; Ciliberti et al., 2022)

- *eReefs/vB3p0*. Designed for water quality in the Australian Great Barrier Reef marine ecosystem, it is a complex model resolving N, P, C, and $O_2$ cycles in pelagic (four phytoplankton and two zooplankton) and sediment (seagrass and coral) environments. It includes carbonate chemistry (Mongin et al., 2016), bio-optics, and bleaching (Baird et al., 2016, 2020).

- *BFM*. A multi-nutrient and multi-plankton model (Álvarez et al., 2022) with more than 50 variables, it includes carbonate chemistry (Cossarini et al., 2015b, 2017), bio-optics (Lazzari et al., 2021), and pollutants (Rosati et al., 2022) and is currently used in the operational system and reanalysis of the Mediterranean Sea (Salon et al., 2019; Cossarini et al., 2021).

- *ERSEM*. Developed for regional (northeastern Atlantic and North Sea) and global studies, it is a complex model (more than 50 state variables) including multiple nutrients, multi-plankton, a carbonate system, and a sediment layer (Baretta et al., 1995; Butenschön et al., 2016).

- *DARWIN*. A complex multi-nutrient model in which the plankton community comprises hundreds of groups by taking into account cell size and functional traits to study the biodiversity and biogeography (Dutkiewicz et al., 2009).

## 3 Conclusions

Given the complexity of marine ecosystems, the development of biogeochemical models is the result of compromises and simplifications, and no single approach can realistically encompass all relevant aspects of marine ecosystem dynamics. Determining the appropriate level of complexity depends on the specific objectives and supporting information for each application, while standard assessment frameworks (Hernandez et al., 2018) represent essential tools to assess model performance. Increasing model complexity does not necessarily mean better performance (Xiao and Friedrichs, 2014; Kwiatkowski et al., 2014; Gehlen et al., 2015; Séférian et al., 2020). Indeed, despite recent significant technological advances in observing systems, the lack of biogeochemical observations, both in terms of the number of variables and spatiotemporal availability, remains the major obstacle for thorough validation and optimization (e.g. tuning parameters).

In addition to inherent uncertainties in model structures and parameterizations, important sources of uncertainty arise from numerical solution settings in spatially discretized domains, e.g. initial conditions, lateral conditions for open boundaries, inputs of chemical compounds and suspended matter from rivers and atmospheric deposition, and ocean dynamics driving the transport of biogeochemical tracers. Despite major advances in high-performance computing, the computational cost of a model still constitutes an issue when the resolution of the numerical solution and the complexity (e.g. the number of biogeochemical tracers) are increased. Many of the biogeochemical models have emerged as community models that should guarantee a distributed and affordable effort to keep them up to date with the advancement in marine ecology knowledge and the requirements of evolving computer science and of the coupling with physical and Earth system models and data assimilation frameworks. Rapidly evolving applications of artificial intelligence in marine biogeochemistry can assist in optimizing model parameters, developing hybrid models to improve predictions and operational system efficiency, and detecting patterns in large data sets from reanalysis. Linking microbial community dynamics to ecosystem processes through metagenomic data can improve models describing nutrient cycling, carbon fluxes, and diversity. New coupling paradigms are needed to promote the integration of biogeochemical models with the dynamics of pollutants, high trophic levels, and Earth system components.

In addition to science-driven developments, operational biogeochemical systems can evolve to respond to societal demands to assess the impacts of heat waves, oxygen depletion and acidification on marine resources, and the role of the oceans in achieving the goal of carbon neutrality.

**Data availability.** No data sets were used in this article.

**Author contributions.** GC prepared the first draft, and all coauthors participated in the review and finalization.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** The authors thank the three referees for their thoughtful and constructive feedback.

**Review statement.** This paper was edited by Stefania Angela Ciliberti and reviewed by three anonymous referees.

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State Planet, 5-opsr, 13, 2025
https://doi.org/10.5194/sp-5-opsr-13-2025


STATE OF THE PLANET



# Numerical models for monitoring and forecasting ocean ecosystems: a short description of the present status

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Received: 10 October 2024 – Discussion started: 24 October 2024
Revised: 14 May 2025 – Accepted: 14 May 2025 – Published: 2 June 2025

**Abstract.** Understanding and managing marine ecosystems under potential stress from human activities or climate change requires the development of models with different degrees of sophistication in order to be capable of predicting changes in living components in relation to human pressures and environmental variables. Recent advances in ecosystem modelling are the focus of this paper, which reviews numerical approaches to analyse the characteristics of marine conditions in terms of typical units, i.e. individuals, populations, communities, and ecosystems. It specifically examines the current classification of numerical models of increasing complexity – from individuals and population and stock assessment models to models representing the whole ecosystem by covering all trophic levels – and presents examples and their operational maturity and readiness, finally demonstrating their use for supporting marine resource management, conservation, planning, and mitigation actions.

## 1 Introduction

Understanding and managing marine ecosystems under potential stress from human activities and climate change requires the development of modelling tools able to monitor and forecast ocean ecosystem dynamics, from physics to fish (deYoung et al., 2004). The challenge is to relate processes occurring at individual, population, or community levels to environmental variables, i.e. to connect the dynamics of marine ecosystems with the quite well-established physical and biogeochemical products that exist for the ocean (Fennel et al., 2022). A large variety of numerical ecosystem models have been developed to predict the growth and dynamics of individuals and populations of marine resources. According to the scope, the approaches are very diverse, ranging from single to multiple species, and might include the effects of various environmental changes and human impacts (Hollowed et al., 2013; Nielsen et al., 2018).

To illustrate approaches that have the potential to become the next generation of operational tools for ocean ecosystem forecasts, this paper provides a structured synthesis of models applied to marine higher trophic levels (i.e. from zooplankton to fish and top predators) that can be connected with lower-trophic-level models (physics and biogeochemistry).

A comprehensive analysis is challenging, but models can be mapped in terms of their main scope and distinguishing approaches incorporating age structure, environmental factors, representative trophic interactions, and spatial structure (Hollowed et al., 2000). Based on the above characteristics, numerical models for marine ecosystems can be divided into six broad classes:

- bioenergetic models representing the processes related to the growth, respiration, and excretion of an individual;

- population and fishery models (typically for single species without trophic interactions and possibly age-structured);

- connectivity models (considering propagule dispersal, the larval cycle, spatial structures, and environmental factors);

– species distribution models (statistical models based on representation of spatial environmental variables and biota);

– minimally realistic models (typically age-structured, representing a few species with trophic interactions); and

– whole ecosystem models (typically covering all trophic levels and based on trophic interactions, which may include size structure and spatial variation).

These six classes of models are reviewed in the sections below, considering the available syntheses and reviews (e.g. Plagányi, 2007; Cowen and Sponaugle, 2009; Stock et al., 2011; Hilborn and Walters, 2013; Itoh et al., 2018; Nielsen et al., 2018; Rose et al., 2024). The work does not pretend to be exhaustive, and readers are referred to the original reviews, which provide in-depth analyses of each class of model. It aims to provide a synthetic integration across different classes, with examples provided to illustrate their application in operational coupling with lower-trophic-level models. For this purpose, the readiness and maturity of each model were subjectively elaborated on based on the model's current application. The maturity of each example was assessed based on the availability of the code, documentation, test cases, routines for assessing model performances, and diagnostics, and this is used by a community of developers that can provide support, updates, and advancement. Stock assessment models routinely applied for fishery management, for example, were considered more mature because the code is publicly available and documented and input and output test cases are developed and accessible. Readiness for operational purposes was defined based on existing knowledge about possible connections of the model example to physical and biogeochemical spatio-temporal models. The existence of such applications, even if scarce, might show the difficulties in connecting (one-way or two-way) with low-trophic-level models. Operational readiness may be regarded as more tentative and less precise, owing to the challenges in establishing a clearly objective definition, particularly in light of its potentially limited application.

For each class of model, some examples are shown in Table 1, including their characteristics in terms of typical units, elemental structure, number of species typically represented, and eventual trophic interactions. The table also contains synthetic information on primary model focus, main output, maturity, and readiness for operational purposes.

## 2 Bioenergetic models

Traditional bioenergetic models describe energy intake from feeding and its allocation to maintenance, activity, growth, reproduction, and excretion (for a review, see Rose et al., 2024). Bioenergetic models are typically used to represent the growth of the individual and can account for external oceanographic conditions influencing uptakes, such as light, nutrients, and temperature for autotrophs (Bocci et al., 1997) or food availability and temperature for heterotrophs (Libralato and Solidoro, 2009), while losses are usually related to temperature and internal conditions (Kooijman, 2010). Bioenergetic models can also explicitly consider gonadic development and egg release (Pastres et al., 2002). Because of these characteristics, bioenergetic models, other than providing realistic individual-level responses to environmental conditions, permit us to project responses at the population and food web levels and can support other classes of approaches (Rose et al., 2024).

A widely used bioenergetic approach for fish and invertebrates is represented by the dynamic energy budget (DEB), which is characterized by an explicit representation of energy dynamics in somatic, gonadic, and storage tissues (Kooijman, 2010). Although the storage is challenging to measure empirically (Pirotta et al., 2022), it allows representation of delayed use of energy in individual development, resulting in improved generality of the approach (Kooijman, 2010; Nisbet et al., 2012). Thus, the DEB has been developed into a theory for scaling the parameters for all life cycles of individuals (from eggs to larvae to juveniles and adults), provides setting parameters for a large number of marine species (see also https://www.bio.vu.nl/thb/deb/deblab/add_my_pet/, last access: 19 May 2025), and is well-documented (Nisbet et al., 2012; Kooijman, 2020). Thus, the DEB is considered to have high maturity for routine use and is adapted to operational applications, and because it is seldom connected to spatio-temporal physical and biogeochemical models, the readiness is considered to be of an intermediate level (Table 1).

## 3 Population and fishery models

Various types of numerical models of single populations are used worldwide to support fishery management by determining populations at sea and the current status of exploited marine populations, thus providing insight for management in a process called stock assessment (for a review, see Hilborn and Walters, 2013). Stock assessment models typically represent the biomass or abundance of one species (Table 1), are routinely used by management agencies, and include probability models to incorporate various sources of observational data (Maunder and Punt, 2013).

The Stochastic surplus Production model in Continuous Time (SPiCT), for example, provides estimates of exploitable biomass and fishing mortality at any point in time from catch and survey data collected at arbitrary and possibly irregular intervals (Pedersen and Berg, 2017). SPiCT is available as an R package in the online GitHub repository at https://github.com/mawp/spict (last access: 19 May 2025).

More sophisticated approaches use catch-by-age or size classes (catch-at-age or catch-at-length models; Maunder and Punt, 2013) to reconstruct the cohorts assuming natu-

**Table 1.** Main characteristics of some widely used numerical models of marine biological resources divided into the six classes. Not available: NA.

| | | | | | | | | Bioenergetic models | | | | | Rose et al. (2024) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Abbreviation | Model | Elemental structure | Model units | Time units | Spatial structure | Number of species | Trophic interactions | Primary model focus, output | Maturity | Readiness for operational use | Physical and biogeochemical processes | Repository (if open access) | Reference |
| DEB | Dynamic energy budget | Individual | Individual weight (gww, gC, or others) or length | d | No | 1 | No | Growth | High | Good | Yes: used as forcings (temperature, light, food, and nutrients) | https://www.bio.vu.nl/thb/deb/deblab/add_my_pet/* | Kooijman (2020) |
| | | | | | | | | Population and fishery models | | | | | Hilborn and Walters (2013) |
| Abbreviation | Model | Elemental structure | Model units | Time units | Spatial structure | Number of species | Trophic interactions | Primary model focus, output | Maturity | Readiness for operational use | Physical and biogeochemical processes | Repository (if open access) | |
| SPICT | Stochastic surplus Production model In Continuous Time | Surplus production | Biomass | Years | No | 1 | No | Biological reference points for fisheries | High | Poor | No | https://github.com/mawp/spict* | Pedersen and Berg (2017) |
| CMSY | Catches at Maximum Sustainable Yield | Surplus production | t | Years | No | 1 | No | Biological reference points for fisheries | Intermediate | Poor | No | https://github.com/SISTA16/cmsy* | Froese et al. (2023) |
| A4a | All for all | Catch-at-age | Biomass (t) | Years | No | 1 | No | Biological reference points for fisheries | Intermediate | Intermediate | No | https://github.com/a4a* | Jardim et al. (2014) |
| SS3 | Stock Synthesis | Catch-at-age | Number of individuals; biomass (t) | Years | Potentially yes | 1 | No | Biological reference points for fisheries | High | Intermediate | Potentially yes | https://github.com/nmfs-ost/ss3-source-code* | Anderson et al. (2014) |
| VPA | Virtual population analysis | Catch-at-age | Number of individuals; biomass (t) | Years | No | 1 | No | Biological reference points for fisheries | Poor | Poor | No | https://noaa-fisheries-integrated-toolbox.github.io/VPA* | Gislason (1999) |
| | | | | | | | | Connectivity models | | | | | Cowen and Sponaugle (2009) |
| Abbreviation | Model | Elemental structure | Model units | Time units | Spatial structure | Number of species | Trophic interactions | Primary model focus, output | Maturity | Readiness for operational use | Physical and biogeochemical processes | Repository (if open access) | |
| LTRANS | Lagrangian transport | Agents (super-individuals) | Number of individuals | d | Yes | Typically one species | No | Distribution of species and connectivity among the sites | Intermediate | Intermediate | Yes (physical processes) | https://github.com/LTRANS/LTRANSv.2b* | North et al. (2008) |
| Ichthyop | Lagrangian tool for simulating ichthyoplankton dynamics | Individuals (early life stages) | Number of individuals | d | Yes | Typically one species | No | Study effects of physical and biological factors on ichthyoplankton dynamics | Intermediate | Intermediate | Yes (physical processes) | https://ichthyop.org/* | Lett et al. (2008) |
| IBM/ABM | Individual-based and agent-based models | Individual | Biomass | d | Yes | Typically a few species | Efficient predator | Ecosystem effects on the target population and connectivity | Poor | Poor (computationally complex) | Yes | NA | Rose et al. (2015) |



CHAPTER 5.4

**Table 1.** Continued.

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Species distribution models | | | | | | | Elith and Leathwick (2009) |
| Abbreviation | Model | Elemental structure | Model units | Time units | Spatial structure | Number of species | Trophic interactions | Primary model focus, output | Maturity | Readiness for operational use | Physical and biogeochemical processes | Repository (if open access) | |
| Ensemble of SDMs | Ensemble of species distribution models | Species abundance, presence, or biomass | Number of individuals or weight per unit surface; presence or absence | Months, years, climatology | Yes | 1 | No | Species distribution; essential fish habitats | Good | Good | Environmental factors can be included | https://github.com/helixcn/sdm_r_packages* | Panzeri et al. (2024) |
| Joint SDMs | Joint species distribution models | Species abundance, presence, or biomass | Number of individuals or weight per unit surface | Months, years | Yes | A few species | Implicit | Distribution of target species | Intermediate | Poor (computationally intensive) | Environmental factors can be included | https://github.com/James-Thorson/spatial_DFA* | Thorson et al. (2016) |
| DEBM | Dynamic Envelope Bioclimate Model | Species biomass | Biomass | Years | Yes | Several species | No | Distribution of multiple species | Intermediate | Good | Yes, included for developing the bio-envelope | NA | Cheung et al. (2013) |
| | | | | | | Minimally realistic models | | | | | | | Plagányi (2007) |
| Abbreviation | Model | Elemental structure | Model units | Time units | Spatial structure | Number of species | Trophic interactions | Primary model focus, output | Maturity | Readiness for operational use | Physical and biogeochemical processes | Repository (if open access) | |
| GADGET | Globally applicable Area Disaggregated General Ecosystem Toolbox | Population in age structure | Biomass derived from population size structure | Years | Yes, can be included | Typically three to four species | Yes, suitability-based, flexible | Ecosystem effects on target population; yearly biomass | Intermediate | Low | Can be coupled with a physical–biogeochemical model | https://gadget-framework.github.io/gadget2/userguide/* | Andonegi et al. (2011) |
| MSVPA and MSFOR | Multi-species virtual population analysis and multi-species forecasting model | Populations in age structure | Numbers at age; biomass | Years | No | Typically three to four species | Yes, suitability-based, efficient predator | Ecosystem effects on target population; yearly biomass | Poor | Poor (seldom applied) | Not usually included | https://noaa-fisheries-integrated-toolbox.github.io/MSVPA_X2* | Gislason (1999) |
| MICE | Model of Intermediate Complexity for Ecosystem assessments | Populations in surplus production and age structure | Numbers at age, biomass | Years | No | Typically six to seven species | Efficient predator | Dynamics of focal species and their predators or preys | Difficult to establish: programmed on purpose | Poor (only a few applications) | Environmental effects can be included | NA | Plagányi et al. (2014) |
| SEAPODYM | Spatial Ecosystem, and POpulation Dynamics Model | Populations in age structure | Biomass | Years | Yes | Typically three to four species | Efficient predator | Ecosystem effects on target population | High | High (already applied for top predators, i.e. tuna) | Can be coupled with physical–biogeochemical model | https://github.com/PacificCommunity/seapodym-codebase* | Lehodey et al. (2015) |
| ERSEM II | Commission for the Conservation of Antarctic Marine Living Resources | Functional group approach | Nutrient | Months | Yes | Limited number of high-trophic-level (HTL) groups | Type II | Effects in both directions | Intermediate | Too complex | Yes, detailed | https://github.com/pmlmodelling/ersem* | Butenschön et al. (2016) |
| Apecosm | Apex Predators ECOSystem Model | Size spectra approach | Biomass | Months | Yes | Few species | Few top predators | Top predator group dynamics | Poor (few applications) | Poor (model complexity) | Yes, included | https://github.com/apecosm/python-apecosm* | Maury (2010) |

**Table 1.** Continued.

| Abbreviation | Model | Elemental structure | Model units | Time units | Spatial structure | Number of species | Trophic interactions | Primary model focus, output | Maturity | Readiness for operational use | Physical and biogeochemical processes | Repository (if open access) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | Plagányi (2007) |
| Whole ecosystem models | | | | | | | | | | | | | |
| ATLANTIS | Atlantis | Functional group approach; populations in age structure | Nutrients | Months | Yes | Can be a very large number, typically order 40 | Flexible, type II, type III, or other | Effects of ecosystem and fisheries in both directions, yearly outputs | High | Poor (model complexity) | Yes, detailed | https://github.com/runatlantis/atlantis* | Fulton et al. (2011) |
| EwE | Ecopath with Ecosim | Functional group approach; populations also in age structure | Biomass, nutrients | Months | Yes (ECOSPACE) | Can be a very large number, typically order 40 | Foraging arena, flexible approach | Effects of ecosystem and fisheries in both directions, yearly outputs | High | Poor (model complexity) | Included as offline coupling | https://ecopath.org/* | Christensen and Walters (2004) |
| OSMOSE | Object-oriented simulator of marine ecosystem exploitation | Size spectra approach | Biomass at different levels of aggregation | Years | Yes | Large number of species | Efficient predator but can starve | Multi-species dynamics | Intermediate | Intermediate (model complexity) | Included as offline coupling | https://osmose-model.org/* | Shin and Cury (2004) |
| FEISTY | FishErIes Size and functional TYpe model | Size spectra approach | Biomass at different levels of aggregation | Years | Yes | Large number of species | Flexible approach | Multi-species dynamics | Intermediate | Intermediate | Included as offline coupling | https://github.com/Kenhasteandersen/FEISTY* | Blanchard et al. (2009) |

* Last access: 19 May 2025.

ral mortality for each class and considering information on species growth, fecundity, and fishery selectivity (Methot and Wetzel, 2013). Stock Synthesis (SS3; Anderson et al., 2014) is an example of a catch-at-age model that can incorporate age or length composition information from surveys, abundance indices, multi-gear effort, selectivity, and spatial data in the most recent and advanced applications (e.g. Punt, 2019; Privitera-Johnson et al., 2022). Projections from stock assessment models are generally made for annual to decadal time periods, and SS3 provides estimates for biological reference points for management decisions (indicators based on maximum sustainable yield; Hilborn and Walters, 2013). As with many stock assessment fishery models, SS3 is routinely used in formal assessments, is well-documented, and is easily accessible (https://github.com/nmfs-ost/ss3-source-code, last access: 19 May 2025), and thus it has a very high degree of maturity. Nevertheless, it is not spatially explicit and does not explicitly consider oceanographic forcings; it might be considered of intermediate readiness for operational oceanographic applications (Table 1).

## 4 Connectivity models

The distribution and survival of small eggs and larvae of marine fish and invertebrates as well as propagules of algae and seagrass seeds are advected and are thus strongly influenced by currents, which can disperse individuals both near spawning sites and in distant areas (Cowen et al., 2007). Therefore, biophysical dispersal (advection, diffusion, and migratory behaviour of organisms) is fundamental for explaining marine population dynamics and connectivity (for a review, see Cowen and Sponaugle, 2009). Connectivity models are used to quantitatively integrate the large spatial and temporal variability of oceanographic processes (physical connectivity) with processes inherent in the biology of marine organisms (life history traits) to investigate the connectivity between and within populations and across larval stages (Gawarkiewicz et al., 2007; Melaku Canu et al., 2021). Connectivity models such as the Larval TRANSport Lagrangian model (LTRANS, North et al., 2008) typically use offline physical parameters (velocity, density, temperature, and salinity) obtained from hydrodynamic models and estimate the distribution of organisms. The advection–diffusion–reaction equation is typically used for biomass distribution (e.g. Sibert et al., 1999; Faugeras and Maury, 2005), while Lagrangian approaches are used to track particles and thus distribute individuals (e.g. Laurent et al., 2020). These approaches consider life history traits such as growth, mortality, and the behaviour of target organisms in terms of seasonal variability, spawning sites, vertical movement, and settlement preferences (Melaku Canu et al., 2021; Paris et al., 2013; Lett et al., 2008). LTRANS is frequently applied and is well-documented, and the code is available at https://github.com/LTRANS/LTRANSv.2b (last access: 19 May 2025), designating it as being at the intermediate level of maturity. It is coupled offline with hydrodynamic models and can incorporate several biological features (North et al., 2008), placing its operational readiness at an intermediate level (Table 1).

## 5 Species distribution models

Species distribution models (SDMs, also called habitat suitability models) are statistical models that predict the occurrence, abundance, or biomass of organisms using geopositional, biotic, and environmental data (for a review, see Elith and Leathwick, 2009). Particularly useful when applied to spatio-temporal scientific surveys of species abundance, these approaches can also exploit opportunistic biological data (e.g. https://www.obis.org, last access: 19 May 2025; https://www.gbif.org, last access: 19 May 2025). SDMs are implemented using various statistical approaches (Maravelias et al., 2003; Melo-Merino et al., 2020; Brodie et al., 2020), machine learning, artificial neural network methods (Catucci et al., 2025), and maximum entropy (Jones et al., 2012; Pittman and Brown, 2011; Reiss et al., 2011). The inclusion of physical and biogeochemical oceanographic covariates, which can have direct and indirect effects on species distributions, can improve the abilities of SDMs to explain observed biotic data compared to using only geopositional variables (Panzeri et al., 2021; Thorson et al., 2015). Recent advances include combining the approaches into an ensemble (Jones et al., 2012; Panzeri et al., 2024) and including multiple species as covariates in so-called joint species distribution models (JSDMs, Pollock et al., 2014; Thorson et al., 2016). The SDMs are increasingly being used to describe current and future distributions of exploited and endangered species, identify hotspots, map essential fish habitats, support conservation development, and feed other ecosystem models (Jones et al., 2012; Colloca et al., 2015; Grüss et al., 2014; Dolder et al., 2018).

The Dynamic Bioclimate Envelope Model (DBEM) estimates species distributions based on environmental preferences and considers population dynamics and dispersal (Cheung et al., 2009). The DBEM makes predictions of future envelopes using physical and biogeochemical data from oceanographic models and considers the response of organisms to natural or anthropogenic environmental changes such as growth, mortality, larval dispersal, and migration (Cheung et al., 2013).

In general, SDMs are widely applied, well-documented, and available (see for example https://github.com/helixcn/sdm_r_packages, last access: 19 May 2025) and thus have an intermediate level of maturity, but given their direct integration with physical–biogeochemical models, they have a good readiness level for operational use (Table 1).

## 6 Minimally realistic models

Dynamic multi-species models or minimally realistic models (MRMs) are models that represent a limited number of species (usually less than 10) that have important interactions with a target species (for a review, see Plagányi, 2007). MRMs often represent an evolution of single-species stock assessment models: for example, GADGET (Globally applicable Area-Disaggregated General Ecosystem Toolbox) is an extension of stock Synthesis in the multi-species framework, where populations can be partitioned by species, size classes, age groups, areas, and time steps (Andonegi et al., 2011). In particular, GADGET is flexible, allowing easy addition or replacement of alternative model components for biological processes such as growth, maturation, and predator–prey interactions representing some species in age classes. GADGET provides estimates of population dynamics under fishery and biological interactions, with the ability to use different growth functions and fitness functions (Plagányi, 2007). Although well-documented (see https://gadget-framework.github.io/gadget2/userguide/, last access: 19 May 2025), its fitting is quite complex and thus has few applications: for these reasons, maturity is considered intermediate and readiness for operational purposes is low because of a lack of interactions with physical and biogeochemical models (Table 1).

An example of a minimally realistic model is the Spatial Environmental POpulation Dynamics Model (SEAPODYM), which is a two-dimensional coupled physical–biological model originally developed for tropical tuna in the Pacific (Lehodey et al., 2003). SEAPODYM includes an age-structured population model for top predators and a movement model based on a diffusion–advection equation modelled as a function of habitat quality (sea surface temperature, ocean currents, and primary production) obtained from oceanographic models and satellites (Lehodey et al., 2015; Senina et al., 2020). SEAPODYM is well-documented and already used for operational global projections (https://github.com/PacificCommunity/seapodym-codebase, last access: 19 May 2025) and thus can be considered to have a high degree of maturity and readiness for operational purposes (Table 1).

## 7 Whole ecosystem models

Whole ecosystem models (WEMs) are designed to represent all trophic levels in an ecosystem, from primary producers to top predators, and to take advantage of data collected in different disciplines (Agnetta et al., 2022). The main distinguishing feature of the different WEMs is the way in which the ecosystem is described: (i) through compartments representing species or groups of species (Christensen and Walters, 2004; Fulton et al., 2011); (ii) through compartments that represent size-structured communities, typically benthic and pelagic communities (Shin and Cury, 2004; Travers et al., 2010); (iii) in a mixture of size-structured and trophic communities (Maury, 2010); and (iv) using dynamic spectra of trophic levels (e.g. Gasche and Gascuel, 2013). All these models are based on biomass and consider rules such as biomass conservation (Table 1; for a review, see Plagányi, 2007).

Ecopath with Ecosim (EwE; Christensen and Walters, 2004) is the most widely used WEM, is freely available (https://www.ecopath.org, last access: 19 May 2025), and has a flexible structure. It represents a suite of models developed for more than 30 years for the whole ecosystem description. EwE has been used to analyse past and future impacts of fisheries, nutrient inputs, invasive species, and climate change (e.g. Heymans et al., 2014; Libralato et al., 2015; Serpetti et al., 2017; Piroddi et al., 2021). It consists of three different interconnected main modules, (i) a static mass-balanced ecosystem network (Ecopath; Christensen and Pauly, 1992), (ii) a temporally dynamic simulation module (Ecosim; Walters et al., 2000), and (iii) a spatially and temporally dynamic module (Ecospace; Walters et al., 1999). EwE contains many additional modules for calibration, uncertainty analysis, calculation of indicators, and simulation of pollutant dynamics (Steenbeek et al., 2016). Recent advances allow direct embedding of two-dimensional monthly results from oceanographic physical–biogeochemical models (Steenbeek et al., 2013). EwE can be considered an approach of high maturity and intermediate degree of readiness for operational applications (Table 1). A large set of WEMs (Table 1) is increasingly being used to address the need for holistic ecosystem approaches, and their framework is often applied to answer strategic medium-term questions related to management strategies, fishery issues, and climate or environmental change (e.g. Tittensor et al., 2021). Notably, WEMs can be coupled with other classes of models (population dynamics, SDMs, and connectivity models) as well as with biogeochemical models, which is why most of the approaches in this class have a high to intermediate level of maturity and readiness (Table 1).

## 8 Conclusions

A wide range of models are used to represent ocean ecosystems at different levels of organization, including individuals, populations, communities, and entire ecosystems. Although categorized into six classes for clarity, some modelling approaches are not confined to a single class. For instance, the DEB modelling approach is used to also represent the growth of individuals in connectivity models and MRM classes (see for example Maury, 2010). Conversely, MICE (Model of Intermediate Complexity for Ecosystem assessment; Plagányi et al., 2014) of the MRM class was developed using different levels of detail for the species represented by combining for example age-structured and surplus production approaches (Morello et al., 2014).

These models have been developed for specific societal issues, i.e. effects of climate change, pollution, nutrient enrichment, and fisheries.

The numerical approaches analysed here have characteristic spatio-temporal resolutions that generally decrease when moving from individual species models to whole ecosystem models (Table 1). Increased represented complexity with the MRM and WEM classes results in a general improvement of realism at the cost of accuracy (generally declining from individual models to the WEM class). Overall, the first set of approaches (bioenergetic and population models) is more adapted for tactical analyses, while the WEM class is currently considered useful, especially in strategic analyses (see Table 1). Although very few of the reviewed approaches are currently used operationally (i.e. SEAPODYM), many approaches are routinely applied to support management (e.g. fishery stock assessment models). Most of the approaches reviewed have a repository for documentation, code, and testing cases and thus have a high degree of maturity (Table 1). Conversely, approaches in the MRM class are not widely applied, are often quite complex to fit, and therefore were categorized as being at a poor level of readiness for operational purposes (Table 1). Nevertheless, all of the tools have some degree of coupling (mainly offline) with physical and biogeochemical variables and thus have great potential to become operational and used for analysing ecosystem dynamics and scenarios, which can be useful for a very wide range of issues and management actions that could be prioritized eventually.

**Code availability.** The different software codes are deposited in different repositories and are available from third parties. A link to the repositories and dates of last access is given in the main text and in Table 1.

**Data availability.** No data sets were used in this article.

**Competing interests.** The author has declared that there are no competing interests.

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**Acknowledgements.** A draft version of this paper benefited from comments and suggestions by Vinko Bandelj (OGS), Elisa Donati (UNITS and OGS), Celia Laurent (OGS), Ivano Vascotto (OGS), Damiano Baldan (OGS), Fabrizio Gianni (OGS), and Davide Agnetta (OGS).

**Review statement.** This paper was edited by Kirsten Wilmer-Becker and reviewed by three anonymous referees.

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State Planet, 5-opsr, 14, 2025
https://doi.org/10.5194/sp-5-opsr-14-2025






# Numerical models for monitoring and forecasting sea ice: a short description of present status

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Received: 13 September 2024 – Discussion started: 20 September 2024
Revised: 16 January 2025 – Accepted: 28 January 2025 – Published: 2 June 2025

**Abstract.** The severe changes in climate resulting in the polar oceans getting warmer – with drastic consequences to their physical, biogeochemical, and biological state – require forecasting systems that can accurately simulate and skilfully predict the state of the ice cover and its temporal evolution. Sea-ice processes significantly impact ocean circulation, water mass formation and modifications, and air–sea fluxes. They comprise vertical processes, mainly related to thermodynamics, and horizontal ones, due to internal sea-ice mechanics and motion. We provide an overview on how these processes can be modelled and how operational systems work, in combination with data assimilation techniques, to enhance accuracy and reliability. We also emphasise the need for advancing research on improving such numerical techniques by highlighting current limits and ways forward.

## 1 Introduction

The main objective of an operational sea-ice forecasting system is to provide users with a reliable estimate of the state of the ice cover and its temporal evolution. To meet this goal, the system needs to be coupled to, or use data from, ocean and atmosphere forecasting systems. Some form of data assimilation is also required to provide the model with the best possible starting position, accounting for the chaotic nature of the atmosphere–ocean–ice system. Users of sea-ice forecasting systems can either be ship captains operating in the polar regions or intermediate service providers. With a changing climate and warming polar oceans, the number of stakeholders interested in operating in ice-infested waters is growing.

Sea-ice processes are profoundly important for the ocean circulation and water mass modifications, so ocean models of the polar regions are always coupled to a sea-ice model, both for operational forecasting and climate projection purposes. Sea-ice models have their origin in the climate modelling community in the 1970s and were subsequently part of the ocean general circulation model. They have since then evolved to provide sea-ice forecasts in their own right and have been made modular to avoid being bound to a given choice of physical ocean model (Blockley et al., 2020). Sea-ice observations from satellites are assimilated in the prediction systems (Buehner et al., 2017). This chapter gives a summary of the short-term (up to 10 d) sea-ice forecasting systems for the polar regions.

## 2 Overview of processes in sea ice

The physical processes simulated by sea-ice models are commonly split into two: vertical processes, related to thermodynamic growth and melt, and mechanical and dynamical processes influencing the horizontal movement of ice. This dynamic–thermodynamic separation has practical advantages for computations.

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### 2.1 Thermodynamics

The ocean can freeze in different phases of sea ice, starting with frazil crystals and their conglomerates into a liquid mush referred to as grease ice, then pancake ice in the presence of waves, or slush when the waves flood the snow (Wadhams, 2000). Slush, grease, pancakes, and ice may sound like a perfect birthday party, until you realise that there is also salt in the ice (Feltham et al., 2006; De La Rosa et al., 2011; Jutras et al., 2016). The latter will be rejected to the ocean through brine channels but usually after its multi-year birthday party (e.g. Notz and Worster, 2009). Once a layer of ice has formed on the surface of the ocean, new ice is mostly formed from below as crystals moving upward from the ocean mixed layer affix to the base of the ice in a process known as "congelation growth". Sea ice also freezes laterally within open leads and between ice floes. Snow accumulates on top of the sea ice and forms an efficient thermal insulator and a white coating that reflects solar radiation back to the atmosphere. A smaller amount of snow ice comes from compacted snow above the ice. The insulating effect of snow inhibits both sea-ice growth in early winter and sea-ice melt in late winter (Bigdeli et al., 2020).

When summertime approaches, the snow melts first and forms melt ponds at the surface of the ice. These dark ponds absorb more solar radiation and enhance the summer melt.

The sea ice itself works as an insulating layer between the ocean and the atmosphere, with thick ice a better insulator than thin ice.

### 2.2 Mechanics

Sea ice deforms under the action of winds and currents. Their surface drag accumulated over hundreds of kilometres of sea ice results in formidable forces able to crack open the thickest ice or pile it up into pressure ridges, cracks, leads, and ridges in what are called linear kinematic features of sea ice. First-year ice (FYI) can become about 1 m thick, while multi-year ice (MYI) is more often deformed via compressive stresses and can easily reach 2 m or above. The convergence of ice is a major threat to navigation, and only a few ice-strengthened vessels or icebreakers are designed to withstand such forces. The deformation of sea ice has been measured by drifting buoys and satellite data, and scaling laws have revealed multi-fractal properties (Weiss and Marsan, 2004) and power law behaviour (Weiss et al., 2009).

Waves formed in the open ocean will often reach the ice and attenuate within the ice pack, flexing and occasionally breaking the ice into smaller floes along the way. Smaller ice floes offer more reflecting edges and are more efficient at scattering waves. Wave scattering represents a negative feedback in the wave–ice interactions, among other nonlinear energy dissipation processes (Squire, 2020). This equilibrium results in a wave-broken marginal ice zone (MIZ), which is typically 100 km wide in the Arctic but can reach 1000 km in the Southern Ocean where waves are bigger and the ice is thinner. Sea ice can also be submerged by waves, making the surface more saline. Wave-breaking effects enhance the lateral melting of ice during summer but also enhance its freezing during winter.

### 2.3 Biogeochemistry

There is life in sea ice, not only the occasional seal innocently sunbathing as a polar bear lurks around, but as dense activity under the sea ice following the growth of red ice algae (Duarte et al., 2017). The availability of light below the ice and the size of brine channels determine the growth of algae and the peculiar ecosystem that depends on them (Arrigo, 2014). The algae will find nutrients in the sea ice; some will be trapped in the ice during freezing, providing a sheltered food store for micro-organisms, and then later ejected to the ocean through brine channels (Lund-Hansen et al., 2024).

Sea ice carries sediments while drifting from the shallow shelf seas to the central Arctic, together with nutrients, various biological materials, and occasionally pollutants (Krumpen et al., 2019).

Sea ice acts as a lid preventing the exchange of greenhouse gases between ocean and atmosphere, but the sea ice also holds its own carbon pump accounting for 30 % of the carbon uptake in the Arctic (Richaud et al., 2023).

## 3 Numerical models

Operational sea-ice models are based on complex community codes, simulating the dynamical properties (the constitutive law or rheology) and the thermodynamics of sea ice. The most widespread rheological model of sea ice is the viscous–plastic model, often met in the elastic–viscous–plastic (EVP) form which is more efficient for massively parallel computing. One or the other is implemented in the Community Ice CodE (CICE), the Sea Ice modeling Integrated Initiative ($SI^3$), the Louvain-la-Neuve sea Ice Model (LIM), the MIT general circulation model (MITgcm), and GFDL's Sea Ice Simulator (SIS2). The previous models all use an Eulerian model grid, but a recent code, the next-generation sea-ice model (neXtSIM), has adopted an adaptive Lagrangian mesh, along with a more recent brittle Bingham–Maxwell rheology (Ólason et al., 2022) that exhibits linear features of sea-ice deformations apparent in Fig. 1. All recent sea-ice models are multi-category models and thus explicitly simulate an ice thickness distribution. They also include a sea-ice age tracer and can thus predict areas of FYI and MYI. Their use in operational forecasts is indicated in Table 1.

The above ocean and sea-ice models are coupled via advanced software (OASIS, ESMF, CCSM) that make them modular, but some ocean models come with an integrated sea-ice model, for example, the NEMO, the MITgcm, the MOM, the HBM and the FESOM2 codes. The latter is using finite volume (Danilov et al., 2017).

**Table 1.** List of present-day short-term global and Arctic forecast systems, including specification of spatial resolution, sea-ice model, assimilation method, variables, and website. Sea-ice variables are SIC concentration, SIT thickness, SIUV motions, SIALB albedo, SNOW snow depth, and SIAGE ice age. Note that the output spatial resolution may differ from the native resolution. Baltic forecasting systems are omitted for brevity. Ocean data assimilated are also omitted.

| Area | Country | System name | Resolution at NP (km) | Sea-ice Model | Assimilation (method and sea-ice data) | Variables distributed | Website (last access: 24 March 2025) |
|---|---|---|---|---|---|---|---|
| Arctic | PR China | ArcIOPS | 18 km | MITgcm | LESTKF SIC, SIT | SIC, SIUV, SIT | http://www.oceanguide.org.cn/IceIndexHome/ThicknessIce |
| Global | USA | RTOFS | 3.5 km | CICE5 | 3DVAR SIC | SIC, SIT, SIUV | https://polar.ncep.noaa.gov/global/ |
| Arctic | Norway | TOPAZ5 | 6.25 km | CICE5 | EnKF SIC, SIUV, SIT | SIC, SIT, SIUV, SNOW, SIALB, SIAGE | https://marine.copernicus.eu/ |
| Arctic | Norway | neXtSIM-F | 3 km (output) | neXtSIM | Nudging SIC | SIC, SIT, SIUV, SNOW, SIALB, SIAGE | https://marine.copernicus.eu/ |
| Global | France | MOi | 3.5 km | LIM2 | SEEK SIC | SIC, SIT, SIUV | https://marine.copernicus.eu/ |
| Global | Canada | GIOPS | 12 km | CICE4 | 3DVAR SIC | | https://science.gc.ca/site/science/en/concepts |
| Arctic | Canada | RIOPS | 3.5 km | CICE4 | 3DVAR SIC | | https://science.gc.ca/eic/site/063.nsf/eng/h_97620.html |
| Global | USA | ESPC | 3.5 km | CICE4 | 3DVAR SIC | SIC, SIT, SIUV | https://www.hycom.org/dataserver/espc-d-v02 |
| Global | Europe | ECMWF | 12 km[a] | LIM2 | 3DVAR SIC | SIC, SIT | https://www.ecmwf.int/en/forecasts/datasets/set-i |
| Arctic | Denmark | DMI | 10 km | CICE4 | Nudging SIC | | http://ocean.dmi.dk/models/hycom.uk.php |
| Global | UK | Met Office coupled DA | 12 km | CICE5 | 3DVAR SIC | SIC, SIT, SIUV | https://marine.copernicus.eu/ |
| Arctic | Japan | VENUS[b] | 2.5 km | IcePOM | n/a | SIC, SIT | https://ads.nipr.ac.jp/venus.mirai/#/mirai |

[a] Output interpolated to 9 km. [b] VENUS is deployed on demand.

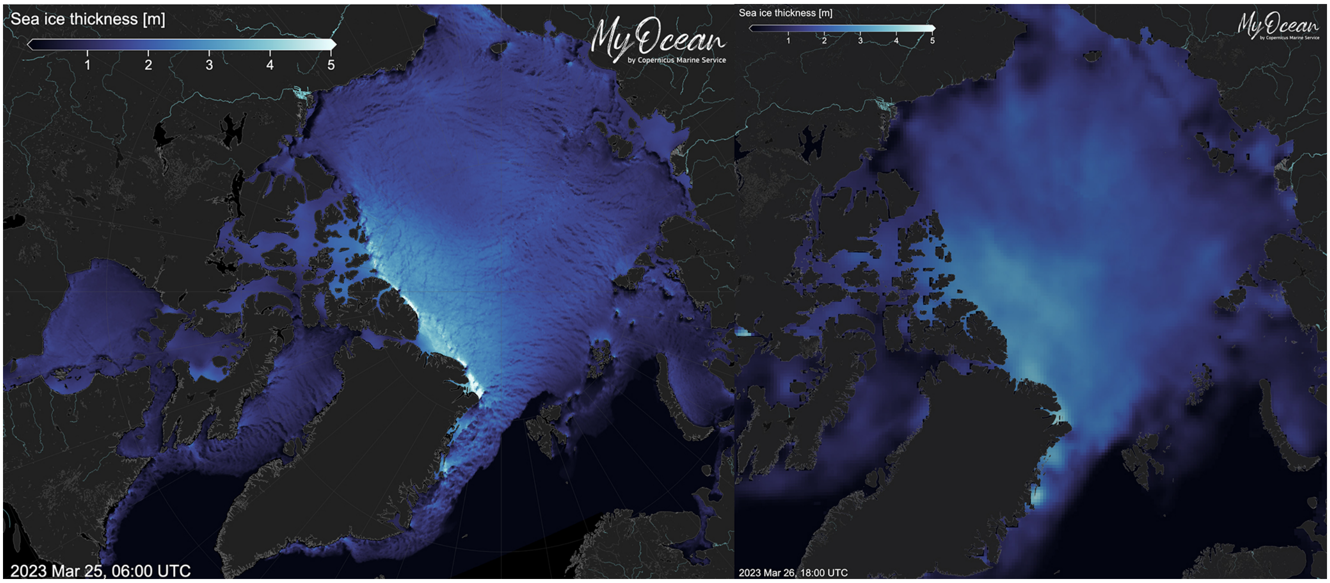


**Figure 1.** Example of sea-ice thickness analysis from the neXtSIM-F (left) system and the assimilated CS2SMOS data; visualisation from the Copernicus Marine Service (http://marine.copernicus.eu, last access: 24 March 2025).

## 4 Data assimilation

The most important step to initialise a forecast is to assimilate the latest available observations into a numerical model. Some of the most important observations are available in near-real time with sea-ice concentration, thickness, and motions, but feeding them into the model is a delicate matter (Bertino and Holland, 2017; Buehner et al., 2017). Unobserved variables and the ocean properties below the ice must be estimated by multivariate update because of the complex processes both within the sea ice and between the ice and ocean. The irregular observational sampling also requires a flow-dependent spatial interpolation. Operational centres run numerical models and data assimilation codes on dedicated high-performance computers (HPCs).

The data assimilation methods in operation are most often the 3D variational (3DVAR) method (Tonani et al., 2015; Waters et al., 2015; Mogensen et al., 2012; Hebert et al., 2015; Smith et al., 2016; Usui et al., 2006), assimilating sea-ice concentration and more recently sea-ice thickness (Mignac et al., 2022). The 4DVAR method is not presently used in operational forecasts but can provide long-term optimised model trajectories that are fully consistent with the model equations (Nguyen et al., 2021). The ensemble Kalman filter (EnKF) is also used in the TOPAZ system to assimilate concentrations, thickness, and motion vectors (Xie et al., 2017) and has been tested with neXtSIM (Cheng et al., 2023), although a cheaper nudging is used operationally (Williams et al., 2021). The EnKF does not intrude in the model software, and the resulting forecast system is modular. Even though operational centres use the state of the art with respect to sea-ice data assimilation, they are still inaccurate in locating the ice edge (about 40 km at analysis time; Carrières et al., 2017) and even less accurate in locating the boundary between FYI and MYI (200 km errors rather than 40 km).

Biases in sea-ice area coverage arise from multiple sources, primarily from biased ocean and atmospheric boundary conditions but also from intrinsic biases of the sea-ice model itself. These biases interact with each other in complex ways (feedback loops or cancellation of errors). Data assimilation methods rely on unbiasedness assumptions and do not remove biases entirely, often transferring them to unobserved variables. Short of a complete observing network, there are ongoing efforts in improving sea-ice models that we believe can reduce biases, provided that incoming biases from new ocean and atmospheric models are also reducing.

With improved observational data coverage, increased computational power, and improved representation of key physical processes, rapid improvements in sea-ice modelling and forecasting capabilities are expected in the coming decade. One research thrust concerns modelling the marginal ice zone, most notably wave–ice interactions (e.g. Boutin et al., 2022) and modelling sea ice as individual floes (e.g. Horvat, 2022). A second thrust is improvements in the sea-ice rheology used for the pack ice (e.g. Ólason et al., 2022). Improved rheology will improve the ice drift and the location of the boundary between FYI and MYI (e.g. Regan et al., 2023). Finally, machine learning approaches are flourishing, which seek to develop fast, surrogate modelling and forecasting capabilities (e.g. Hoffman et al., 2023; Durand et al., 2024; Gregory et al., 2024). Sea-ice exists at the boundary between the atmosphere and ocean, so sea-ice forecasts depend on accurate atmosphere, ocean, and even wave forecasts. Improving those is, therefore, very important for improving sea-ice forecasts. We see fully coupled atmosphere–ocean–wave–ice models with fully coupled data assimilation as a vital long-term goal for sea-ice forecasting systems.

Even though every improvement to the atmosphere, ice, and ocean models is welcome, they require time-consuming rounds of testing in forced and coupled models. In the meantime, post-processing techniques, now aided by machine learning, are a novelty in sea-ice forecasting (Palerme and Müller, 2021; Palerme et al., 2024) and reanalysis (Edel et al., 2025).

**Data availability.** Data used in Fig. 1 are freely available at https://doi.org/10.48670/moi-00004 (EU Copernicus Marine Service Product, 2024a; Williams et al., 2021) and https://doi.org/10.48670/moi-00125 (EU Copernicus Marine Service Product, 2024b; Ricker et al., 2017).

**Author contributions.** LB prepared the article with contributions from all co-authors.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** The authors are grateful to Stefania Ciliberti and two anonymous reviewers who have helped improve the original manuscript.

**Financial support.** This research has been supported by the European Union's Horizon Europe project ACCIBERG (grant no. 101081568); Office of Naval Research (grant no. N00014-20-1-2772); DOE (grant no. DE-SC002317); NSF (grant no. 2103942); and Met Office Advancing Arctic meteorological and oceanographic capabilities and services programme, which is supported by the Department for Science, Innovation and Technology (DSIT).

**Review statement.** This paper was edited by Swadhin Behera and reviewed by two anonymous referees.

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STATE OF THE PLANET



# An introduction to operational chains in ocean forecasting

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Received: 11 September 2024 – Discussion started: 19 September 2024
Revised: 17 December 2024 – Accepted: 17 December 2024 – Published: 2 June 2025

**Abstract.** Operating the ocean value chain requires the implementation of steps that must work systematically and automatically to generate ocean predictions and deliver ocean data information in standard format. This task, which represents the backbone of operational forecasting systems, implies the design of robust workflows that organize pre-processing of the upstream data, run the core models, and handle post-processing before the final delivery. Operational chains require dedicated computational resources to supply demanding modeling runs but also processing and analysis of big volumes of data in relation to the specific spatial scale and consistently for the forecast lead times. The monitoring of each step of the workflow through key performance metrics can support not only timely delivery but also identifying problems and troubleshooting. The paper illustrates the main challenges foreseen by operational chains in integrating complex numerical frameworks from the global to coastal scale and discusses existing tools that facilitate orchestration of operational chain components, including examples of existing systems and their consolidated capacity to provide high-quality and timely ocean forecasts.

## 1 Introduction

Operational ocean forecasting systems integrate advanced numerical modeling, aimed at resolving ocean dynamics and processes from the global to coastal scale, and robust computational suites that are devoted to running models and orchestrating different data pre- and post-processing blocks, with the ultimate goal of providing high-quality and reliable ocean forecasts to enhance decision-making, monitoring, and planning for the sustainable use of ocean resources. In the last years, ocean observations – from remote sensing (Gould et al., 2013) and in situ (Le Traon et al., 2015) platforms – available for operational oceanography have increased in number, quality, and timeliness, making it possible to improve ocean models, to validate numerical ocean products, and to support monitoring activities (Tonani et al., 2015; Davidson et al., 2019). Data assimilation techniques, aimed at blending the observations into the model, have evolved numerically to provide the most accurate description of the past and the best initial conditions for the forecast. As computing power has increased, numerical solvers have evolved towards high-resolution models that can capture small-scale features enabling global, regional, and coastal simulations and predictions at higher resolution and over longer time spans. The numerical information produced is then processed to make it usable by operational applications and services. Some recent ocean modeling examples in support of operational ocean and coastal services are compiled in Sect. 4.2. Therefore, as shown in Chap. 4 of Alvarez Fanjul et al. (2022), the architecture of an operational ocean forecasting system includes pre-processing of ocean observations, quality control assessments, objective analysis, data assimilation, initial field generation, numerical forecasting, and data post-processing, together with the generation and dissemination of products. All these steps have influenced the evolution of forecasting systems from a technological point of view to accommodate the need to harmoniously interconnect complex steps towards final delivery to users. Section 2 provides an overview of the technical characteristics of processing suites that guarantee reliable operations and product provision.

## 2 Technical characteristics of an operational chain for ocean forecasting

The objective of an operational chain is to systematically and automatically perform a series of complex numerical steps to ensure the generation of ocean predictions and the delivery of related products to end users. The main phases of its workflow are pre-processing, modeling component runs, and post-processing. Figure 1 shows, as an example, the overall workflow of the chain implemented for the Global Ocean Forecasting System operated by NMEFC (China). Here, the main steps, as designed for the specific operational system, include data pre-processing, data assimilation, numerical simulation, and production for final delivery.

Pre-processing consists of accessing and preparing upstream data (i.e., observations, atmospheric forcings, and other model outputs to be used as boundary conditions) to be ingested by the modeling component. In the case of ocean observations, it is responsible for collection, transmission, analysis, and quality control. The time consumption of data assimilation depends on the amount of data used and on their complexity. Ocean models also need atmospheric forcing fields. Indeed, the performance of ocean operational forecasting systems is very sensitive to the type of atmospheric forcing used (Li et al., 2021), and atmospheric forecasting variables need to be collected and interpolated into the ocean model grid to compute wind stress, surface heat fluxes, or surface water exchanges. The time needed for the preparation of the atmospheric forcing, usually part of the first step of an operational suite, depends firstly on the (scheduled) atmospheric model forecast availability and secondly on the computational efficiency, as well as the computational efficiency in having the atmospheric forcing data ready to be used by the ocean model.

Other forcing data sources, such as freshwater inputs from river discharges, are progressively being included in ocean forecast models. Unlike in global ocean models, in regional models, this pre-processing block must include the preparation of the necessary data (usually from a global or basin model) that will be imposed as boundary conditions along the open boundaries of the regional domain.

Incorporating observations (from both satellites and in situ platforms) into an ocean model via data assimilation is desirable for operational forecasting (and reanalysis) systems to obtain accurate estimates of the ocean state (Tonani et al., 2015) and initial conditions for the forecast. Complex methodologies are developed and implemented in oceans forecasting chain that are strongly linked to the ocean model used, to the model resolution, and to the observations assimilated using different classes of data assimilation (Cummings et al., 2009)

Running an ocean model is the most complex and demanding part of the operational chain. Numerical models include physical parameterizations and solvers for the numerical integration of the Navier–Stokes equations. This complexity can be computationally demanding, so by employing parallel computing, we can distribute this workload across multiple cores. This allows us to run high-resolution ocean models faster. Hence, the use of multiple cores and parallelization is crucial in state-of-the-art ocean modeling.

Once the model run is complete, the resulting data must be post-processed by interpolating the numerical outputs (if needed) onto specific regular spatial grids and by applying procedures aimed at transforming the raw model data into a standardized format (e.g., CF-compliant; https://cfconventions.org, last access: 28 February 2025). Such post-processing must be executed afterwards as an independent process or in parallel while the model is running.

Finally, the ocean forecast products are released directly to users through different specific dissemination mechanisms (such as FTP, THREDDS, web services and API, and cloud-based solutions).

From a computational point of view, the execution of an operational chain may require significant computing resources, while the number of cores used must be such that the forecast is produced on time: they can therefore be executed in dedicated clusters, benefitting from heterogeneous computing capabilities by using CPU or GPU resources.

The operational chain is then required to orchestrate a complex sequence of tasks in a flexible and efficient way, allowing for monitoring and troubleshooting. When designing an operational chain, it is important to decide which programming language is most appropriate for coding each task belonging to each of the main steps: this choice depends on the characteristics of the numerical procedure to be adopted for solving a specific task. For example, for acquisition of upstream data from various external databases or data stores, the forecaster can adopt the following.

- Bash or Shell scripting offers functions like wget or curl for accessing files made available by a provider, as well as cron for scheduling its execution.
- Python codes are available for accessing data through web APIs (for example, the Copernicus Marine Toolbox that is a Python-based tool for accessing the Copernicus Marine Data Store) and for performing some initial basic manipulation (i.e., subsetting in space and time, interpolation to target grid).

The ocean model couple to data assimilation scheme is technically much more complex to run and there are also some compilation and performance requirements to be met. The

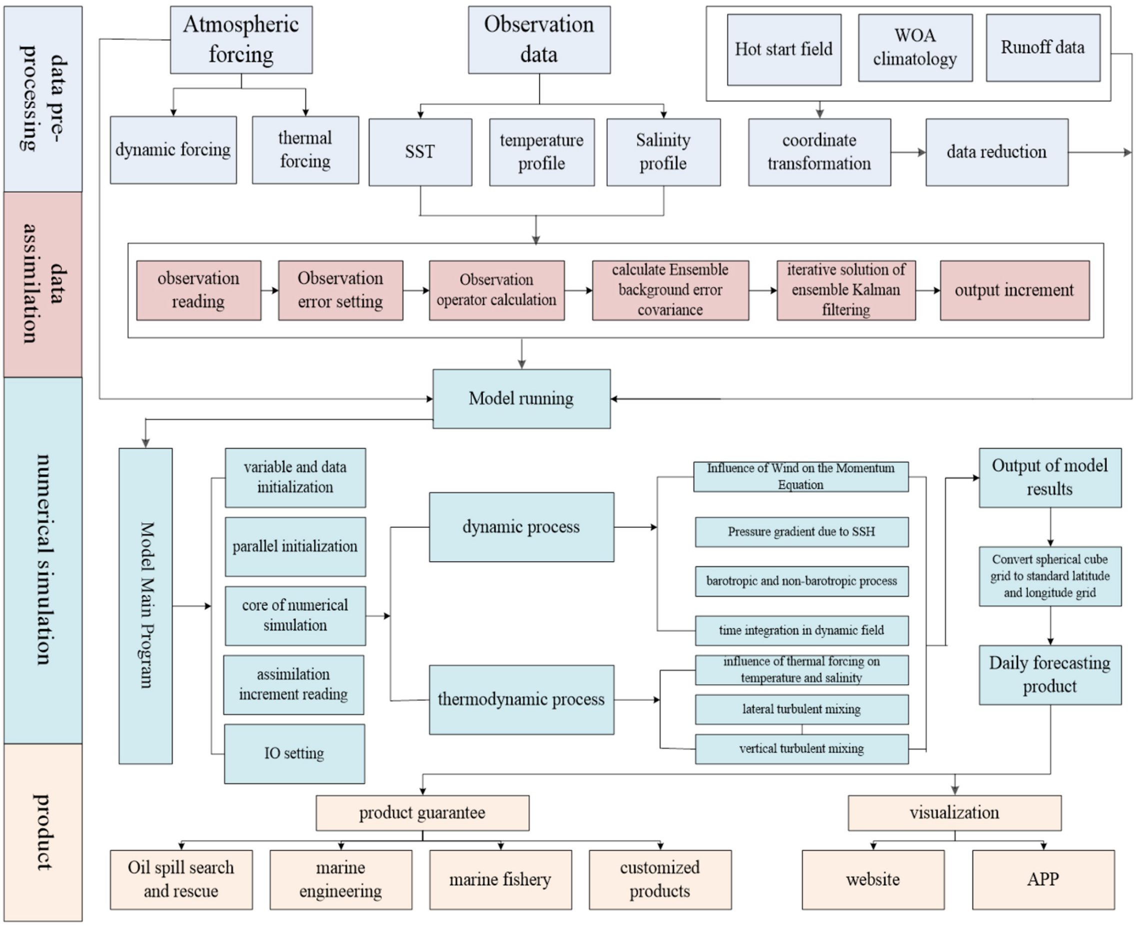


**Figure 1.** Operational chain of an ocean forecasting system (example of a global system in NMEFC, China).

operational chain is then instructed to launch a task that submits each model run to be executed directly on the dedicated core(s) or to a job scheduler that verifies resource availability. In addition, the ocean model itself is usually coded in a pre-defined programming language (such as Fortran, C/C++, or other) and can be executed in parallel mode using MPI/OpenMP or GPU-based parallel paradigms (i.e., CUDA, OpenCL, OpenACC).

Data post-processing, product generation, and product delivery can usually be done in parallel during the model run time as independent tasks from the overall workflow: again, it can adopt procedures coded in Bash/Shell, Python, Julia, or other interpreted languages that can guarantee flexibility, simplicity, and preliminary data analysis tasks.

The operational chain workflow engine can be coded ad hoc to sequentially organize the tasks to be executed. A basic approach can be determined through the implementation of a software package that includes the following:

- A main script, designed to collect the specific tasks and subtasks as requested by the operational chain
- A list of scripts, each representing the task to execute
- One or more specific scripts that are designed to track the status of the operational chain execution by creating logs to further support monitoring

The evolution of this approach towards systematic monitoring of the overall workflow and automatic detection of issues are represented by the adoption of a workflow manager. It is a tool that assists the forecaster in orchestrating complex sequences of tasks, including detection of anomalies during the execution and supporting the seamless processing of information. The workflow manager adopted by the Earth science community includes the following.

- ECFLOW (https://confluence.ecmwf.int/display/ECFLOW, last access: 28 February 2025), developed by ECMWF
- Cylc (https://cylc.github.io/, last access: 28 February 2025)

Others, extensively used by industry but also progressively chosen by forecasting centers, are the following.

- Apache Airflow (https://airflow.apache.org, last access: 28 February 2025)

– Prefect (https://www.prefect.io/, last access: 28 February 2025)

## 3 Key performance metrics

To ensure that an operational ocean forecasting system delivers accurate and timely products, it is necessary to identify metrics that can be implemented for measuring performances and that can support the resolution of potential anomalies and issues.

Based on the analysis performed in Ciliberti et al. (2023), the main properties of an operational forecasting system that can be used to monitor its performance are as follows.

– *Quality* certifies that the delivered product or service consistently performs well and provides useful results. This can be measured by providing relevant metrics aimed at measuring the degree to which the forecast product matches the observation (through validation exercises).

– *Reliability* refers to whether the user can rely on the forecast product to make decisions. As shown by the World Climate Service (https://www.worldclimateservice.com/2020/07/06/what-is-forecast-reliability/, last access: 28 February 2025), it is a measure of the quality of a probability forecast that varies between 0 % (i.e., the a posteriori observation is never in the forecast range) and 100 % (i.e., the a posteriori observation is always in the forecast range).

– *Timeliness* is a measure of the time between the expectation that the information will be available and the time when it is actually available for use. To save time, it is usual to execute in parallel two or three parts of the operational chain. However, not all parts can run in parallel. Pre-processing and data assimilation should be finished before the ocean model starts running. In contrast, post-processing, product generation, and release can be done in parallel with model running. Timeliness management depends on characteristics of different cases or different user needs. With coupled and ensemble model development, it is difficult to have a strict time control.

– *Accessibility* refers to the capacity for a user to get access to forecast product, including authentication and authorization (if needed).

– *Usability* involves the adoption of standards for data and metadata to ensure that the product can be used well and is self-describing. Data with a defined file format, adequate documentation, and high quality can be used and reused. This metric can be measured through user surveys.

Timeliness management depends on characteristics of different cases or different user needs. With coupled and ensemble model development, it is difficult to have a strict time control (Liu et al., 2018).

The adoption of a workflow engine facilitates the monitoring phase of the operational chain workflow. Figure 2 illustrates an example of how an operational forecasting service needs to monitor all the components of a specific operational suite to generate the proper KPIs (key performance indicators) that should later be managed to ensure timely service. The example shows how all the elements previously discussed, such as pre-processing, model execution, and post-processing of raw model outputs, together with some time dedicated to the data push to catalogs and later storage, are included in this operational monitoring performed by the Copernicus Marine Iberia–Biscay–Irish Monitoring and Forecasting Center (IBI-MFC) for its operational suites. This control of the different components is recommended and helps operators to identify issues in the operational suites and in the environment that could potentially lead to incidents. Likewise, this monitoring by component helps to manage delays in the service related to different types of incidents. The operational KPIs for service timeliness that are usually used to verify that the service is meeting the timeliness requirements stated in its proposed service level agreement (SLA) are computed using the time statistics provided daily by these time control monitoring processes. This monitoring is also important to identify and manage temporary incidents or continuous problems that may result in service delays or product outages.

## 4 Other operational-chain-relevant aspects

It is important to outline and summarize some general characteristics a user needs to consider in the setup of numerical ocean models for ocean forecasting.

– *Infrastructure aspects*.

  – It is highly desirable that a model performs well on most of the most powerful HPCs available. In practice, this requires that the code is parallelized (using domain decomposition with MPI and/or OpenMP), is not excessively memory-bound (particularly on CPU machines), and supports the low-level parallel processing required by GPUs. This requires analysis of the scalability and portability of the code as well as the restartability and reproducibility of the numerical ocean model solution.

  – Workflow tools can support proper monitoring of the computing process workflow and facilitate troubleshooting as well as scalability of the operational configuration.

  – The network is an essential element in the infrastructure of an operational chain; it must allow an

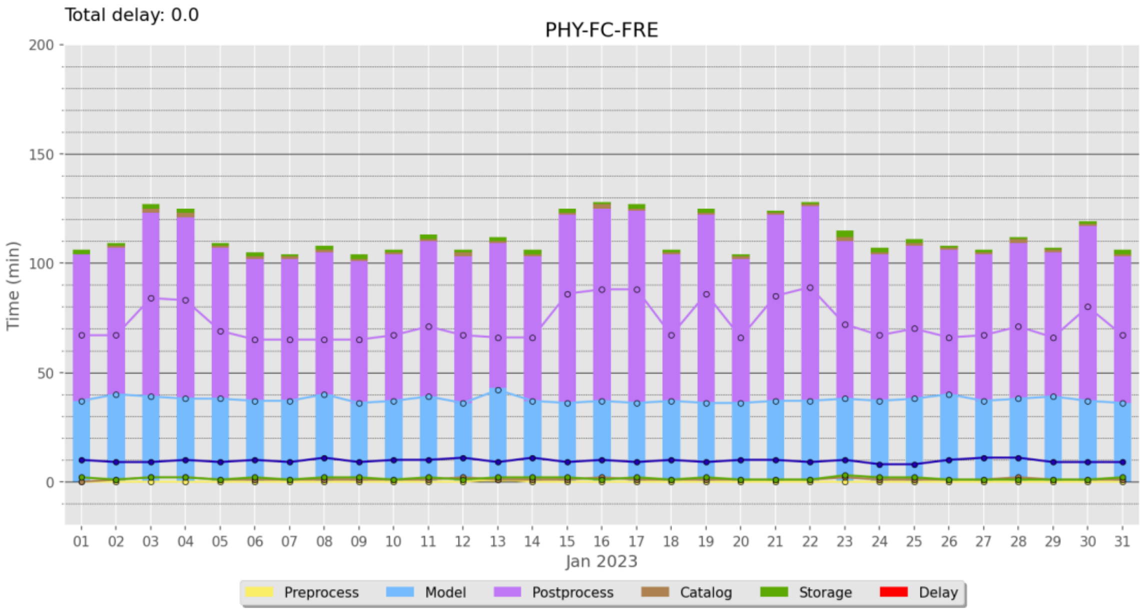


**Figure 2.** Example from the Copernicus Marine IBI-MFC Service Monitoring. Monthly summary statistics (for January 2023) from the time control monitoring performed for the IBI physical forecast operational suite. Monitoring of all the operational suite components (i.e., input data pre-processing, model execution, post-processing of raw model outputs, and processes to push products into the catalogs and later storage) is included.

effective link between the distribution centers upstream and downstream of the production centers.

- Storage must be linked to the HPC center to ensure effective back-up of production and enable production to be restarted if necessary.

- *Interfaces*. To appropriately handle the spatiotemporal scale of the ocean process that requires reproduction, the following steps are necessary.
  - Select a proper state-of-the-art option for subgrid-scale parameterization: if the option is incompatible, the model should be able to generate an error message and stop.
  - Use state-of-the-art bathymetries for the setup of new configurations. The user should also be able to use and specify smoothing techniques that can be applied to avoid model instabilities while also taking into account the topographical peculiarities that can play a fundamental role, especially in coastal models.
  - Specify time-varying river inflows (i.e., discharges, nutrients) as inputs, generated from climatologies or from real-time data (e.g., from observations).
  - Specify surface fluxes of momentum, heat, and freshwater and ancillary data such as surface temperatures and surface wave fields.
  - Couple the model to models of other physical systems (e.g., atmospheric, sea ice, or wave models) through one or more of the standard coupling systems (e.g., OASIS, US system); in some cases (like with waves and sea ice) alternative or ad hoc coupling approaches should be provided.
  - Run biogeochemical (BGC) models as part of the overall integration (on line coupling) or generate data to run the BGC model in offline mode.
  - Interface the ocean model with data assimilation systems.
  - Generate restart and diagnostic files in a flexible manner.

- *Design and documentation*. To meet quality assurance requirements, it is highly desirable that the model
  - has a clear design,
  - has a well-chosen modularity,
  - is easily readable,
  - is written in a familiar language (such as Fortran90 or Python),
  - has a user guide and a developer guide, and
  - can be further developed without excessive effort.

- *Sustained support*. The model needs to be sustainably supported by a lead agency, a consortium of agencies, a committed user community, or a combination of the above. This support should aim to ensure the following.

- The model's formulation is improved as the state of the art evolves.
- Novel improvements are documented in peer-reviewed publications.
- The code documentation is openly available and kept up to date.
- The code is openly accessible or made available subject to "legal" agreement (which might include, e.g., a commitment by a new user to contribute to further developments and testing of source code).
- New users are supported by instructions for setting up relatively simple configurations which can easily be compiled and run and outputs can be checked.
- New releases of the code are properly version-controlled.
- The methods by which the code is verified are described in its documentation.
- The results from standard test cases are made publicly available (an aspiration at this stage).

**Code and data availability.** The data and code are available from the websites, which are all mentioned in the paper:

- Argos data: ftp://ftp.ifremer.fr/ifremer/argo/latest_data (Argo Program Office, 2025)
- TOGA data: https://www.pmel.noaa.gov/gtmba/ (Global Tropical Moored Buoy Array, 2025)
- SLA data: https://doi.org/10.48670/moi-00149 (CMEMS, 2022a)
- SST data: https://doi.org/10.48670/moi-00165 (CMEMS, 2022b)
- MERCATOR reanalysis: https://doi.org/10.48670/moi-00021 (CMEMS, 2022c)

Other data are available from the authors upon request.

**Author contributions.** All the co-authors share common authority and made contributions.

**Competing interests.** At least one of the (co-)authors is a member of the editorial board of *State of the Planet*. The peer-review process was guided by an independent editor, and the authors also have no other competing interests to declare.

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**Acknowledgements.** This work was supported by the National Key Research and Development Program of China (grant no. 2021YFC3101504) and the National Natural Science Foundation of China (grant no. 42176030).

**Financial support.** Liying Wan was supported by the National Key Research and Development Program of China (grant no. 2021YFC3101504) and the National Natural Science Foundation of China (grant no. 42176030). Stefania Ciliberti, Roland Aznar, and Marcos Sotillo contributed to this publication as experts from the Copernicus Marine Service for the IBI region (funded within the framework of the Copernicus Marine Service EU (CMEMS) contracts 21002L6-COP-MFC IBI-5600 and 24252-COP-MFC-5000-Lot6). Mike Bell's research has been supported by the Met Office Hadley Centre Climate Programme.

**Review statement.** This paper was edited by Enrique Álvarez Fanjul and reviewed by two anonymous referees.

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# A description of validation processes and techniques for ocean forecasting

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Received: 17 September 2024 – Discussion started: 19 September 2024
Revised: 21 February 2025 – Accepted: 25 February 2025 – Published: 2 June 2025

**Abstract.** The architecture of operational forecasting systems requires clear identification of best practices for assessing the quality of ocean products: it plays a key role not only for the qualification of prediction skill but also for the advancing of the scientific understanding of the ocean dynamics from global to coastal scales. The authors discuss the role of the observing network in performing validation of ocean model outputs, identifying current gaps (i.e. different capacity to assess physical essential ocean variables versus biogeochemical ones) but also emphasizing the need for new metrics (tailored for end users' comprehension and usage). An analysis on the level of maturity of validation processes from global to regional systems is provided. A rich variety of approaches exist, and the more we move towards the coast, the higher the complexity in calculating such metrics is, due to increased resolution, but we are also somehow limited by the lack of coastal observatories worldwide. An example is provided of how the Copernicus Marine Service currently organizes product quality information from producers (with dedicated scientific documentation, properly planned and designed) to end users (with publication of targeted estimated accuracy numbers for its whole product catalogue).

## 1 Introduction

Product quality assessment is a key issue for operational ocean forecasting systems (OOFSs). There is a long tradition in scientific research related to model validation, and, through coordinated community initiatives, in recent times there has been important progress in this field, related to operational oceanographic services (Hernandez et al., 2015, 2018).

Strong efforts to define operational oceanography's best practices have started, among others the Ocean Best Practices (Pearlman, et al., 2019 and https://www.oceanbestpractices.org/, last access: 30 April 2025) and the Guide on Implementing Operational Ocean Monitoring and Forecasting Systems delivered by ETOOFS (Expert Team on Operational Ocean Forecasting Systems, https://www.mercator-ocean.eu/en/guide-etoofs/, last access: 30 April 2025; Alvarez Fanjul et al., 2022). In the latest ETOOFS guide, several sections are dedicated to model validation, i.e. Sect. 4.5 on validation and verification, and sub-sections on validation strategies for ocean physical models (Sect. 5.7), sea ice models (Sect. 6.2.6), storm surge (Sect. 7.2.6), wave models (Sect. 8.7) and biogeochemistry models (Sect. 9.2.6), as well as a specific section (Sect. 12.9) on quality assessment for intermediate and end users.

The main goal of this paper is to describe the status of the validation of ocean forecasting products. In Sect. 2, the crucial role that observational data sources play in the validation of ocean models is discussed, as well as how identified gaps in the observations determine model validation processes, limiting them for some Essential Ocean Variables on some temporal scales and in specific zones (i.e. on shelf and in the coastal zone). An analysis on the level of maturity of validation processes applied by OOFSs is provided in Sect. 4. Operational processes implemented in the Copernicus Marine Service for product quality across global and (European) regional model systems are analysed in Sect. 4.1, whereas Sect. 4.2 provides a view of model validation approaches applied by (non-European) regional and coastal operational services around the world. Finally, conclusions are delivered in Sect. 5.

## 2 Observations for model validation

The lack of observations is the primary, and obvious, difficulty of validating an OOFS at a specific site. In that sense, it is very difficult to overcome observational gaps, and, if they exist, OOFS validation processes are seriously hindered by them.

Validation is a global necessity and challenge. Capet et al. (2020) provide a complete overview and mapping of the current European capability in terms of OOFSs, including contributions from 49 organizations around Europe about 104 operational model systems, mostly simulating hydrodynamics, biogeochemistry and sea waves. This contribution shows how, and to what extent, different observational data sources are used for model skill assessment. As shown in Fig. 1, most of the model validation systems mainly use fixed platforms, satellite remote sensing and coastal tide gauges.

It is important to note that the aggregated results of the study do not provide differences between basin/regional systems and the more coastal ones. Indeed, in this contribution most of the near-real-time (NRT) systems of the Copernicus Marine Service regional monitoring and forecasting centres are included, causing some observational data sources that are not so coastally oriented such as the Argo to be used by a high number of European OOFSs. The same may happen with the use of spaceborne remote sensing products, which are more limited in their use for validation OOFSs as we move to more limited small coastal model domains.

Use of satellite products for OOFS validation is common in the case of global, basin and regional systems but limited in the case of coastal ones. If used, it is done mainly by those coastal systems that present a bigger spatial geographical coverage (going beyond the shelf break). Furthermore, new incoming observational technologies (i.e. the new Sentinel missions, swath altimetry, HF radars, BGC-Argo, etc.) and opportunities to use new coastal observing systems (links with member state networks and/or specific research and development projects) will enhance model validation capacities. New validation tools may also be developed for coordinated Observing System Experiments (OSEs) and Observing System Simulation Experiments (OSSEs), related to the optimization of these observation networks. Taking advantage of the framework of these OSSEs, AI-emulated variables will be developed, which will increase validation capacities. Increased awareness of the need for enhancing observing networks, bringing new initiatives and efforts to better integrate existing ocean observing systems with the OOFS validation processes, is needed.

## 3 OOFS validation: a matter of EOVs

In terms of ocean model validation, there is a different level of application depending on which Essential Ocean Variable (EOV) is targeted. The Copernicus Marine Service, a comprehensive multi-product service dealing with more than 150 operational products that involves more than 60 EOVs for the blue, green and white ocean, can illustrate such differences across EOVs. The document that provides the terms of reference for all the product quality (PQ) assessment done within the service and the long-term strategy for the PQ enhancement (Copernicus Marine PQ Strategic Plan; Sotillo et al., 2021) includes the following points about the different level of maturity in terms of model validation across EOVs in its analysis of strengths and weaknesses.

- In terms of the physic blue world versus the green biogeochemistry component, the assessment of physical parameters is more developed than the one for biogeochemistry parameters; the Copernicus Marine Service identifies the need of special efforts for biogeochemical model product validations. The lack of biogeochemistry observations conditions not only the biogeochemical model validation but even the modelling itself. Due to the lack of in situ data, some phenomena such as primary production and bloom of phytoplankton are assessed using chlorophyll Ocean Colour satellite data most of the time, which have some limitations related to coverage and resolution, especially for the coastal zones. Furthermore, it is necessary to also assess the factors that cause these blooms (i.e. transport of nutrients) in biogeochemical models. Carbon, oxygen and ocean acidification are parameters of interest at both regional and global scales that need better validation. BGC-Argo floats can enhance the monitoring but mostly off shelves and far from coastal areas. Finally it is mentioned that in the biogeochemical model validation, it is important to evaluate the errors in the physical system together, particularly vertical transport and mixing, which strongly impact the coupled biogeochemical models. Thus, monitoring of errors on key parameters of the physical forcing should help to characterize the causes of errors of biogeochemical products.

- Sea ice concentration, due mainly to observation by satellites, is assessed and brings validation to sea ice extent, sea ice drift, sea ice thickness and sea ice edge. New validation metrics (some related to end-user needs) should be developed for sea ice temperature and iceberg concentration maps, and specific assessments of multiyear sea ice parameters need to be specifically addressed on interannual timescales.

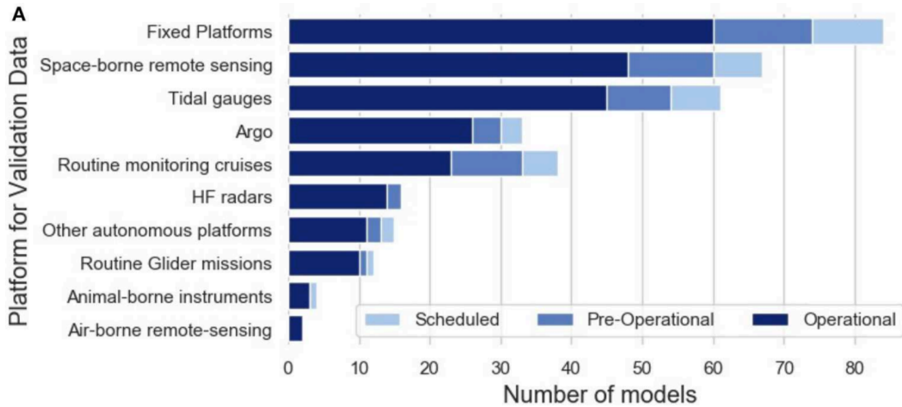


**Figure 1.** From Capet et al. (2020). Observing platforms providing data used for model skill assessment and validation purposes and number of models (from the EuroGOOS survey that uses them).

- Sea surface temperature is the most used EOV, being the most monitored parameter that is usually assessed with (in situ and remotely sensed) multi-product approaches that consider regional specificities (for high-frequency products, particular attention should be paid to diurnal cycle and tidal mixing effects). Generally, validation on surface layers is privileged with respect to the rest of the layers across the water column, a clear decreasing gradient existing towards deeper levels. The availability of in situ observations has greatly improved since the 2000s with the Argo programme. At depth, $T$ and $S$ data are the most used observations in product quality assessment. However, at synoptic scales, water mass distribution stays partially sampled in the upper ocean. There are significant regional differences, the coastal areas not always being the privileged ones (indeed, the autonomous Argo measure network changed the usual fact of coastal and on-shelf areas being the more sampled traditionally).
- In the case of salinity, in situ measurements from fixed moorings, Argo drifters, or offshore coastal profiles with CTD or XBT instruments, as well as surface transects with thermo-salinometers, are the most common data sources used for OOFS model validation. Averaged maps of sea surface salinity derived from remotely sensed satellite data (such as the SMOS ones) can be used to validate models, especially far from coastal areas.
- The approach to regionally validate sea level model solutions is based on comparison to satellite altimetry, at the scales of interest, from open-ocean to coastal dynamical responses. Enhancement of sea level validation in coastal and on-shelf areas is needed, and preparation for the use of the new wide-swath altimetry products should be done in the coming years. On the other hand, comparisons of coastal OOFS model products with in situ sea level measurements from tide gauge are quite common. External metrics linked to storm surge services (including total sea levels, tidal solution and residuals) are considered. For many coastal forecast systems, especially for those with more limited spatial coverages, the comparison of the simulated sea level with local observation from a tide gauge, usually installed in ports and the unique NRT ocean measurement available, is the only feasible direct model–observation comparison.
- Ocean currents and associated transport, especially near the surface, are parameters with a strong impact in many applications. Their assessment is usually done using independent observations (as most of today's systems do not assimilate this kind of observation). For this purpose, in situ observations from current meters and acoustic Doppler current profilers (ADCPs), installed at mooring buoy stations, as well as remotely sensed data from coastal HF radar systems, are used to validate simulated currents at specific locations. The proliferation of surface velocity products derived from drifters' observations as pseudo-Eulerian estimated maps at global and regional scales also contributes to the validation of ocean models. Finally, satellite altimetry can also be used to assess geostrophic/non-geostrophic properties of the ocean, and some derived estimation of currents from satellite synthetic-aperture radar (SAR), or from sea surface temperature (SST) or Ocean Colour images, can also be used in specific areas.

## 4 Operational validation: status across different OOFSs

A discussion on the status of operational validation across different existing OOFSs is provided here. There are significant differences in the status of the operational validation procedures applied by global, basin and regional systems and the ones applied by the coastal services.

To illustrate how operational validation is being performed by basin and regional OOFSs, Sect. 4.1 provides the approach followed by the Copernicus Marine Service as an example. In this service, outcomes from the validation of several global and regional models contribute to the generation of a variety of product quality information across products that is delivered to users.

On the other hand, in the case of more localized national/coastal OOFSs, there is a variety of model validation approaches. Section 4.2 reviews them, providing the European space information from the EuroGOOS coastal model capability mapping, and different examples are given from systems located all over the world (including North and South America, Africa, and Asia).

### 4.1 Validation of global, basin and regional model systems: the Copernicus Marine example

The Copernicus Marine Service (Le Traon et al., 2019) delivers consistent, reliable and state-of-the-art information derived both from space or in situ observations and from models – including forecasts, analyses and reanalyses – on the physical and biogeochemical state over the global ocean and the European regional seas. As stated in the previous section, the extensive multi-product portfolio offered, comprising more than 150 operational products and involving more than 60 EOVs for the blue, green and white ocean, established the Copernicus Marine Service as a benchmark in operational oceanography. The service relies on a network of producers, interconnecting several European OOFSs at global and regional scales: 7 Copernicus Monitoring and Forecasting Centers (MFCs) run ocean numerical models, assimilating data, in order to generate long-term reanalysis products, as well as conducting near-real-time analysis and 10 d forecasts of the ocean.

Model validation in the Copernicus Marine Service is closely linked to the operational production performed at the OOFS level. This connection spans all service phases, from design to the operational delivery of products, including associated communication and training activities. Furthermore, a scientifically sound and effectively communicated product quality assessment stands as one of the key cross-cutting functions of the Copernicus Marine Service, Further details of its achievements during the first phase of the service can be found in Sotillo et al. (2022).

Individual OOFSs, producers of the regional components of the Copernicus Marine Service, verify the scientific quality of their model products (i.e. NRT forecast/analysis and MY reanalysis) daily, using quantitative validation metrics, described in standard protocols and plans, and using any available observational data sources extensively, as referred to in previous sections. Regular updates of a subset of the validation metrics assessed by the own producers, including Class 2 validation of model products at mooring sites and Class 4 regional validation metrics, are made available to end users through a dedicated website (the Copernicus Marine Product Quality Dashboard, http://pqd.mercator-ocean.fr, last access: 30 April 2025).

Furthermore, the Copernicus Marine Service is responsible for informing end users about relevant PQ information in a transparent way. For this purpose, reference scientific PQ documentation is issued for each delivered product. These documents, stating the expected quality of a product by means of validation metrics computed along the qualification phase of the new model system, are updated for every quality change associated with any new operational release.

The Copernicus Marine Service model production needs to be carefully monitored at each step, and then, the quality of any upstream data used in the model runs can be properly assessed (even if such upstream data are quality-controlled by the data providers). Indeed, regular exchanges are organized between observations and model producers within the service to discuss data assimilation and validation issues. Scientific quality is one of the key performance indicators for the OOFS, and producers report quarterly to the service on quality monitoring activities. Any change affecting model solutions required to be justified from a product quality perspective.

The consistency in the choice of model validation metrics, and in the way they are presented, can be important because it makes it easier for users to understand the product quality information provided across products and to browse in the service portfolio which products are fit for purpose. However, given the wide range of Copernicus Marine products and production methods, it is not always scientifically meaningful to provide the same type of information across products and for all involved systems. The product quality cross-cutting strategy (Sotillo et al., 2021) thus aims to strike a balance between the level of homogeneity of the information delivered and its relevance. Indeed, the Copernicus Marine Service is a first achievement towards the interconnection of operational oceanography services at basin scale, and digital ocean platforms based on cloud technology will enable new validation capacities, facilitating the set-up of dynamic uncertainty for most of their products. The frequency of the updates will also increase to better serve coastal OOFS, where short-term forecast and quality information should be delivered on a daily (preferred) or weekly basis.

### 4.2 Validation of coastal OOFSs: a world of variety

There is not a common operational validation approach in coastal OOFSs, and the degree of operationality for the model validation is highly dependent on the type of forecasting system set-up (i.e. system with data assimilation scheme activated, generating analysis, or on the other hand, OOFSs based on a free forecast model system); the extension of the area of interest (being different for very limited coastal systems or going into a larger regional extent); the service purpose (system targeted on a primary end user with specific interests or needs, or if the OOFS delivers a general multi-parameter/purpose service); and finally in the availability, and degree of operational access, of local in situ observational data sources.

Most of the OOFSs have some system validation. Even those models used for research purposes or in the process of maturing their operationality (pre-operational state) have some kind of model validation, typically the early stages of the model set-up configuration, often running in hindcast mode for specific time periods to take advantage of existing observational data campaigns. In pre-operational systems, or in the early stages of OOFS services, an operational validation system is not so common, while model providers are working on the configuration of operational processes for an automatic PQ model assessment and, meanwhile, maintaining some offline model validation (using available observations or focused on specific targeted periods when outstanding events occurred or when observational campaigns are available).

It is worth noting that Capet et al. (2020) conclude that only 20 % of models provide a dynamic uncertainty together with the forecasted EOVs, which would be required for a real-time provision of confidence levels associated with the forecasts (e.g. as is usual for instance in weather forecasts). Usually, model providers perform operational and offline validations, focusing mostly on the best-estimate solution and not so on the forecast skill assessment; scientific statistical metrics are computed using available in situ observational data sources from their own networks or external observational data providers (using observational products from core services such as Copernicus; other national, regional or local public providers; or the industry, if available); in coastal high-resolution systems, with quite limited geographical domains, the use of satellite data is not so common for model validation due to both the lack of remotely sensed product coverage and the higher uncertainty of remotely sensed coastal data. This is the case of many OOFSs all over the world. For instance, the South African ocean forecast system (SOMISANA – Sustainable Ocean Modelling Initiative: a South African approach; https://somisana.ac.za/, last access: 30 April 2025) delivers downscaling of global model products for specific coastal applications in key coastal areas. In these cases, scientific model validation is mostly done offline by model producers, comparing their best estimated hindcast solutions with the existing historic observations. Given the coastal nature of the models, the validation process is focussed mainly on coastal moorings with the model domains. These include coastal temperature recorders, bottom mounted thermistor strings, wire-walker moorings and ADCP moorings from previously published datasets (e.g. Lucas et al., 2014; Pitcher et al., 2014; Goschen et al., 2015) as well as unpublished datasets from local institutes. Currently, there is no direct transfer of information about the product quality from the service to the OOFS users, neither computation of forecast skill assessment nor end-user-oriented metrics. However, some interesting initiatives, mostly linked with the engaging of stakeholder and product disseminations through end-user services platforms, are ongoing, and in the SOMISANA OOFS roadmap the implementation of an operational validation protocol is included, including forecast assessment.

The most common situation is that model validation is performed by the OOFS providers themselves. However, in some cases (usually targeted services), there may be options for some external validation, performed not by the provider itself but directly by the targeted end user(s). This is the case of the DREAMS service (Hirose et al., 2013, 2021) on the west Japanese coast, where model solutions are validated directly by the end users of the service: in this case, fisheries, through a programme with fishing boats as the ship of opportunity (Ito et al., 2021). The DREAMS model provider states the following:

> The fishers watch the coastal ocean carefully to achieve better catches. They are inevitably the serious users who can claim the quality of prediction.

In the case of the Brazilian REMO service (Lima et al., 2013; Franz et al., 2021), the validation is done in-house only for targeted end users, either by the Navy or by the PETROBRAS oil company teams. On the PETROBRAS side, they have several current meter sites where they compare in situ measurements, not only with the REMO forecast but also with all the other available ocean forecasting systems that deliver forecasts on that given day. On the Navy side, they do several validations that include the thermohaline structure and Taylor diagrams for a few properties, as well as the transport for the Brazil Current and the tidal analysis of both level and currents where they have data available. Furthermore, there can be very high resolution coastal OOFSs that can be implemented for specific purposes, running only along designated periods, to provide model data as input, for instance, during the design and construction phases of large infrastructures. In such cases, the implementation of the specific model solution can go together with some monitoring activity in the targeted area, allowing some model validation throughout the construction phase and after operations commence. In this type of service, modelling and validation are typically done in-house, with products and results rarely being publicly disseminated, not contributing to the literature.

There are coastal systems that have big domains (going into regional) and that may include data assimilation schemes or pure forecast local coastal systems (run by providers of regional/basin systems in which the local systems are nested) that tend to have operational validation systems (taking advantage of the extensive use of the observational data sources done for assimilation purposes). There are examples of OOFSs supported by state agencies, such as the Canadian Government CONCEPTS (Canadian Operational Network for Coupled Environmental Prediction Systems) that develops and operates a hierarchy of OOFSs. These include the whole downscaling approach: going in this Canadian case from the Global Ice Ocean Prediction System (GIOPS; Smith et al., 2016) used to initialize coupled deterministic medium range predictions (Smith et al., 2018), as well as ensemble predictions (Peterson et al., 2022). The global system provides boundary conditions to the Regional Ice-Ocean Prediction System (RIOPS; Smith et al., 2021), which in turn provides boundary conditions and nudging fields for the Coastal Ice Ocean Prediction System (CIOPS; Paquin et al., 2024). Recently, six port-scale prediction systems have also been put in place. Paquin et al. (2019) presented the prototype of the mentioned port models, whereas Nudds et al. (2020) presented the initial intercomparison projects that took place to compare the NEMO model implementation described in Paquin et al. (2019) with an unstructured model implementation using the Finite Volume Community Ocean Model (FVCOM). CONCEPTS also develops and operates deterministic and ensemble wave and storm surge prediction systems. Proposed changes to these systems must follow a set of formalized verification standards. Evaluation of forecast skill as a function of lead time is also done. Monitoring systems are also in place to ensure the quality of real-time analyses. Forecasts are evaluated in near-real time as part of the OceanPredict Class 4 intercomparison activity (Ryan et al., 2015), and evaluations are predominately made against available observations, but also include comparison to analyses for the longer-range coupled forecasts. These include assimilated satellite (sea level anomaly, sea surface temperature, sea ice concentration) and in situ observations (Argo, buoys, moorings, gliders, field campaigns, etc.). Additional independent evaluations are made against tide gauges, ADCPs, HF radars, drifters and ice beacons (Chikhar et al., 2019) and estimates of sea ice and snow thickness. Evaluations are also done of transports across reference sections and of surface fluxes (both against observations as well as in terms of budget; e.g. Roy et al., 2015; Dupont et al., 2015). Finally, user-relevant verification is done in terms of sea ice (e.g. probability of ice, ice formation and melt dates) and ocean (e.g. eddy identification and properties) features (Smith and Fortin, 2022). An ongoing effort is underway to quantify unconstrained variability in the systems and to provide uncertainty estimates to users.

There are also coastal OOFSs delivered by national agencies or organisms that run their own observational networks. This is the case in Spain of ocean model systems from different state and regional government agencies: i.e. Puertos del Estado (SAMOA; Sotillo et al., 2019; García-León et al., 2022), SOCIB (WMOP; Mourre et al., 2018), MeteoGalicia (MG; Costa et al., 2012) or the case of the Marine Institute ocean forecasting systems in Ireland (Nagy et al., 2020), with coastal systems focused on very limited, highly monitored bay areas. In these cases, usually they take advantage of synergies of the combination of high-resolution model solutions and operational observational data sources (the in situ operational observational capacity being developed by running operational networks or through the sustained periodic measurement at fixed stations) progressing towards more operational validation procedures. Even in these optimal cases, operational validation is mainly limited to model best-estimate solutions, and generation of end-user metrics or uncertainty estimation is still missing but is still in the long-term evolution roadmaps.

## 5 Summary, conclusions and outlook

This paper reviews the status of the validation of operational ocean forecasting products. Recent advancements in the field of operational oceanographic services have significantly contributed to scientific research on model validation. This is achieved by the OOFS individually but also through coordinated efforts, such as those developed within the Copernicus Marine Service and other international initiatives, like the evolution of GODAE to OceanPredict.

The crucial role of observations in ocean model validation is discussed, highlighting how gaps in observational capabilities significantly impact the validation processes in OOFSs. These limitations particularly affect the validation of essential ocean variables at specific temporal scales and in certain regions, such as shelf areas and coastal zones. Most model validation systems primarily rely on observations from fleets of floats, drifters, fixed in situ mooring platforms, coastal tide gauges and satellite remote sensed data products. It is pointed out how there are notable differences between the validation of global/basin systems and more coastal-focused ones. Some observational data sources, such as Argo, are crucial for validating global, basin and regional systems; however, they are less relevant for coastal systems due to coverage limitations. Similarly, while satellite products are commonly used for validating global, basin and regional OOFSs, their use is more constrained in coastal OOFSs, with much smaller coastal model domains.

Across EOVs there are also significant differences. The assessment of physical parameters is more developed than the one for biogeochemistry parameters, the lack of biogeochemistry observations certainly being a shortcoming for the validation of biogeochemical models. Generally, it is seen that model validation tends to prioritize surface layers over the rest of the water column. Likewise, there are significant regional differences, and coastal areas are not always the most prioritized. Indeed, the Argo network shifted the traditional favoured focused on coastal and on-shelf areas to open ocean. Among the physical EOVs, temperature is the most widely sampled and therefore validated. Ocean current, particularly the near surface one, is a critical parameter for many applications; however, it is less well monitored and thus less validated. Recently, the scatter in situ monitoring has been reinforced locally in coastal zones with HF radar systems. For sea level, the regional modelling solutions are typically validated with satellite altimetry, while comparisons of coastal

OOFS model products and in situ sea level measurements from tide gauges are also quite common. Lastly, simulated sea ice parameters are primarily validated with satellite remote sensing.

An analysis of the maturity of validation processes from global to regional forecasting systems is presented, using the approach followed by the Copernicus Marine Service as an example. This service connects more than seven regional production centres that run models for ocean physics, including sea ice and wave modelling systems, as well as biogeochemistry. It delivers forecast and reanalysis products for several EOVs, ensuring homogenized product quality information across the entire range.

The Copernicus Marine Service organizes product quality information from producers, providing dedicated scientific product quality documentation that is well planned and designed. This PQ information is then communicated to end users: every product in the Copernicus Marine product portfolio is accompanied by the relevant product quality documents, and online publication of updated estimated accuracy values for the entire product catalogue is also ensured through the Copernicus Product Quality Dashboard.

A wide variety of approaches exist as OOFSs work closer to the coast. For high-resolution coastal models with very limited geographical domains, the complexity of calculating validation metrics increases. This is due to the need of higher resolution to validate local processes, but operational validation is also often constrained by the scarcity of near-real-time coastal observations. The review presents examples of model validation approaches used by regional and coastal operational services worldwide, particularly from outside Europe, to complement the European Copernicus approach described earlier. Detailed examples of OOFSs from Canada, Brazil, South Africa and Japan are also included. The case of coastal OOFSs delivered by national agencies or organizations that operate their own observational networks is also highlighted as successful examples of operational model validation. These OOFSs benefit from synergies between high-resolution model solutions and operational observational data sources, advancing towards more robust operational validation procedures. However, even in these optimal cases, operational validation in most coastal OOFSs is primarily limited to the validation of best-estimate model solutions, typically on a daily basis at best.

Looking ahead, uncertainty estimation of OOFS products is identified as a key focus and is included in the long-term evolution roadmap of services like Copernicus Marine. The operational delivery of end-user-tailored metrics is still largely lacking, with this being more feasible in coastal OOFSs targeted and co-designed with specific end-user purposes in mind (e.g. services for ports or support for specific activities, such as aquaculture) than in regional, basin or global systems. New observational technologies (e.g. the upcoming Sentinel missions, swath altimetry, HF radars, BGC-Argo) and the opportunities presented by new coastal observing systems (through links with member state networks and/or specific research and development projects) will enhance model validation capabilities. Improvements in sea level validation in coastal and on-shelf areas are expected using new wide-swath and higher-frequency altimetry products in the coming years. Finally, the integration of operational validation tools with future Observing System Experiments (OSEs) and Observing System Simulation Experiments (OSSEs) aimed at optimizing observation networks could provide significant benefits. Leveraging these OSSE frameworks, AI-derived emulated variables may be developed, enhancing validation capacities. Overall, increasing awareness and fostering new initiatives to better integrate existing ocean observing systems with OOFS validation processes will be a key focus for the future.

**Data availability.** No datasets were used in this article.

**Author contributions.** MGS wrote the article. MD and FH participated in the conception, initial redaction and overview of the article.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** The authors acknowledge the COSS-TT group, especially Jennifer Veitch, Gilles Fearon, Naoki Hirose, Greg Smith, Mauro Cirano and Tomasz Dabrowsky, for their valuable comments and inputs for the description of validation processes across different coastal systems in the world (Sect. 4.2). Fabrice Hernandez contributed as IRD researcher to this publication initiative of the OceanPrediction Decade Collaborative Centre as part of an in-kind IRD contribution to Mercator Ocean International in 2024 and 2025.

**Review statement.** This paper was edited by Enrique Álvarez Fanjul and reviewed by two anonymous referees.

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# A description of model intercomparison processes and techniques for ocean forecasting

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Received: 1 October 2024 – Discussion started: 7 October 2024
Revised: 29 January 2025 – Accepted: 30 January 2025 – Published: 2 June 2025

**Abstract.** The availability of numerical simulations for ocean dynamics past estimates or future forecast worldwide at multiple scales is opening new challenges in assessing their realism and predictive capacity through an intercomparison exercise. This requires a huge effort in designing and implementing a proper assessment of models' performances, as already demonstrated by the atmospheric community that was pioneering in that sense. Historically, the ocean community has only recently launched dedicated actions aimed at identifying robust patterns in eddy-permitting simulations: it required definition of modelling configurations, execution of dedicated experiments that also deal with the storing of the outputs and the implementation of evaluation frameworks. Starting from this baseline, numerous initiatives like WCRP/Climate Variability and Predictability (CLIVAR) for climate research and the Global Ocean Data Assimilation Experiment (GODAE) for operational systems have arisen and are actively promoting best practice through specific intercomparison tasks, aimed at demonstrating the efficient use of the Global Ocean Observing System and its operational capabilities, sharing expertise, and increasing the scientific quality of the numerical systems. Examples, like the Ocean Reanalysis Intercomparison Project (ORA-IP) or the Class 4 near-real-time GODAE intercomparison, are introduced and commented on, also discussing ways forward for making this kind of analysis more systematic using artificial intelligence approaches for addressing monitoring of ocean state in operations or facilitating in-house routine verification in ocean forecasting centres.

## 1 Historical development of model intercomparisons

Historically, in oceanography, model comparisons began with evaluations of "free" and "forced" numerical simulations of ocean circulation over the same space and time frames, assessing their differences within comparable situations. The international Atmospheric Model Intercomparison Project (AMIP), under the World Climate Research Programme (WCRP), played a pioneering role in guiding the oceanic modelling community (Gates, 1992). AMIP's primary objective was to comprehensively evaluate each model's performance and document systematic errors. From an academic standpoint, this intercomparison aimed to identify avenues for enhancing future atmospheric models and driving further developments. Consequently, this approach aligns clearly with the validation framework outlined in Sotillo et al. (2025, in this report). To provide an objective assessment of each "competing" model's performance, a common "reference truth" was selected, such as climatology or atmospheric reanalysis (deemed more realistic than the AMIP simulations). This process involved analysing a series of targeted key variables extracted from the model state to provide an overview of the model's skill in representing various atmospheric aspects.

Published by Copernicus Publications.

In 1996, the same atmospheric community, involved in climate studies, settled the basis of the Coupled Model Intercomparison Project (CMIP) under the auspice of the WCRP/Climate Variability and Predictability (CLIVAR) panel to document systematic errors of global couple climate simulations in support of the Intergovernmental Panel on Climate Change (IPCC) framework (Meehl et al., 1997). Over the six phases of the CMIP, intercomparisons have refined the assessments, increasingly including the physical, biochemical and ecosystem components of the Earth system, by testing various climate scenarios of past, present and future $CO_2$ emissions. In the current phase, the CMIP6, the variety of models, simulations and their objectives have led the community to redefine the federated structure through a common specific framework, the Diagnostic, Evaluation and Characterization of Klima (DECK) experiments, which set out the simulations and scientific questions to be addressed. The DECK is the new acceptance criterion for a climate intercomparison project in the CMIP (Eyring et al., 2016). The evolution of the CMIP has been accompanied by the gradual adoption by the climate community of common standards, coordination, infrastructure and documentation, accessible to all. This persistent framework aims to ensure continuity in climate model performance assessment of future CMIP phases in which re-processed historical simulations defined in the AMIP would allow changes and benefits of more elaborated components of the Earth system models (ESMs).

The ocean modelling research community adopted a similar approach to the AMIP when the first global- or basin-scale eddy-permitting ocean simulations were achieved in the 1990s. The US–German Community Modelling Effort (CME), in support of the World Ocean Circulation Experiment (WOCE), started to infer model parametrization and sensitivity studies in modelling the North Atlantic basin (Böning and Bryan, 1996). Sources of errors like ocean boundaries or vertical mixing parametrization were identified. The DYNAMO project, dedicated to offering intercomparison among three classes of ocean models of the North Atlantic Ocean in a similar numerical experiment framework (Meincke et al., 2001), allowed patterns of the North Atlantic Ocean circulation to be identified that were robust and other patterns that were sensitive to model parametrization. In this case, the intercomparison approach brought another benefit than just identifying performances among the simulations: the common and matching patterns represented by the simulations were considered updated knowledge of the North Atlantic circulation. In other terms, the "ensemble pattern" from the simulations is identified as a robust representation of the "ocean truth" at the scales simulated by these models.

This first initiative led to the development of a common ocean modelling framework from the ocean community also involved in the CMIP projects, the Coordinated Ocean-ice Reference Experiments (COREs), aiming to provide common references for consistent assessment from a multi-model perspective (Griffies et al., 2009). CORE-I intends to evaluate model mean biases under a normal year forcing, using a prescribed series of metrics (e.g. Danabasoglu et al., 2014). The CORE-II framework extends the ocean model evaluation under the common interannual forcing – starting in 1948 – proposed initially by Large and Yeager (2009). It offers more direct comparison to ocean observations and to the effective ocean interannual variability. An intercomparison of 18 time-dependent ocean numerical simulations have been performed so far, with useful outcomes for global ocean model improvements. The CORE-II approach is the foundation of the Ocean Model Intercomparison Projects (OMIPs) carried out in support of the successive CMIPs, with a coordinated evaluation of the ocean, sea ice, tracer and biogeochemistry simulations forced by common atmospheric datasets (Eyring et al., 2016). The OMIP version 1 contribution to CMIP6, with ocean simulations' intercomparisons over the 1948–2009 period, is described by Griffies et al. (2016) and contains a comprehensive list of metrics and guidance to evaluate ocean–sea ice model skills as part of ESMs. A companion article by Orr et al. (2017) proposes the evaluation framework for the biogeochemical coupled model simulations in CMIP6. Under the CLIVAR Ocean Model Development Panel (OMDP) coordination, OMIP version 2 is ongoing using the more recent JRA-55 reanalysis forcings (Kobayashi et al., 2015). Metrics of the ocean (equivalent here to diagnostics) endorsed by the OMIP are those recommended for the assessment of ocean climate behaviour, impacts and scenarios in the CMIP DECK.

These first ocean intercomparison projects witness the community effort, trying to commonly define modelling strategies; conduct the simulations individually; and then intercompare the simulations in order to evaluate the model's performance with regard to observed realistic references. The projects bring better characterization of model errors and weaknesses considering specific ocean processes, from physical to biogeochemical aspects, over decadal, interannual and seasonal timescales. Implicitly, these efforts have involved strategies for distributing, storing and sharing simulations and metrics, under constraints of computer server limitations in capacity and communication bandwidth. In practice, this added to the common technical definition of standards shared by all participants and a fitness-for-purpose evaluation framework to be applied in similar ways for every simulation. And finally, a common synthesis effort is carried out in order to provide valuable conclusions.

The first intercomparison project that involved the operational oceanography has been carried out in the frame of the CLIVAR Global Synthesis and Observation Panel (GSOP). In practice, this involved intercomparing different ocean reanalyses computed over several decades and providing "ocean synthesis" on ocean state estimation through a chosen series of essential ocean variables (EOVs) considered in climate research (Stammer et al., 2009). A step was taken since it was no longer comparison of model outputs but of products issued from the more complex system producing each reanalysis (observation + model + assimilation), increasing the factors of discrepancies among them. The idea is that multi-system ensemble approaches should be useful to obtain better estimates of the ocean evolution. The GSOP objectives were (1) to assess the consistency of the synthesis through intercomparison; (2) to evaluate the accuracy of the products, possibly by comparison to observations; (3) to estimate uncertainties; (4) to identify areas where improvements were needed; (5) to evaluate the lack of assimilated observations that directly impacted the synthesis and propose future observational requirements; and (6) to work on new approaches, like coupled data assimilation. One of the outcomes was to highlight common behaviour among some products, that is, evidence "clusters" and correlated patterns that sometimes had just inappropriate biases.

In the atmospheric and weather-forecast side, usually responsible for marine meteorology predictions, routine intercomparison for wave forecast has been settled for many years under the World Meteorological Organization (WMO) framework. The European Centre for Medium-Range Weather Forecasts (ECMWF) hosts the ongoing WMO Lead Centre for Wave Forecast Verification where 18 regional and global wave forecast systems are compared (https://confluence.ecmwf.int/display/WLW, last access: 29 January 2025). Beyond wave forecasts' verification and quality monitoring, the ECMWF commits to maintaining an archive of the verification statistics to allow the generation and display of trends in performance over time.

A first dedicated intercomparison of ocean operational systems, operated on routine, was achieved by the Global Ocean Data Assimilation Experiment (GODAE) community (Bell et al., 2009), through an intercomparison of hindcasts over 2008. The main objectives were to (a) demonstrate GODAE operational systems in operations, (b) share expertise and design validation tools and metrics endorsed by all GODAE operational centres, and (c) evaluate the overall scientific quality of the different GODAE operational systems. The preliminary task was to define the validation concepts and methodologies (Hernandez et al., 2015a), with the so-called "Class 1 to 4 metrics" described in this report (Sotillo et al., 2025), and those directly inherited from the weather forecast verification methods (Murphy, 1993). A demanding task was to provide similar "Class 1", "Class 2" and "Class 3" files from each Operational Ocean Forecasting System (OOFS) and then to carry out the evaluation through intercomparison and validation against "truth references" (Hernandez, 2011).

## 2 Key findings for state-of-the-art model intercomparison

### 2.1 From academia to operation: adoption of best practice

The legacy of the first 10 years of GODAE was the implementation of an expert community for OOFS intercomparison: the Intercomparison and Validation Task Team (IVTT). This group was created during GODAE, continuing its activity in GODAE OceanView and, up to present day, in Ocean Predict (https://oceanpredict.org/, last access: 29 January 2025). A second benefit was the development of an ad hoc validation and intercomparison methodology, improved and tested regularly since, until it was adopted as best practice and recommended by the Expert Team on Operational Ocean Forecasting Systems (ETOOFS; Alvarez-Fanjul et al., 2022).

As a result of these activities, it was found that performing intercomparison of OOFSs and models brought the following aspects to address:

- Characterize the performance of individual OOFSs of the same kind relatively to a given "truth", identify outliers and give clues for further OOFS improvements.

- Allow "ensemble estimation" that provides qualitatively more robust and reliable estimates, i.e. the "ensemble mean" approach. In some cases, if the "ocean truth" is missing, the ensemble mean can be considered a reference and be used to validate individually the systems.

- Provide an ad hoc methodology for operational qualification; see Sotillo et al. (2025) for detailed explanation on OOFS qualification or "calibration". In other words, when the OOFS is upgraded, inter-comparing the old and new systems informs on the benefits of the upgrade and justifies "go/no-go" decisions.

- Adopt or refine technologies supporting large exchanges of information among the community: in this sense, the NetCDF file format and climate forecast standardization has greatly facilitated the "shareability" (Hernandez et al., 2015a, b) and prefigured the FAIR best practice (Findability, Accessibility, Interoperability and Reuse of digital assets), proposed more recently (Wilkinson et al., 2016).

An exceptionally illustrative intercomparison example emerged from the tragic crash of the Rio de Janeiro–Paris Air France plane in 2009 and the subsequent intensive search for the wreckage in the tropical Atlantic. Evaluation of the accuracy of current fields from OOFSs and observed products, a user-centric approach based on dispersion and Lagrangian metrics, was employed within an intercomparison framework. It was demonstrated that the ensemble mean yielded more reliable results compared to individual estimates (Drévillon et al., 2013). A similar approach was also adopted to identify the crash area for the March 2014 Malaysia Airlines flight MH370 in the Indian Ocean (Griffin and Oke, 2017; Durgadoo et al., 2021).

### 2.2 Intercomparison: key aspects to be addressed

Intercomparing routinely or during specific phases OOFSs and their products is now common practice in operational centres. However, various aspects need to be reiterated and addressed:

- Common validation/verification methodology needs to be adopted by all participants, preferably adopting recommendations, as reiterated in this report (Sotillo et al., 2025).
- Interoperability, shareability of products and common standards are key: the large number of products offered by the different centres cannot be spread in every single centre. The FAIR principles of best practice are essential.
- Representativity is a central aspect of intercomparison: scales and ocean processes represented in each product (observations and models) need to be correctly documented to reduce mis-interpretation when intercompared. In particular, the following points should be noted.
  - Re-gridding by downscaling or upscaling ocean products toward a common grid might generate errors and not conservative effects of ocean dynamics.
  - Comparing ocean re-gridded products with re-gridded observations containing different ocean scales might create double penalty scores.
  - Due to operational oceanography growing activity, it is worth remembering that an increasing number of products are available for each EOV, for each area. The Copernicus Marine Environment Monitoring Service (CMEMS) Data Store is a good illustration of this, with a large number of products derived from models or from space or in situ observations for a given EOV. This reinforces the importance of an a priori assessment of the representativity of each product before any intercomparison.
- Intercomparison is a first path toward ocean state estimation from various sources and products: it is promising to use novel approaches based on data mining, consensus clustering, machine learning, and other tools developed in the frame of ensemble estimation and forecast (e.g. Sonnewald et al., 2021).
- User-oriented metrics and process-oriented metrics are increasingly being implemented in operational centres. They are also new insight for establishing the performance of intercompared OOFSs into the user-oriented framework.

## 3 Ongoing ocean models and forecasting systems intercomparison activities

### 3.1 Class 4 metrics: model intercomparison in the observation space for verification forecast

Ocean observations provide an accurate estimation of the "ocean truth". However, the Global Ocean Observing System (GOOS) provides a sparse representation over time of three-dimensional ocean dynamics. Their quantity and quality have increased substantially with permanent mooring and programmes such as Argo and the Global Drifter Program, together with satellite measurements (e.g. Tanhua et al., 2019). The GOOS is providing these recent years a valuable representation of the large-scale dynamics and some aliased representation of the ocean fine scales where measurements are performed. This led to the evaluation of OOFS performance by direct comparison with observations and to the definition of the Class 4 metrics detailed in Sotillo et al. (2025).

In summary, Class 4 metrics aims to compare observations with the equivalent model forecast at the same time and place, for different lead times (Hernandez et al., 2015a). Thus, these metrics, for different kinds of ocean variables, characterize the performance of a given OOFS against observations in the observation space. One of the advantages of using the observations as the reference frame is that other OOFSs can similarly be compared to the same data, in the same manner. Hence Class 4 metrics have been used since the beginning when comparing several OOFSs and their performance with the same "truth" (Hernandez et al., 2015a). When the observations are not assimilated by the OOFS, one can get a fully independent error assessment that can be statistically representative of the overall quality of the OOFS. Otherwise, one can consider that the overall error level is underestimated. However, this still provides an objective measure of the actual gap between the OOFS estimate and the "ocean truth" at the exact location and time of the observation used as reference.

Within GODAE OceanView, the Class 4 intercomparison project has been operating since 2013. A first set of intercomparison of six global OOFSs (Ryan et al., 2015) was an opportunity to present new metrics (radar plot, Taylor diagrams, best system mapping, bar charts, rank histograms, etc.). The same Class 4 information was also used with more specific metrics around Australia (Divakaran et al., 2015), with the objective of the Australian Bureau of Meteorology to identify a path of improvements for its own OOFS. This was also a first demonstration of one of the benefits of such intercomparison: the in-house routine validation in Australia took advantage of the internationally shared and compared multi-system Class 4 information to enhance its own daily basis verification procedures. The Class 4 intercomparison is still routinely performed (Fig. 1) and is continuously extended. A recent intercomparison based on Class 4 for surface velocity using drifters by Aijaz et al. (2023) offers an additional evaluation of OOFS surface dynamics performance, key for applications like search and rescue, marine pollution forecasts, and many other drift-dependent applications.

Another issue of Class 4 comparison to observations was the routine evaluation of the overall quality of the GOOS. Performing comparisons with observations of several OOFSs also gives more confidence in identifying observation outliers and incorrect measurements: a feedback procedure was proposed to inform data centres that could carry out a second loop of data corrections, for the benefit of all data users (Hernandez et al., 2015b). This approach is now considered in the frame of the recent project SYNOBS endorsed by the United Nations Ocean Decade programme (Fujii et al., 2019, 2024). SYNOBS aims at evaluating the best combinations of ocean-observing platforms through observing system design carried out by different operational centres (e.g. Balmaseda et al., 2024a). The existing intercomparison framework will allow faster common assessment among the different contributors.

Mentioned above, comparison to observations raises the key issue of representativity, both from the observation and the modelling side. And subsequently, double penalty effects must be taken into account when measuring the skill of a given product for given scales or ocean regimes. It is necessary to carefully address the following questions: what are the scales sampled by a given observing system? What are the effective scales and ocean processes represented by a given OOFS? What ocean processes do they represent? The classical example is comparison of satellite altimetry and/or tide gauge observations with the sea surface height given by an OOFS: if the latter does not represent the tidal dynamics, obviously, observations need to be pre-processed to filter out tidal signals. This is the reason that the concept of "internal" metrics, aiming to measure the efficiency of the OOFS at the expected scales, was distinguished from the concept of "external" metrics, where operational products' reliability and fitness for purpose need to be assessed in the light of the user's requirements (Hernandez et al., 2018) and taken into account while performing intercomparisons. In addition, particular attention needs to be given to the representativity and uncertainty of observations. It is mandatory to take them into account while comparing several OOFSs with observations, in particular when referring to re-processed/re-gridded observation products (also called Level 4 or L4 type of observed products).

### 3.2 Ensemble forecast comparison: assessment through ensemble mean, ensemble spread and clusters

The atmospheric community developed ensemble forecasts, first to represent uncertainties of seasonal predictions considering the stochastic behaviour of atmospheric simulations. This was done using an individual forecasting system, by running a series of deterministic forecasts in parallel where some initial or forcing conditions were stochastically modified between members. The purpose of performing the intercomparison of the forecast members was to (1) identify common patterns from the probability distribution for eventually defining clusters, (2) compute probabilistic occurrences of specific events, and (3) use the ensemble spread as a proxy for forecast skill and performance assessment and try to separate outliers. The associated verification framework has been largely documented (e.g. Casati et al., 2008) and defined for the atmospheric components of the seasonal forecast activities (e.g. Coelho et al., 2019). For the ocean environment, this approach is currently used by weather prediction centres in charge of marine meteorology forecasting, i.e. wind and wave forecasts. For instance, the evaluation exercise performed by the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Prediction (NCEP), evaluating ensemble and deterministic forecasts, concluded, among other results, that the ensemble wave skill score at day 10 outperformed the deterministic one at day 7 (Campos et al., 2018). Another example is the recent intercomparison of seasonal ensemble forecasts from two centres contributing to the Copernicus Climate Change Service (C3S), which quantified their respective skill on sea surface height, ocean heat content and sea surface temperature (Balmaseda et al., 2024b).

At this stage, unlike weather prediction centres, ensemble forecasting from individual systems is not generalized in operational oceanography, although dedicated experiments are carried out in many areas (e.g. Pinardi et al., 2011; Schiller et al., 2020). And through specific data assimilation methods like the ensemble Kalman filter (Evensen, 2003), several centres are producing ensemble forecasts routinely (e.g. Lisæter et al., 2003; Keppenne et al., 2008; Seo et al., 2009). However, a large community effort dedicated to intercomparisons of ensemble forecasts produced by different centres has not yet been achieved.

Here we propose to illustrate ensemble approach benefits with a multi-system intercomparison as proposed by the CLIVAR/GSOP initiative (mentioned above) and the Ocean Reanalysis Intercomparison Project (ORA-IP) (detailed in Sect. 3.4 below and also discussed by Storto et al., (2019)). Figure 2 illustrates the assessment of a commonly used indicator for the so-called "Atlantic Niño" regimes in the tropical Atlantic, associated with the "Atlantic zonal mode" and targeting the equatorial cold tongue that develops in the Gulf of Guinea from April to July (Vallès-Casanova et al., 2020).

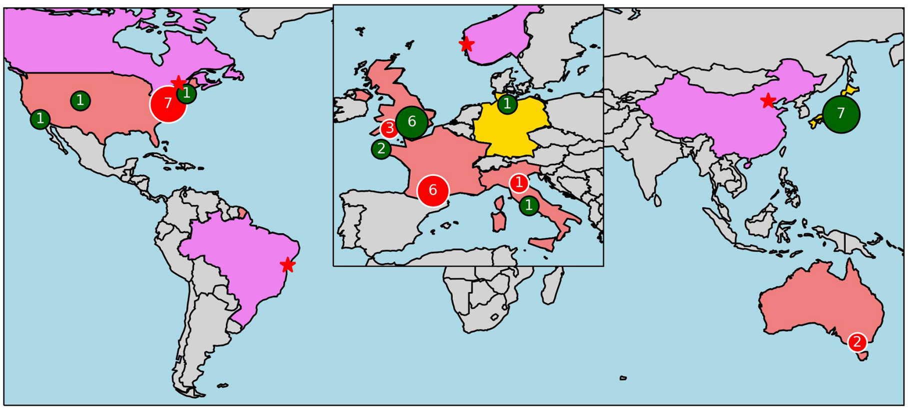

**Figure 1.** Operational centres and countries involved in a common intercomparison international framework during the last 20 years. Circles indicate their size and numbers the products/locations participating in the ORA-IP (Balmaseda et al., 2015). Green circles for ORA-IP only and red circles for centres that are contributing in addition to the Class 4 routine intercomparison (Hernandez et al., 2015a). Red stars indicate centres solely participating in the Class 4 intercomparison. Countries in pink, yellow and orange contribute, respectively, to Class 4, ORA-IP and both exercises.

All products –observation-derived-only and reanalysis estimates (see Balmaseda et al., 2015, for products' details) – give a consistent representation of the seasonal and interannual variability, from which an interannual trend can be deduced over the 1980–2024 period (ensemble-average trend in Fig. 2c of 0.02 °C per year). The ensemble average is computed like the multi-product-mean in Uotila et al. (2018) and without ARMOR3D, the observation-derived-only product used as "ground truth" (Guinehut et al., 2012), and without the GREP reanalysis, already an ensemble average of various reanalyses (Masina et al., 2015). Figure 2b shows the time series of the so-called SST (sea surface temperature) index: the box-averaged temperature anomalies relative to the annual climatology (computed with the ensemble average). All products exhibit the same interannual patterns, although some discrepancies are observed at intra-seasonal timescales. This is reflected by the small differences in the standard deviations computed for each time series over the denser period (1993–2023). A more precise view of the differences of each product's SST index with the ensemble average is given by Fig. 2a, quantified by their respective root-mean-square differences. Before 1993, the ensemble average is computed only with the ERA5 reanalysis and the OSTIA-observation-derived-only product, covering this period. Consequently, Fig. 2a exhibits a large discrepancy of these two products with respect to the ensemble average. The 1993–2023 period is chosen to assess the relative merit of each product, quantified using the ARMOR3D observation-derived-only product, not included in the ensemble-average computation in the Taylor diagram (Fig. 2d). First, one can see very large differences with OSTIA, the other observation-derived-only product, suggesting that the impact of their respective representativity of SST in the ATL3 box and possibly mapping/observation errors should be investigated further. The lesson here is that the "ground truth" also presents subjective drawbacks that need to be taken into account while measuring the relative merit in this multi-product ensemble assessment. The Taylor diagram reflects the very close performances of all products altogether in a cluster. The ensemble average performs better than individual reanalyses. The GREP multi-reanalyses product presents also good performances in representing the ATL3 index relatively to ARMOR3D. This confirms previous findings (e.g. Masina et al., 2015; Uotila et al., 2018; Storto et al., 2019) showing the "bias-reduction" benefits of ensemble averaging. In practice, the ensemble average provides a valuable estimate of the decadal SST trend in the ATL3 box. The ensemble-average estimate is also useful in identifying outliers.

Note that in recent methodologies, ensemble forecast comparison is performed using "ensemble clustering", also called "consensus clustering", which aims at producing a synthesis among an identified cluster from a given dataset (e.g. Hakobyan, 2010). The construction of the clusters from the initial dataset (here the different members of the ensemble forecast) can use many criteria. In the frame of GODAE OceanView, the Class 1 metrics were designed to compare OOFS variables on specific model grids and layers in similar ways (Hernandez et al., 2015b). In the Class 1 approach, OOFS outputs are re-gridded and resampled in a common grid and time frame (e.g. daily 2D model fields) and compared to a common reference (e.g. a regular L4 mapping of sea surface temperature from satellite retrievals). In this intercomparison, Class 1 files from various global OOFSs were used to compare and evaluate the quality of the ensemble mean; the weighted ensemble mean; and the *k*-mean clustering algorithm mean (Hartigan and Wong, 1979), which proved to be the more accurate (Hernandez et al., 2015b). Consensus clustering is now used for machine learning, and this might be one of the next stages associated with model products' intercomparison and ocean state estimation in the near future.

### 3.3 Regional forecast intercomparison and nesting strategy evaluation

Over recent years, the validation methodology proposed by the GODAE global ocean community has been adopted by many operational regional centres (some examples are given by Hernandez et al., 2015b), in particular because the coastal community started to relate inside GODAE OceanView with the IVTT. Specific assessments also started to be carried out, like assessing the behaviour of the ocean under tropical cyclone conditions using several OOFSs and ad hoc metrics (Zhu et al., 2016) or predicting the beaching of *Sargassum* in the Caribbean using global and regional OOFSs (Cailleau et al., 2024).

On a regional basis, specific systematic multi-product validation tools are gradually developed (e.g. Lorente et al., 2016, 2019). These tools, operated by a given operational centre, are efficient essentially if an inter-operable data server policy is implemented among the operational ocean community, in order to allow the real-time intercomparison of different sources of products. In parallel, regional and coastal system evaluation relies on specific local observing systems, like high-frequency (HF) radar, offering an "ocean truth", representing the ocean dynamics at higher resolution (Kourafalou et al., 2015), which cannot be represented by global OOFSs.

However, it is worth noting that comprehensive multi-product operational intercomparison is not common at regional scales. Unlike global OOFSs, there are rarely many fine-scale regional OOFSs that overlap in a given coastal region, even along the well-covered European marginal seas (Capet et al., 2020). And conducting a regional intercomparison gathering essentially global OOFSs would provide little information compared with the global intercomparison initiatives already underway.

But there is an increasing number of operational centres, or programmes like the CMEMS, that operate both regional and global systems over the same area and that have started to intercompare their different systems. For instance, two OOFSs of the same kind, Mercator and MFS (Mediterranean Forecasting System), are compared in the western Mediterranean basin, and their respective strengths and weaknesses are evaluated over specific subdomains (Juza et al., 2015). The benefit of improving the resolution of a regional OOFS is measured by comparing the coarse and fine grid systems using the same metrics (Crocker et al., 2020). In the CMEMS, most regional systems are nested into the global system. Hence, intercomparison between "parent" and "child" systems started to arise with the objective of measuring the benefit and added value for users of proposed regional and coastal products (De Mey et al., 2009). Several overlapping regional systems in the CMEMS can be compared to the global solution (Juza et al., 2016; Lorente et al., 2019). Examples can also be given for the Canadian Arctic and North Atlantic regional OOFS (Dupont et al., 2015), the US East Coast OOFS and reanalyses (Wilkin et al., 2022), and the Australian global and regional OOFS evaluations that focus on specific case studies and applications: disaster/search and rescue, defence/acoustic, and sea level/coastal management (Schiller et al., 2020). Some of these intercomparisons compare the regional OOFS of interest with several global products in order to measures both the local and global forecast skill, considering fine scales. In this case, using similar metrics, typically Class 4, for evaluating all these systems brings a series of questions. Which are the scales represented by the child system that is lacking in the parent system or in the observations? What is the impact of the different kind of forcings and different kind of assimilated dataset? How do errors propagate from the global to the nested system and degrade the expected seamless transition from the open ocean to coastal dynamics? How are specific ocean processes of interest represented in different systems? How reliable are they for end users' needs in different systems?

### 3.4 Evaluating retrospective views of the ocean dynamics: dedicated ocean reanalyses intercomparison project and ways to improve intercomparison methodologies

Past numerical simulations and ocean reanalyses were naturally the first step built in academia to study ocean processes over long periods, with the support of the increasing number of ocean observations over time and the improvement of assimilation techniques. Evaluation of such reanalysis representing decades of ocean behaviour through comprehensive intercomparison projects requires considerable resources and preparation. Most are conducted outside of routine operations by forecasting centres. They represent a milestone in progress in the field, from the point of view of both the evaluation of the system/reanalysis itself and the new validation methodologies that have been tested and implemented.

In the direct line of the GSOP project, the Ocean Reanalysis Intercomparison Project (ORA-IP) brought together more than 20 operational centres in order to intercompare more than 25 products (including observed products) spanning 20 to 50 years and focusing on eight EOVs – ocean heat content, steric height, sea level, surface heat fluxes, mixed layer depth, salinity, depth of the 20 °C isotherm and sea ice (Fig. 1). One of the objectives was to infer a new ocean state estimation of the global ocean, trying to reduce the so-called structural uncertainty, i.e. the uncertainty associated with the state estimation methodology, which cannot be sampled with a single system. Uncertainty is sensitive to the temporal variations of the observing system and to the errors of the ocean model, atmospheric fluxes and assimilation system, which are often flow-dependent and not easy to estimate. Following the Class 1 metrics approach, the ORA-IP is based on common

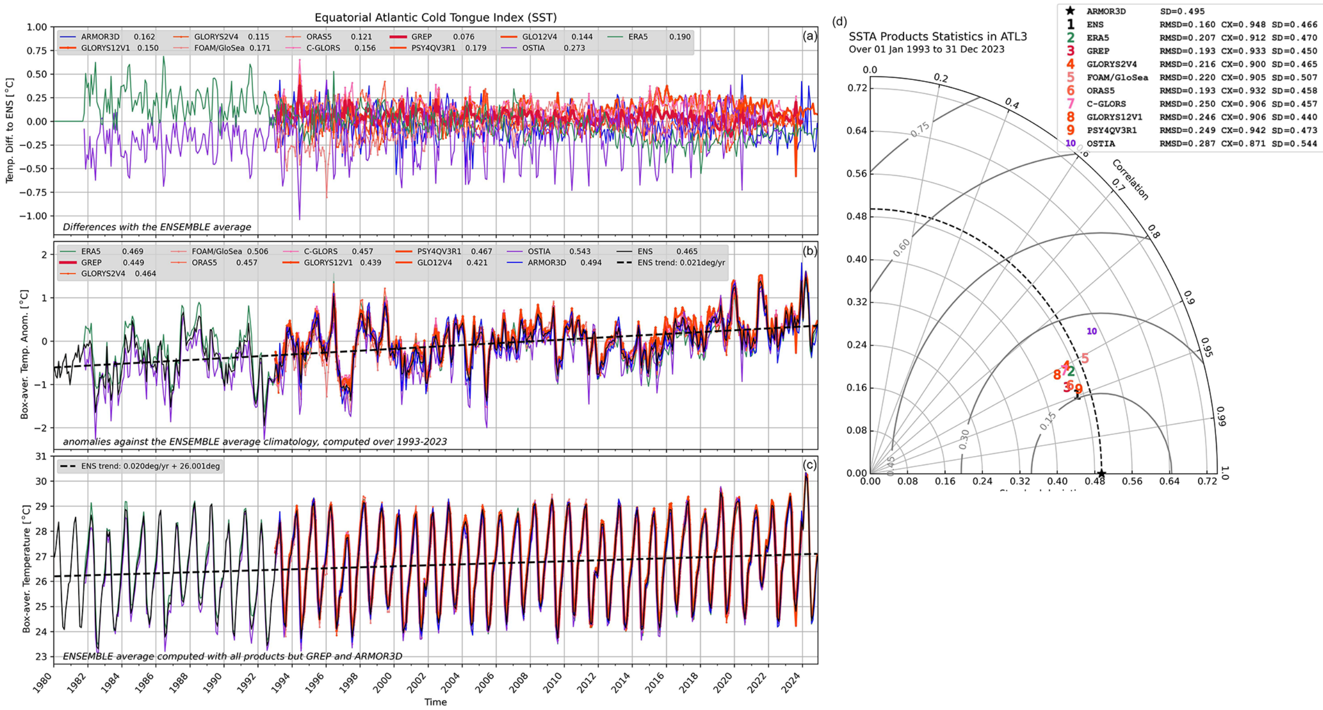


**Figure 2.** **(a)**–**(c)** Time series from 1980 to 2024 of SST products, monthly and spatially averaged into the ATL3 box located in the eastern equatorial band [20° W–0° E, 2.5° S–2.5° N] of the tropical Atlantic. **(a)** Differences relative to the ensemble average (root-mean-square differences (RMSDs) indicated in the legend). **(b)** The ATL3 index computed as anomalies relative to the climatology mean (standard deviations indicated in the legend). **(c)** The time series of box-averaged SST in the ATL3 box. **(d)** The associated Taylor diagram of the ATL3 index, using the ARMOR3D product as a reference. Statistics of root-mean-square differences, correlation with ARMOR3D and standard deviations for each product are given in the legend. All products were extracted from the Copernicus Marine Data Store and Climate Data Store.

grid re-interpolated products and monthly averages that were compared similarly over the 1993–2010 period under the responsibility of a leading expert for each of the eight EOVs. Results highlighted impacts of model resolution, components of the observing system assimilated, complexity of the ocean models and the data assimilation scheme, and quality of external forcing (Palmer et al., 2015; Shi et al., 2015; Storto et al., 2015; Toyoda et al., 2015a, b; Valdivieso et al., 2015; Chevallier et al., 2016).

New independent metrics were tested and used to evaluate each product and also the ensemble mean. The ensemble spread was identified as a measure of uncertainty. Following Storto et al. (2019), ocean reanalyses offer state-of-the-art representation of the past and present state of the global and regional oceans. Their accuracy depends on many factors, one of the most important being the observations available and the constraints they provide. Intercomparison helps in identifying the impact of their absence in the past and defines where they are most crucial in the quality of present and future reanalyses. And consequently, suggestions for improvements of the GOOS are provided.

Figure 2 shows that multi-product intercomparisons allow key indicator of the ocean environment changes to be inferred together with estimates of their uncertainties. Beyond reanalyses assessment based on EOVs, the next stage of ocean reanalyses intercomparison should first target key ocean processes that affect the climate system, identify their past occurrences, and better unravel their mechanisms and interactions, in order to estimate their present and future impacts. Machine learning approaches are expected to explore ocean variability in a multi-system framework more systematically and disentangle ocean key mechanisms for further identification in ocean simulations (e.g. Ahmad, 2019; Sonnewald et al., 2021; Salman, 2023). In particular, in ESM simulations, initial conditions are crucial: more realistic clusters of ocean reanalyses with better characterization of their errors and limitations (with or without the support of artificial intelligence) would ensure more reliable global and regional climate projections and associated skill assessment. Following this framework, ocean reanalyses intercomparison initiatives should also target end users' applications and societal impacts and identify requirements in terms of OOFS resolution, frequency and complexity, together with adequate observing systems, able to provide reliable and useful answers. Emerging international panels like the OceanPrediction Decade Collaborative Centre should help in providing intercomparison standards and recommendations from the user's point of view (Ciliberti et al., 2023). As already commented above, large and comprehensive multi-reanalyses intercomparisons are demanding and bring technical challenges in terms of storage, access, distribution and shareability. Cloud computing, ad hoc data mining technics and other artificial intelligence approaches will be needed to obtain valuable outcomes from the increasing number of available numerical ocean products resolving finer scales over longer periods.

### 3.5 A perspective of ocean reanalyses intercomparison: ocean state monitoring

An important outcome of the ORA-IP has been the development of the Real Time Multiple Ocean Reanalysis Intercomparison, carried out routinely every month by NOAA/NCEP, whose main objective is to gather operational hindcasts in order to perform ocean state monitoring (OSM) over the tropical Pacific, inferring the state of the ocean by computing the ensemble mean and identifying robust patterns using the ensemble spread (Xue et al., 2017). Note that OSM has growing importance in operational oceanography: through key EOVs it offers an assessment of the evolution of the ocean component as part of the real-time climate system evolution. Validation performed in the frame of OSM also provides a level of uncertainty for seasonal forecasts performed every month by many centres nowadays. OSM activity brought the CMEMS into routine calculation of Ocean Monitoring Indicators (OMIs), whose reliability and uncertainty are estimated through intercomparison of multiple products. Using OMIs, in 2018 the CMEMS started to produce the Ocean State Report (von Schuckmann et al., 2018) on an annual basis, now on its eighth edition (https://marine.copernicus.eu/access-data/ocean-state-report, last access: 29 January 2025).

**Data availability.** Ocean products used to produce Fig. 2 were downloaded in November 2024 from the Copernicus Marine Data Store and Climate Data Store (https://marine.copernicus.eu/ and https://climate.copernicus.eu/, last access: 29 January 2025).

- ERA5: https://doi.org/10.24381/cds.f17050d7 (Hersbach et al., 2023).
- OSTIA: https://doi.org/10.48670/moi-00165 (CMEMS, 2023a; Good et al., 2020).
- GLORYS12V1: https://doi.org/10.48670/moi-00021 (CMEMS, 2023b; Lellouche et al., 2021).
- ARMOR3D: https://doi.org/10.48670/moi-00052 (CMEMS, 2024a; Guinehut et al., 2012).
- GLO12V4 and PSY4QV3R1: https://doi.org/10.48670/moi-00016 (CMEMS, 2024b; Lellouche et al., 2018).
- GREP and FOAM/GloSea and C-GLORS and ORAS5 and GLORYS2V4: https://doi.org/10.48670/moi-00024 (CMEMS, 2024c; Masina et al., 2015).

Figures 1 and 2 are produced using Python 3.6 Matplotlib modules.

**Author contributions.** FH wrote the article and produced Figs. 1 and 2. MGS and AM participated in the initial redaction and the overview of the article.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** Fabrice Hernandez contributed as IRD researcher to this publication initiative of the OceanPrediction Decade Collaborative Centre as part as an in-kind IRD contribution to Mercator Ocean International in 2024 and 2025. Fabrice Hernandez thanks the Mercator Ocean International validation team, Marie Drévillon and Charly Regnier for their helpful comments ; the Ocean Predict Intercomparison and Validation Task Team and Greg Smith for the continuous efforts in providing Class 4 files for routine intercomparison that could be discussed in this article ; the Copernicus Marine Monitoring and Forecasting Centre Product Quality Working Group for their pioneering efforts in validation and intercomparison approaches. Marcos Garcia Sotillo contributed to this publication as leader and product quality expert of the Copernicus Marine Monitoring and Forecasting Centre for the IBI region. The authors thank the reviewers for their helpful comments that suggested an extended and updated view on intercomparison activities.

**Financial support.** This research has been supported by grants of the European Union's Horizon Europe programme (project SEACLIM, grant no. 101180125, and project FOCCUS, grant no. 101133911), awarded to Angélique Melet, and by an EU CMEMS grant (contract 21002L6-COP-MFC IBI-5600), awarded to Marcos Garcia Sotillo.

**Review statement.** This paper was edited by Enrique Álvarez Fanjul and reviewed by two anonymous referees.

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State Planet, 5-opsr, 18, 2025
https://doi.org/10.5194/sp-5-opsr-18-2025


STATE OF THE PLANET



# Atmospheric forcing as a driver for ocean forecasting

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Received: 22 August 2024 – Discussion started: 9 October 2024
Revised: 21 February 2025 – Accepted: 21 February 2025 – Published: 2 June 2025

**Abstract.** The connection of the ocean component with the Earth system is subject to the way the atmosphere interacts with it. The paper illustrates the state of the art in the way atmospheric fields are used in ocean models as boundary conditions for the provisioning of the exchanges of heat, freshwater, and momentum fluxes. Such fluxes are typically based on numerical weather prediction (NWP) systems which ingest observations from remote sensing and in situ instruments. This study also discusses how the ocean–atmosphere fluxes are numerically ingested in ocean models from global to regional to coastal scales. Today's research frontiers on this topic are opening challenging opportunities for developing more sophisticated coupled ocean–atmosphere systems and improved ocean–atmosphere flux datasets.

## 1 Introduction

The exchanges of heat, freshwater, and momentum between the oceans and the atmosphere play a critical role as boundary conditions in global, regional, and coastal operational ocean forecasting systems (OOFSs). Nowadays, the two primary sources of information regarding air–sea fluxes used in OOFSs are satellite-based observations and atmospheric model forecasts which assimilate various data types.

More specifically, using observation-based surface flux products is, by definition, a way to drive an ocean monitoring system or to produce an ocean reanalysis. Using an atmospheric forecast appears mandatory to produce an ocean forecast. In Sect. 2, we discuss the atmospheric forcing for ocean forecasts, for ocean analyses/monitoring systems, and for ocean reanalyses. Some basic aspects of air–sea flux datasets of heat, freshwater, and momentum (which is equivalent to wind stress), including their uncertainties, are also presented in Sect. 2. For further information about the challenges associated with the closure of ocean–atmosphere energy and water budgets, we refer the reader to Yu (2019) and the literature quoted therein. Section 3 discusses options for the implementation of ocean–atmosphere fluxes in OOFSs, and Sect. 4 discusses applications of air–sea flux datasets in OOFSs.

In recent years, several new flux products, which contain fields at sub-daily and hourly timescales, have become available. This tendency has been driven, in part, by the high time resolution possible with atmospheric forecasts and the need to include high-frequency variability in forcing fields for OOFSs. A complete survey of the wide range of flux datasets and their technical details is beyond the scope of this document. Instead, an overview of the main flux datasets is presented in Sect. 4, with frequently used datasets in OOFSs highlighted.

Sea-ice boundary conditions depend on the formulation of sea-ice models and how they are implemented in an OOFS. For example, sea-ice models can be part of an OOFS or a numerical weather prediction (NWP) system or be coupled to both. Consequently, respective input sourced from external datasets depends on the exact model architecture. Sea-ice boundary conditions are not discussed any further in this study.

## 2 Atmospheric forcing for different applications in ocean models

### 2.1 Atmospheric forcing for ocean forecasts

Currently, all OOFSs in forecast mode rely on forcing parameters provided by NWP systems. This is primarily due to the ubiquity and low latency of these systems and to the convenience of receiving gridded outputs. Although NWP products may not always be perfectly accurate, their self-consistency is a key factor when considering the forcing for OOFSs. These NWP systems often assimilate relevant satellite observations, noting that surface heat fluxes are not directly observed by remote sensors but are computed by the NWP systems by using a mixture of different observed geophysical variables and parameterizations. These derived surface fluxes are then used by OOFSs; hence, we briefly describe some of the remotely sensed observations in the subsequent paragraphs.

The net air–sea heat flux is the sum of four components: two turbulent heat flux terms (the latent and sensible heat fluxes) and two radiative terms (the shortwave and longwave fluxes). Satellite-based estimates of air–sea heat flux terms suffer because it is not yet possible to reliably measure near-surface air temperature and humidity directly from space. For example, satellites measure radiances in various wavelength bands which must then be inverted to obtain temperature. Bulk formulae are employed to estimate the latent and sensible heat fluxes, whereas radiative fluxes are determined either from empirical formulae or from radiative transfer models (Josey, 2011). These indirect techniques lead to a source of uncertainty in the turbulent heat flux terms, which are critically dependent on the sea–air temperature and humidity difference near the interface (Hooker et al., 2018; Tomita et al., 2018). Estimates of the radiative flux terms are available from various sources, e.g. Pinker et al. (2018), and can be combined with indirect estimates of the turbulent fluxes to form net heat flux products.

In contrast, wind stress has been well determined from scatterometers since Seasat-A (1978), ERS-1 (1991), QuikSCAT (1999) (Jones et al., 1982; Portabella and Stoffelen, 2009; Hoffman and Leidner, 2005), and subsequent satellite missions. Global wind measurements by synthetic aperture radar (SAR) go all the way up to the coast due to its high resolution, filling critical gaps in ocean wind speed and direction observations in coastal areas (Khan et al., 2023). However, despite quite some efforts having been devoted to SAR wind retrievals over the past 2 decades (e.g. Horstmann and Koch, 2005), there is currently no SAR wind processor that can provide a coastal wind stress product of sufficient quality and/or coverage for use in operations, while its use for OOFS development purposes must be cautious and on a test-case basis.

Precipitation is also remotely sensed using various techniques, including infrared measurements of cloud top brightness temperature (which acts as a proxy for rain rate) and passive microwave measurements. Launched in 2014, the US–Japanese-led Global Precipitation Measurement Mission (GPM) is an international network of satellites that provides global observations of rain and snow at different times of the day (Hou et al., 2014). However, validation of these fields over the ocean is challenging due to the lack of high-quality measurements from rain sensors and the difficulty in taking these measurements (Weller et al., 2008). As a consequence, uncertainty remains in the precipitation fields over follow-on effects for estimating the associated air–sea freshwater flux (evaporation minus precipitation) (Josey, 2011).

Satellite-based fluxes are observations that lack a forecast range, whereas OOFSs need forecasts – this is a significant reason for using NWP models in forecast mode. Consequently, NWP models have become a major source of complete sets of air–sea flux fields for OOFSs at high resolution (3-hourly or better) with global spatial coverage. Furthermore, air–sea fluxes from NWP systems are an attractive option for OOFSs because of their operational reliability and timely release of forcing fields akin to the operational cycles of OOFSs. NWP models assimilate a wide range of observations, including surface meteorological reports, radiosonde profiles, and remote sensing measurements. The turbulent flux terms are estimated from the model's surface meteorology fields, while the shortwave and longwave flux are output from the radiative transfer component of the atmospheric model. However, NWP systems are, of course, dependent on the model physics, which, although constrained to some extent by the assimilated observations, has the potential to produce biases, particularly in the radiative flux fields and precipitation (Trenberth et al., 2009; Weller et al., 2022) and in the wind stress vector components (Belmonte Rivas and Stoffelen, 2019; Trindade et al., 2020).

### 2.2 Atmospheric forcing for ocean analysis/monitoring systems

An analysis is a snapshot of the state of the ocean or atmosphere at any given time. It is created by using a model and observations to provide a best fit. An ocean or atmosphere analysis is generally used as a starting point for forecasts to make them as close to reality as possible (i.e. with all the data available). Consequently, surface forcing derived from the analysis of an atmospheric forecasting system can be used to calculate an ocean analysis, together with ocean in situ and remotely sensed observations. Ocean analyses are a common by-product of an OOFS, especially when run with data assimilation. An example is the Copernicus Marine Service operated by Mercator Ocean International, which provides global near-real-time (NRT) analysis datasets and forecasts of the 3D ocean regularly every day, forced by the ECMWF IFS atmospheric forecasting product (Drillet et al., 2025).

### 2.3 Atmospheric forcing for ocean reanalyses

An ocean reanalysis consists of modelling the state of the ocean over a long period of time (several years) while correcting it with the best available past observations. Ocean reanalyses can be used for validating OOFSs and enable past case studies. For these purposes, using atmospheric reanalyses or any best fit of observed atmospheric data is recommended. Fixed versions of NWP models run over multidecadal periods are commonly referred to as atmospheric reanalyses – two examples are those from the National Centers for Environmental Prediction and the National Center for Atmospheric Research (NCEP/NCAR) and ECMWF (Table 1). Although not suitable for near-real-time OOFSs due to their delayed-mode operation, air–sea fluxes derived from atmospheric reanalyses have proven to be a valuable tool for testing OOFSs during their development stages and in scenario simulations and analyses of past extreme events. In essence, atmospheric reanalyses are often used in OOFS development and in ocean reanalyses for the following reasons: they are typically of higher quality than output from operational NWP systems (where there is less time for quality control); they are available over an extended period of time, often covering multiple years to decades, which allows the exploration of various weather and climate phenomena in the ocean model in response to the atmospheric forcing; and model parameters in an atmospheric reanalysis are kept constant over the integration period, thus producing a consistent dataset.

In addition to the primary classes of flux datasets described above, flux fields for OOFSs are available from several other types of products. An example is surface fluxes available from various ocean synthesis efforts; that is, ocean models with data assimilation such as the Estimating the Circulation and Climate of the Ocean (ECCO) model (Stammer et al., 2004). These systems are typically forced by global atmospheric reanalysis fields which are then adjusted as a result of the assimilation and optimization process. Similarly to atmospheric reanalyses, air–sea datasets based on delayed-mode synthesis efforts are suitable for testing OOFSs during their development stages.

## 3 Implementation of atmospheric forcing fields in OOFSs

This section briefly lists methods for implementing ocean–atmosphere fluxes applicable in ocean forecasts, monitoring and reanalyses. The four most common approaches are as follows:

- directly using the atmospheric fluxes produced by NWP systems of national meteorological services. Typically, NWP systems produced by national meteorological services provide atmospheric surface forcing fields to OOFSs in order to compute water, heat, and momentum fluxes. Such fields may also be supplemented by real-time or near-real-time observations, e.g. satellite data, and other averaged datasets including climatology. For example, Trindade et al. (2020) show how scatterometer-derived wind stress can be used to remove NWP model output local biases. Relevant points to consider when using NWP products in OOFSs are data availability, space–time resolution, and domains for regional/coastal OOFSs (see next section). Table 1 provides examples of widely used global atmospheric NWP and reanalysis products.

- using a so-called “bulk” forcing to simulate the near-surface ocean–atmosphere interactions (Josey, 2011). This method permits the use of sea-surface temperature to compute in line and at each time step the turbulent fluxes and upward radiative fluxes and so to introduce a pseudo-coupling. The bulk forcing requires some atmospheric data: air temperature, air humidity, downward shortwave radiation, downward longwave radiation, precipitation, wind speed, and wind stress. The latter can also be calculated from the wind speed. This method raises the same questions as the previous one, plus the choice of the surface flux parameterization and associated choice of coefficients in the bulk formulae.

- using an intermediate simplified atmospheric model (e.g. Lemarié et al., 2021) driven by atmospheric NWP 3D fields and producing ocean–atmosphere fluxes consistent with the ocean evolution and resolution. This method is more complex than the bulk forcing but improves the feedbacks between the upper ocean and lower atmosphere, especially when the intermediate atmospheric model and the ocean model have the same horizontal resolution, in order to provide high-resolution atmospheric fields (Alvarez Fanjul et al., 2022).

- using a fully coupled ocean–atmosphere modelling system where the surface fluxes are an integral part of the coupled system. Although this is the most advanced physical approach to simulate ocean–atmosphere interactions, it comes at a relatively high numerical/computational cost, including the initialization/assimilation. The advantages of a fully coupled system (compared to the first three methods) are that there is no (or, for regional OOFSs, a lower) dependence on the data availability from external sources and that it ensures a two-way consistency of the ocean–atmosphere fluxes.

## 4 Applications of air–sea flux datasets in OOFSs

Each of the implementations described above has its own advantages and disadvantages, and it is not possible to recommend a best air–sea flux product based on the method for implementing surface fluxes in an ocean model; rather, the

**Table 1.** Examples of global atmospheric forcing products and providers. Adapted from Alvarez Fanjul et al. (2022).

| Dataset | Description | Provider |
|---|---|---|
| GFS | Global Forecast System, produced by the National Centers for Environmental Prediction (NCEP), that provides analysis and forecast atmospheric fields for the global ocean at a resolution of about 28 km | https://www.ncei.noaa.gov/products/weather-climate-models/global-forecast (last access: 27 February 2025) |
| NAVGEM | Navy Global Environmental Model run by the United States Navy's Fleet Numerical Meteorology and Oceanography Center (FNMOC) | https://www.usno.navy.mil/FNMOC/meteorology-products-1m (last access: 27 February 2025) |
| ECMWF IFS and ERA5 | European Centre for Medium-Range Weather Forecasts that provides reanalysis, analysis, and forecast atmospheric fields at medium, extended, and long range | https://www.ecmwf.int/ (last access: 27 February 2025) |
| Met Office UK | United Kingdom Meteorological Office that produces the Unified Model, a numerical model of the atmosphere used for both weather and climate applications | https://www.metoffice.gov.uk/ (last access: 27 February 2025) |
| GEM | Global Environmental Multiscale model, an integrated forecasting and data assimilation system developed in the Recherche en Prévision Numérique (RPN), the Meteorological Research Branch (MRB), and the Canadian Meteorological Centre (CMC) | https://www.canada.ca/en/environment-climate-change.html (last access: 27 February 2025) |

choice of flux dataset must be guided by the scientific feasibility and by the application in mind. For example, near-real-time NWP products are needed for operational ocean forecasting purposes, whereas a reanalysis product might be appropriate and more convenient to use during the development stages of an OOFS and for validation purposes. Hence, we offer some examples of possible air–sea forcing fields in OOFSs in Table 1, but they are by no means complete or prescriptive.

### 4.1 Applications in global OOFSs

Global NWP models, like those operated by centres listed in Table 1 at present, have typical horizontal grid resolutions of 20 km or better (and 60 vertical levels or more). With this kind of horizontal resolution, it is possible to capture large-scale synoptic weather phenomena and associated signals in the air–sea fluxes used to force ocean models.

However, in NWP systems with such grid resolutions, it is not possible to accurately simulate smaller-scale ocean–atmosphere interactions, such as oceanic fronts and orographic features like land–sea circulation or air–sea interactions associated with mesoscale oceanic eddies, noting that the synoptic (eddy) scale in the ocean is on the order of $\sim 100$ km, which is about 1 order of magnitude smaller than in the atmosphere at about $\sim 1000$ km.

Atmospheric forcing fields are typically interpolated onto the respective grid points of the ocean model, e.g. momentum fluxes onto the velocity grid points, air–sea heat fluxes onto the temperature grid points and evaporation minus precipitation onto the salinity grid points of the ocean model (plus volume or mass flux in the continuity equation). This interpolation can be accomplished either by using an internal interpolation routine of the ocean model; by using bulk formulae at the ocean grid to calculate surface fluxes of heat, freshwater, and momentum; or by using specific coupling software, e.g. Craig et al. (2017), for fully coupled ocean–atmosphere–wave–sea-ice models.

### 4.2 Applications in regional and coastal OOFSs

There is a plethora of regional and coastal ocean models with fixed, variable, and adaptive grids and with horizontal resolutions often in the 10–100 m range (Kourafalou et al., 2015). It is therefore not possible to provide specific guidance about the appropriate choice of air–sea fluxes required for these types of models.

Regional- to basin-scale OOFSs are typically forced with air–sea fluxes from the latest high-resolution global NWP systems, e.g. O'Dea et al. (2012). In contrast, coastal OOFSs require a different approach. Coastal air–sea circulation and topographic features, like small islands and their interactions with air–sea fluxes, are not reproduced by global-scale atmospheric models; hence, much higher resolution coastal atmospheric models are needed to provide reliable upper-ocean boundary conditions. This can be accomplished by direct coupling of high-resolution atmospheric models to coastal ocean models or by using air–sea fluxes from a stand-alone NWP higher-resolution coastal model (Hordoir et al., 2019). Other examples of regional atmospheric models are the UK Met Office Unified Model–JULES Regional Atmosphere and Land configuration (Bush et al., 2023) and the Weather Research and Forecasting (WRF) model (Skamarock et al., 2008). Either way, these atmospheric models need to be nested (in multiple) within coarser-resolution regional and/or global models which provide lateral and upper boundary conditions. This is an active field of R&D, where the development of coastal NWP and OOFSs often goes hand in hand with efforts to develop fully coupled ocean–atmosphere forecasting systems. However, it should be noted that, for both components, atmosphere and ocean, not just suitable lateral boundary conditions from coarser-component models are required, but it is also highly desirable to have an appropriately dense atmospheric and oceanic observing system to constrain these models and improve (coupled) forecasts.

High-resolution air–sea fluxes, which are based on remotely sensed fluxes, can also be used to evaluate the quality of the forcing fields in coastal ocean models. An example is the synthetic aperture radar (SAR)-based remotely sensed regional ocean wind speed and direction database, which has been made available by the Australian Integrated Marine Observing System (Khan et al., 2023). The dataset is a kilometre-resolution ocean wind speed and direction database over coastal seas of Australia, New Zealand, the western Pacific Islands, and the Maritime Continent. It is obtained from Europe's Copernicus Sentinel-1A and Sentinel-1B SAR satellites from 2017 up to the present. The dataset is a first of its kind in the region and captures the spatial variability in coastal ocean winds over a wide swath (250 km). However, and, as stated above, any SAR-derived wind stress product available to date and its use for OOFS development purposes needs to be treated with caution and should be assessed on a case-by-case basis.

## 5 Conclusions

This study provides some information about the diverse range of air–sea flux datasets that are now available for the community to use as air–sea forcing in OOFSs. NWP systems provide the majority of flux products to force today's OOFSs. Generally speaking, the quality and usefulness of these datasets are influenced by the spatial and temporal resolutions of remotely sensed and in situ observations that are assimilated into the NWP systems and are limited by associated biases which should be taken into account when choosing such datasets. Consequently, air–sea flux datasets for OOFSs should be chosen with the applications and users of the outputs in mind.

**Data availability.** No datasets were used in this article.

**Author contributions.** AS prepared the article with contributions from all co-authors.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** The authors would like to thank the Compilation Team at the OceanPrediction Decade Collaborative Centre for their guidance and support during the drafting of this article. Two anonymous reviewers provided helpful comments which led to a significantly improved article.

**Review statement.** This paper was edited by Stefania Angela Ciliberti and reviewed by two anonymous referees.

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# The representation of rivers in operational ocean forecasting systems: a review

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Received: 17 August 2024 – Discussion started: 24 September 2024
Revised: 27 February 2025 – Accepted: 8 March 2025 – Published: 2 June 2025

**Abstract.** The connection between the ocean and the land is made possible thanks to rivers, which are a vital component of the Earth's system. They govern the hydrological and biogeochemical contributions to the coastal ocean through surface and subsurface water discharge and influence local circulation and the distribution of water masses, modulating processes such as upwelling and mixing. This paper provides an overview of recent approaches to representing coastal river discharges and processes in operational ocean forecasting systems (OOFSs), with a particular focus on estuaries. The methods discussed include those currently adopted in coarse-resolution ocean forecasting systems, where mixing processes are primarily parameterized, as well as more advanced modelling and coupling approaches tailored to high-resolution coastal systems. A review of river data availability is also presented, illustrating various sources of freshwater discharge and salinity, from observational data to climatological datasets, alongside operational river discharge products that enhance the representation of water discharges in operational systems. New satellite-derived datasets and emerging river modelling techniques are also introduced. In addition, responses from a survey of existing OOFS providers are synthetized, with a focus on how river forcing is treated, from global to coastal scales. Challenges such as data accuracy, standardization, and model coupling are discussed, highlighting the need for improved interfaces between monitoring and modelling systems. Finally, some recommendations and ways forward are formulated in relation to identified limitations in current OOFSs.

## 1 Introduction

Rivers form the primary link between land and sea, delivering approximately 36 000 $km^3$ of freshwater and over $20 \times 10^9$ tons of solid and dissolved material to the global ocean each year (Milliman and Farnsworth, 2011). River discharge into the ocean is a major component of the global hydrological and biogeochemical cycles, which have undergone significant changes under the influence of climate and human activities (Shi et al., 2019; Yan et al., 2022; Qin et al., 2022; Chandanpurkar et al., 2022). Estuaries act as transitional zones where freshwater fluxes influence ocean circulation, salinity, and upper-ocean stratification, which in turn affects the mixed layer depth, ocean currents, and air–sea interaction (Chandanpurkar et al., 2022; Dzwonkowski et al., 2017; Sprintall and Tomczak, 1992; Sun et al., 2017; Pein et al., 2021; Pein and Staneva, 2024). Freshwater inputs to the ocean also modulate coastal upwelling events. Altogether, these factors impact the productivity of the coastal marine environment (Sotillo et al., 2021a).

Despite rivers' influence on the coastal and basin-wide circulation and dynamics, in global- and regional-scale models, effectively accounting for riverine freshwater discharge into the oceans is a challenging problem (Sun et al., 2017; Verri et al., 2020). Accurately incorporating river flow into numerical ocean models requires appropriate parameterizations and boundary conditions. The setup of practical open boundary conditions (OBCs) is dependent on flow dynamics, model resolution, data availability, and other factors (Blayo and Debreu, 2005). At coarse scales that cannot resolve the estuarine dynamics, but even at finer scales in some cases, river outlets are often represented in a simplistic way, with climatological runoff and zero or constant salinity values, implicitly neglecting estuarine mixing and exchange as well as seasonal and non-seasonal variability (Sun et al., 2017; Verri et al., 2020, 2021; Pein et al., 2021; Pein and Staneva, 2024). As a result, key natural processes are often omitted, and depending on how river forcing is defined, ocean model outputs may vary significantly. These discrepancies are most pronounced in shelf areas, particularly in regions of freshwater influence (ROFI), but can also propagate to regional and global scales (Tseng et al., 2016).

This paper reviews existing methods and datasets used in operational ocean forecasting systems (OOFSs) to represent river forcing. As the focus is on freshwater discharges, the river supply of nutrients and other materials are neglected in this review but are partly addressed in a separate contribution by Cossarini et al. (2025, in this report).

The paper is structured as follows: Sect. 2 reviews approaches for representing river forcing in global, regional, and coastal ocean models, including estuarine mixing parameterizations and coupling techniques. Section 3 describes available data sources from operational centers and data providers as well as emerging techniques for estimating river discharge. Section 4 presents examples of river forcing methods and data sources implemented in existing OOFSs, summarizing findings from a survey conducted within the OceanPredict community. Finally, Sect. 5 provides a summary and recommendations regarding identified limitations in current OOFSs.

## 2 River forcing in ocean models

### 2.1 Capturing seasonal and non-seasonal river variability

Accurate representation of river discharges and associated variables (e.g. salinity, temperature), whether model-derived or observation-based, is crucial for capturing both seasonal and non-seasonal effects in the coastal ocean. The Bay of Bengal is one example where the inclusion of seasonal river discharges and salinity in regional model simulations significantly improves the representation of sea surface temperatures, near-surface salinity, stratification, mixed-layer depth, and barrier-layer thickness, leading to a better simulation of the formation, progression, and dispersion of the freshwater plume (Jana et al., 2015).

Seasonal variability in river discharge not only impacts coastal salinity and temperature but also contributes to the sea level changes both locally and remotely, mostly via a halosteric sea level contribution. This effect was observed, for example, between the mouth of the Amazon River and the continental shelves of the Gulf of Mexico and Caribbean Sea (Giffard et al., 2019). Similarly, in the US Atlantic and Gulf coasts, river discharge and sea level changes were found to be significantly correlated (Piecuch et al., 2018). Such dynamic sea surface height (SSH) signals driven by river discharge can explain 10 %–20 % of the regional-scale seasonal variance around major rivers, such as the Amazon, Ganges, Brahmaputra, Irrawaddy, Ob, Lena, and Yenisei (Piecuch and Wadehra, 2020).

While the seasonal effects of river discharge on ocean processes have been extensively documented, non-seasonal influences of river runoff on sea level changes remain largely unexplored due to the lack of consolidated discharge databases (Durand et al., 2019). These influences, however, can be significant when considering river runoff jointly with wind-driven transport and heat fluxes, which also play a major role in modulating regional sea level variability (Verri et al., 2018).

### 2.2 Freshwater input in coarse-resolution models: towards a parameterization of estuarine mixing processes

Because many ocean models operate at resolutions too coarse to resolve estuarine processes explicitly, an appropriate parameterization of estuarine mixing is required to capture their influence on freshwater transport. In nature, estuaries transport and transform water properties along their length, due to tidal mixing, deposition, and resuspension, and up- and down-estuary advection. Saltwater intrusion driven by tides and other coastal signals (e.g. storm surges) controls the estuarine water exchange and affects the net estuarine outflow and corresponding salinity values (Sun et al., 2017; Verri et al., 2020). However, although water properties at the head differ from those at the mouth, in models too coarse to resolve the estuaries, river discharge observed far from the river outlet is typically inputted at the coast with zero salinity (Verri et al., 2021; Herzfeld, 2015). Alternatively, salinity values can be prescribed based on constant annual or monthly values derived from sensitivity tests and/or in situ campaigns, when available (Verri et al., 2018).

Herzfeld (2015) describes and assesses the performance of various methods for inputting freshwater into regional ocean models. A first approach, referred to as a point source input, adds a term of freshwater flux, entering as surface point sources into one or more layers of the model to the divergence of flow in the vertically integrated continuity equation, with no associated velocity profile. It affects the vertical velocity surface boundary condition of the free surface equation and the surface boundary conditions for the diffusive heat and salt fluxes. A second approach, the flow input, considers the inertia of the river flow and prescribes a velocity profile at the boundary whose vertical integral is equal to the inflow flux. These two methods must have a predefined depth at the boundary over which to distribute the volume inflow. A more accurate approach is to add an artificial channel to the coastline to give momentum to the flow and initiate mixing between freshwater and saltwater (Lacroix et al., 2004; Sobrinho et al., 2021).

The horizontal distribution of the runoff plays an important role in the regional salinity distribution and in the vertical stratification and mixing (Tseng et al., 2016). Additional subtleties arise for large rivers or deltas, where the coastal source points need to be spread laterally to avoid numerical instabilities if inflow values are locally too large (Polton et al., 2023). In global ocean models, however, freshwater inflow is frequently added at the ocean surface, either as an increased precipitation rate over a specified area or by reducing surface salinity (i.e. a virtual salt flux) rather than being introduced as a lateral inflow at the coastal boundary. This freshwater can be distributed vertically over several layers or diffused horizontally using enhanced mixing (Sun et al., 2017; Tseng et al., 2016; Yin et al., 2010).

Several plume responses may result from the choice of the horizontal and vertical distribution of freshwater input. However, most model applications produce plumes whose types differ from plumes associated with real river discharges (Tseng et al., 2016; Garvine, 2001; Schiller and Kourafalou, 2010). Larger-scale offshore stratification is also expected to be impacted by this choice.

MacCready and Geyer (2010) established the theoretical foundation for estuarine mixing parameterizations, which underpins some physics-based methods used to simulate unresolved estuarine processes in regional and global ocean models, such as the estuary box model (EBM); see, for example, Fig. 1 (Sun et al., 2017). These models attempt to parameterize mixing processes and to account for baroclinic and barotropic flow, typically using a two-layer formulation (e.g. Verri et al., 2020, 2021; Herzfeld, 2015; Rice et al., 2008; Hordoir et al., 2008). From these representations, analytical solutions can be found for the volume fluxes and outflow salinity. Applied globally to the Community Earth System Model (CESM), such an approach revealed substantial localized, regional, and long-range effects when compared to cases without parameterization, highlighting once again the strong sensitivity of ocean models to the treatment of rivers (Sun et al., 2017).

New hybrid approaches, such as Hybrid-EBM (Maglietta et al., 2025; Saccotelli et al., 2024), combine physics-based models with machine learning techniques to predict the salt-wedge intrusion length and salinity at river mouths. Hybrid-EBM outperforms the classical EBM and addresses the shortcomings of the dimensional equations in the physics-based EBM, which rely on several tunable coefficients and require site-specific calibration, by substituting them with machine learning algorithms (Maglietta et al., 2025).

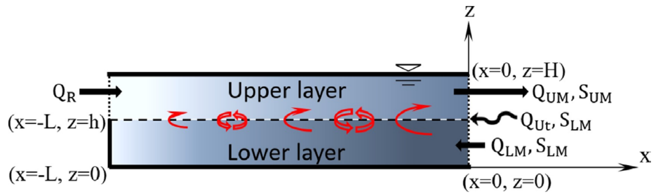


**Figure 1.** Schematic diagram of the estuary box model (EBM) implemented in the Community Earth System Model (CESM) (Sun et al., 2017). The EBM is depicted as a two-layer rectangular box with constant width, uniform local depth ($H$), and a time-varying length ($L$). Each layer has a fixed thickness ($h$ for the lower layer and $H-h$ for the upper layer), with vertically uniform but horizontally variable salinity and density. Thick solid lines represent closed boundaries, dotted lines mark open boundaries, and the dashed line shows the interface between layers. Volume fluxes ($Q$) and salinities ($S$) are indicated by arrows at open boundaries: riverine freshwater discharge ($Q_R$) enters at the estuary head, oceanic saltwater flows into the lower layer at the mouth ($Q_{LM}$), and $Q_{Ut}$ represents the average tidal volume flux during half a tidal cycle, driving net horizontal salt flux into the upper layer at the mouth. Shear-induced turbulent mixing (shown by paired upward and downward open arrows) and upward advection from exchange flow (solid upward arrows) link the upper and lower layers. The colour gradient illustrates salinity variation, from fresher (lighter shades) to saltier (darker shades) waters. Reprinted from Sun et al. (2017, p. 140), © Elsevier Ltd. (2017), with permission from Elsevier.

## 2.3 Freshwater input in high-resolution models: unstructured modelling of the river–sea continuum

In contrast, when the model resolution is higher than the estuary width, the latter can be resolved explicitly by extending the grid for some distance inland using either real bathymetry or a straight channel approximation. When extending it beyond the salinity intrusion limit and/or the head of tides, a freshwater flux can be directly specified at the upstream boundary. This is the preferred option in many east coast US studies (Herzfeld, 2015) (e.g. RISE – Liu et al., 2004; LATTE – Choi and Wilkin, 2007; MerMADE – Hetland and MacDonald, 2008).

The use of unstructured grids offers various advantages, including a more accurate treatment of the freshwater inputs from rivers, a realistic representation of river–sea interactions and estuarine processes at spatial and temporal scales usually not resolved in the ocean, and an improved interface between estuaries and the open ocean, sometimes with higher-order spatial discretizations (Staneva et al., 2025, in this report). In addition, the unstructured grid modelling combined with an efficient vertical coordinate system can better resolve the coastal sea dynamics (Verri et al., 2023).

With seamless grid transitions between models or domains, flexibility and cross-scale capabilities are augmented (Zhang et al., 2016). As examples, a river–coastal-ocean continuum model has been developed for the Tiber River delta, reproducing the coastal dynamic processes better than the classic coastal ocean representation, including the salt-wedge intrusion, and revealing new features near the river mouth induced by river discharge and coastal morphology (Bonamano et al., 2024). In the Columbia River estuary, where both shelf and estuarine circulations are coupled, a multi-scale model has proved to be able to reproduce key processes driving the river plume dynamics in a region characterized by complex bathymetry and marked gradients in density and velocity (Vallaeys et al., 2018). Likewise, Vallaeys et al. (2021) used a similar model in a topographically challenging area of the Congo River estuary, characterized by high river discharge, strong stratification, and great depth. Similarly, Maicu et al. (2021) simulated the circulation in the Goro Lagoon and Po River delta branches using downscaling and a seamless chain of models integrating local forcings and dynamics into a coarser OOFS based on a cascading approach.

While these examples were successful in representing dynamical processes across temporal and spatial scales, in some contexts, the large inward tidal extent and/or complex bathymetries and coastlines, often featuring coastal infrastructure, pose significant challenges for explicitly resolving estuaries, making it impractical in many coastal models. As a result, this approach has yet to become standard practice in OOFSs.

### 2.4 One-way and two-way coupling

Coupling techniques can be used to link two or more models to allow one-way data exchange, for example, between a hydrological model and an ocean model. In this approach, external forcing is reduced to a limited set of variables, simplifying computational requirements but potentially overlooking key processes at the land–sea interface. Additionally, it requires extending the ocean domain boundaries far inland, beyond the limit of tide and storm-surge propagation. While some parameterizations (see Sect. 2.2) or use of unstructured grids (see Sect. 2.3) can partly alleviate these shortcomings, in a compound flooding context, two-way coupled models are preferred because both land and ocean processes can be represented along with their interactions (Bao et al., 2022; Cheng et al., 2010). The inclusion of momentum flux exchanges between land and ocean improves the simulation of estuarine water levels by capturing nonlinear feedbacks between runoff and residual ocean water levels. In a case study of Hurricane Florence, Bao et al. (2022) achieved significant improvement in simulated water levels (20 %–40 % at the head of Cape Fear River estuary) during the post-hurricane period by using a two-way coupled model compared to a stand-alone and linked (one-way coupled) approach.

Alternative approaches for assessing the risk of compound flooding have been proposed, including integrated hydrodynamic and machine learning methods to predict water level dynamics (Sampurno et al., 2022). Such approaches are particularly valuable in data-scarce regions, where developing fully calibrated, computationally intensive models can be impractical or infeasible.

## 3 Data sources

### 3.1 Freshwater discharge

A persistent challenge in OOFSs with respect to river forcing is the lack of a global network for observed river flows to the oceans. While advances are being made in creating such a network, several challenges remain pertaining to data quality, accessibility, and timeliness at the required spatial and temporal scales.

In situ river discharge observations are necessary to build climatologies. They represent a key component of the calibration of hydrological models and thereby of any reanalysis, near-real-time (NRT) analysis, and forecast products. The various types of discharge products used in OOFSs are described in the following.

#### 3.1.1 Climatologies

Most ocean models use climatologies to introduce river forcing based on multi-decadal averages of observed and/or modelled freshwater discharges, along with zero or constant salinity values. Although climatological data are commonly used, even in cases where estuarine dynamics are not explicitly resolved, more realistic volume flux and salinity estimates would improve the modelling of coastal (e.g. river plumes) to basin-wide circulation and dynamics (e.g. dense water formation, overturning circulation cells, water exchange at straits) (Verri et al., 2018), especially during non-seasonal (e.g. storm-induced) events (Chandanpurkar et al., 2022). Moreover, given the global decline of the hydrometric networks, building climatologies is not always possible, especially for small or less-studied rivers and even for large rivers in regions where routine monitoring is absent (Campuzano et al., 2016; Mishra and Coulibaly, 2009). Furthermore, monthly climatological products are not adequate for high-resolution coastal models where temporal variability at daily or even higher frequency is needed (Sotillo et al., 2021a).

#### 3.1.2 River discharge databases

In contrast, river databases and services are progressively becoming available and provide better estimates of coastal runoff and river discharges at the global scale (Sotillo et al., 2021a). These databases typically assemble information from multiple data providers into coherent, gap-free, and quality-controlled datasets. Examples below are categorized by data source.

*In situ databases.*

- The Global Runoff Data Center (https://grdc.bafg.de/, last access: 2 May 2025) (GRDC), under the WMO, archives quality-controlled historical mean daily and monthly discharge data from over 10 000 stations across 159 countries. The Freshwater Fluxes into the World's Oceans (https://fwf.bafg.de/, last access: 2 May 2025) dataset, based on the water balance model WaterGAP, provides annual runoff estimates from 1901–2016.

- The Global Streamflow Indices and Metadata Archive (GSIM) is a collection of metadata and indices derived from more than 35 000 daily streamflow time series worldwide gathered from 12 open databases (7 national and 5 international collections) (Do et al., 2018; Gudmundsson et al., 2018).

- A global dataset of monthly streamflow for 925 of the world's largest rivers connecting to the ocean was built by Dai et al. (2009), updated from Dai and Trenberth (2002).

- A global database of monthly mean runoff for 986 rivers was incorporated in the NCOM, now HYCOM, US model (Barron and Smedstad, 2002). It expands on the work of Perry et al. (1996) with corrections and additions derived from monthly mean streamflow from the U.S. Geological Survey (USGS) (Wahl et al., 1995) and extends the basic RivDIS database (Vörösmarty et al., 1998) to adjust for missing discharge attributed to small (ungauged) rivers.

*Model-derived databases.*

- A 35-year daily and monthly global reconstruction of river flows (GRADES) at 2.94 million river reaches, with bias correction from machine-learning-derived global runoff characteristics maps, was developed in support of the Surface Water and Ocean Topography (SWOT) satellite mission (Lin et al., 2019).

- A dataset of historical river discharge from 1958 to 2016 was created using the CaMa-Flood global river routing model and adjusted runoff from the land component of JRA-55 (Suzuki et al., 2018; Tsujino et al., 2018).

- A global freshwater budget is included in the CORE.v2 datasets that have an accompanying database for continental runoff from rivers, groundwater, and icebergs. These are estimated from continental imbalances between precipitation, evaporation, and storage and then distributed between bordering ocean basins based on river routing schemes and flow estimates (Large and Yeager, 2009).

*Hybrid database.*

- EMODnet Physics (https://emodnet.ec.europa.eu/geoviewer/, last access: 2 May 2025) provides ocean physics data and data products built with common standards, consisting of collections of in situ data, reanalysis, and aggregated in situ data and model outputs. As part of the available parameters, the operational river runoff data include near-real-time data from European river stations and a subset of the GRDC focusing on coastal areas and stations located near river mouths, which extend beyond European borders. About 1200 rivers worldwide are connected and operationally available.

*Satellite-derived database.*

- The largest known dataset compiles publicly available river gauge data, with satellite-based rating curves used to fill in the temporal gaps (Riggs et al., 2023).

Regional databases also exist, such as

- long-term (1993–2011) satellite-derived estimates of continental freshwater discharge into the Bay of Bengal (Papa et al., 2012)

- a database of pan-Arctic river discharge (R-Arcticnet, https://www.r-arcticnet.sr.unh.edu/v4.0/index.html, last access: 2 May 2025)

- a database for Greenland liquid water discharge from 1958 through 2019 (Mankoff et al., 2020)

- a river discharge climatology and corresponding historical time series for all rivers flowing into the Adriatic Sea with an average climatological daily discharge exceeding 1 $m^3 s^{-1}$ (Aragão et al., 2024).

Of particular importance is the fact that some of these databases use model-simulated runoff ratios (e.g. from Community Land Model (CLM) or river routing model) over gauged and ungauged drainage areas to estimate the contribution from the areas not monitored by the hydrometric network and adjust the station flow to represent river mouth outflow (e.g. Dai et al., 2009). This allows more precise derivation of the total discharge into the global oceans through the sum of both gauged and ungauged discharges.

Unless explicitly stated (e.g. for EMODnet Physics), most of these databases lack clearly stated update schedules; some remain static, while others update at irregular intervals. Such databases are useful in the context of a reanalysis but less so in an operational context where near-real-time data feeds are required. Furthermore, a detailed comparative assessment of these various data sources is still lacking.

Alternatively, indirect approaches using tidal statistics at the estuarine entrance from tidal stations rather than direct flow measurements have been developed to estimate the net freshwater discharge at the mouth of an estuary, with the advantage of integrating processes at the basin scale, downstream of the last hydrometric station (Moftakhari et al., 2013, 2016). Because tide gauge records at the coasts were often installed well before the onset of systematic river gauging (Talke and Jay, 2013), such inverse techniques make it possible to extend flow records back in time.

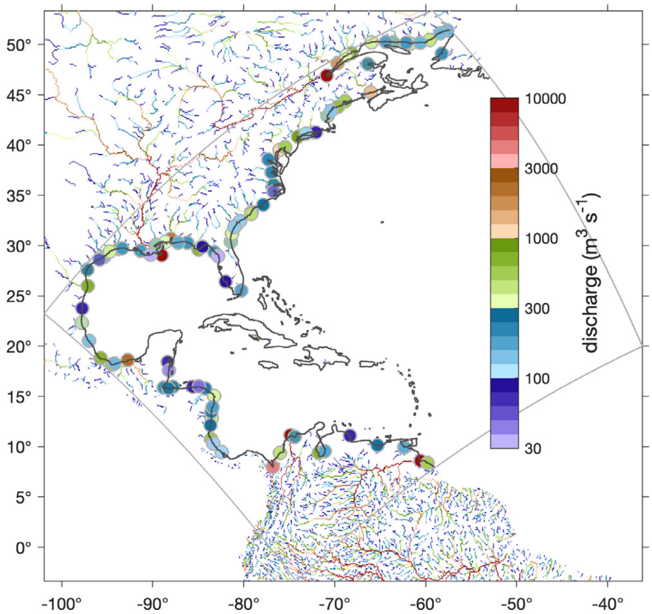


**Figure 2.** Annual mean surface water discharge (m$^3$ s$^{-1}$) in 0.1° × 0.1° cells of the GloFAS analysis from Harrigan et al. (2020) for the year 2023. Filled circles show the locations of 93 point sources in the prototype East Coast Community Ocean Forecast System (ECCOFS) ROMS model (domain denoted by the gray perimeter box) associated with GloFAS points near the coast that have long-term mean (2009–2019) discharge exceeding 50 m$^3$ s$^{-1}$. River networks come from GloFAS.

### 3.1.3 Operational river discharge products

While most river discharge databases are static, operational products have been developed for near-real-time applications. For example, the Global Flood Awareness System, GloFAS-ERA5, is an operational global river discharge reanalysis produced consistently with the ECMWF ERA5 atmospheric reanalysis and providing global gridded data products from 1979 to near-real time (within a 7 d delay) (Harrigan et al., 2020). Figure 2 illustrates the resolution of the river network that emerges in the GloFAS gridded data and the association of discharge at the coast to point sources in a regional model of the northwest Atlantic Ocean that is in development for future operations.

Several centers are also producing continental- and global-scale hydrological (ensemble) forecasts operationally: the European Flood Awareness System (EFAS) (Thielen et al., 2009), the European Hydrological Predictions for the Environment (E-HYPE) (Donnelly et al., 2015), the Hydrologic Ensemble Forecast System (HEPS) in the US (Demargne et al., 2014), the Flood Forecasting and Warning Service (FWWS) in Australia, the National Surface and River Prediction System (NSRPS) in Canada (Fortin et al., 2023), and globally World-Wide HYPE (WWH) (Arheimer et al., 2020) and GloFAS (Harrigan et al., 2023). Notably, as part of the GloFAS service evolution, global daily ensemble river discharge reforecasts (20-year) and real-time forecast (2020–present) datasets are made freely and openly available through the Copernicus Climate Change Service (C3S) Climate Data Store (CDS) (Harrigan et al., 2023).

Other projects have been supported by the Copernicus Marine Environment Monitoring Service (CMEMS): for example, the LAMBDA project regionally focused on the European Atlantic façade and the North Sea. The resulting freshwater model estimates and in situ observations are operationally updated and made available via the project viewer web interface (http://www.cmems-lambda.eu/home.html, last access: 2 May 2025; Sotillo et al., 2021a).

The FOCCUS project (Forecasting and Observing the Open-to-Coastal Ocean for Copernicus Users; https://foccus-project.eu/, last access: 2 May 2025) further enhances operational hydrological models by addressing the land–ocean continuum through improved river runoff estimations and the development of advanced coupling between hydrological and coastal ocean models. FOCCUS builds on existing pan-European hydrological frameworks, such as E-HYPE and LISFLOOD, to provide dynamic freshwater inputs, including nutrient and inorganic matter transport. Additionally, the project integrates novel AI techniques to optimize estuarine modelling and freshwater forcing for coastal systems. These innovations directly contribute to refining CMEMS and supporting all European coastal services with more accurate and seamless coastal monitoring and forecasting capabilities.

In some instances, the regional products may appear to be the preferred option for some regional or local studies, as they were designed to specifically represent the hydrological characteristics of a given region, sometimes with higher resolution and accuracy. However, a global solution is attractive in data-scarce areas and where consistency between discharge products and across all forcing variables is required over large domains (Polton et al., 2023).

### 3.1.4 Remotely sensed discharges

Remote sensing of river discharge is a rapidly advancing research field (see Gleason and Durand, 2020, and references therein). With the SWOT satellite launched in December 2022, global discharge products will soon be available at a nominal resolution of 10 km for river reaches wider than 100 m, thus vastly expanding measurements of global rivers in both gauged and ungauged basins (Durand et al., 2023). Significant improvements in global uncalibrated models are expected (Emery et al., 2018). SWOT-derived discharge data are expected to improve global hydrological cycle representation and enhance ocean model solutions near the coast.

### 3.1.5 Machine-learning-derived discharge estimates

Machine learning is increasingly used in hydrology for rainfall runoff modelling, with long short-term memory (LSTM) networks (Greff et al., 2017; Hochreiter and Schmidhuber, 1997) proving particularly effective in capturing both periodic and chaotic patterns in time-series data while accurately learning long-term dependencies (Fang et al., 2017a; Hu et al., 2019; Mouatadid et al., 2019). In numerous hydrological studies, LSTM has demonstrated superior performance over traditional process-based models in simulating runoff, primarily in data-rich regions (Feng et al., 2020, 2021a; Frame et al., 2022; Gauch et al., 2021; Hunt et al., 2022; Konapala et al., 2020; Kratzert et al., 2019; Lees et al., 2021; Li et al., 2023; Luppichini et al., 2024; Nearing et al., 2021; Reichstein et al., 2019). However, limited efforts have explored the transferability of LSTM models to data-scarce regions (e.g. Akpoti et al., 2024), with Ma et al. (2021) and Muhebwa et al. (2024) (and references therein) being examples of such exceptions. Recently, researchers have explored the potential of LSTM models for global river discharge estimations (Rasiya Koya and Roy, 2024; Tang et al., 2023; Yang et al., 2023; Zhao et al., 2021). However, extensive validation beyond the training basins is required to fully evaluate their suitability for global-scale implementations.

### 3.2 Salinity and temperature

Estuarine mixing influences salinity distribution and its seasonal variability near river mouths (Sun et al., 2019). Models are particularly sensitive to salinity in shelf areas and ROFI zones, most often due to the diverse treatment of OOFSs given to coastal and river freshwater forcing (Sotillo et al., 2021a). Therefore, to assess the impact of a chosen formulation and evaluate model performances, sea surface salinity (SSS) and temperature (SST) are typically used. The World Ocean Atlas climatology (Locarnini et al., 2013; Zweng et al., 2013) often overestimates nearshore salinity, making it unsuitable for model evaluation in coastal regions. As an alternative, Sun et al. (2019) built on the original World Ocean Database and developed an improved salinity and temperature climatology with an enhanced representation of the coastal ocean. In situ data and satellite observations from SMOS, Aquarius, and SMAP (Bao et al., 2019) can also be used to assess the impact of river forcing on sea surface salinity (Feng et al., 2021b). However, seasonal variability in the skill of SSS retrievals can be associated with SST-dependent bias and strong land–sea differences in microwave emissivity, making satellite observations unreliable within some 70 km of the coast (Grodsky et al., 2018; Menezes, 2020; Vazquez-Cuervo et al., 2018). Higher-resolution coastal satellite products have been developed based on empirical relationships between local salinity and ocean colour observations (Geiger et al., 2013; Chen and Hu, 2017), using deep neural networks trained on Sentinel-2 Level-1C top-of-atmosphere (TOA) reflectance data (Medina-Lopez and Ureña-Fuentes, 2019; Medina-Lopez, 2020) or by relating the reflectance of the visible bands from Sentinel-2 imagery with electrical conductivity, influenced by the concentration and composition of dissolved salts (Sakai et al., 2021), although these are not applied globally.

A recent study in the German Bight (Thao et al., 2024) demonstrated the critical role of high-resolution salinity inputs at estuarine mouths in improving the predictive capabilities of coupled wave–ocean models. Using GCOAST (Geesthacht Coupled cOAstal model SysTem), which seamlessly integrates estuarine and coastal dynamics with regional ocean models, researchers validated salinity and temperature fields against in situ observations. The results highlighted that estuarine inflows significantly enhance the accuracy of coastal ocean models.

Alternatively, salinity predictions in estuaries and at river mouths have been successfully estimated using machine learning approaches. A few examples can be found in the recent literature: Qiu and Wan (2013) developed an autoregressive model relating salinity at a given time to past observations of salinity and physical drivers (freshwater inflow, rainfall, tidal elevation) in the Caloosahatchee River estuary; Fang et al. (2017b) used a genetic algorithm coupled with a support vector machine to predict salinity in the Min River estuary; Qi et al. (2022) applied four neural network models to emulate salinity simulations in the Sacramento–San Joaquin Delta from a process-based river, estuary, and land modelling system; Guillou et al. (2023) were able to reproduce the seasonal and semi-diurnal variations in sea surface salinity at the mouth of the Elorn estuary (Bay of Brest), with support vector regression performing best among all tested algorithms.

Despite these advancements, sustained high-resolution salinity monitoring is needed to build confidence in numerical solutions near the coast. Integrating salinity, temperature, and additional parameters such as nutrients and sediments directly into river outflows could further improve model accuracy (Verri et al., 2018; Thao et al., 2024). While these factors play a secondary role in influencing oceanographic processes, their inclusion could advance research on coastal hypoxia, carbon cycling, and regional weather and climate, ultimately supporting seamless predictions of land–ocean–atmosphere feedbacks in next-generation Earth system models (Feng et al., 2021b).

## 4 Examples of current OOFSs

This section describes how river forcing is implemented in current OOFSs. The objective is to get a picture of the current landscape of approaches and data sources. While Cirano et al. (2025, in this report) provide a comprehensive overview of existing OOFSs worldwide, the representation of rivers in these systems remains poorly documented and often buried in model configuration files. The list of systems presented in Appendix A is therefore not exhaustive and is limited to a compilation of comments received as part of a survey con-

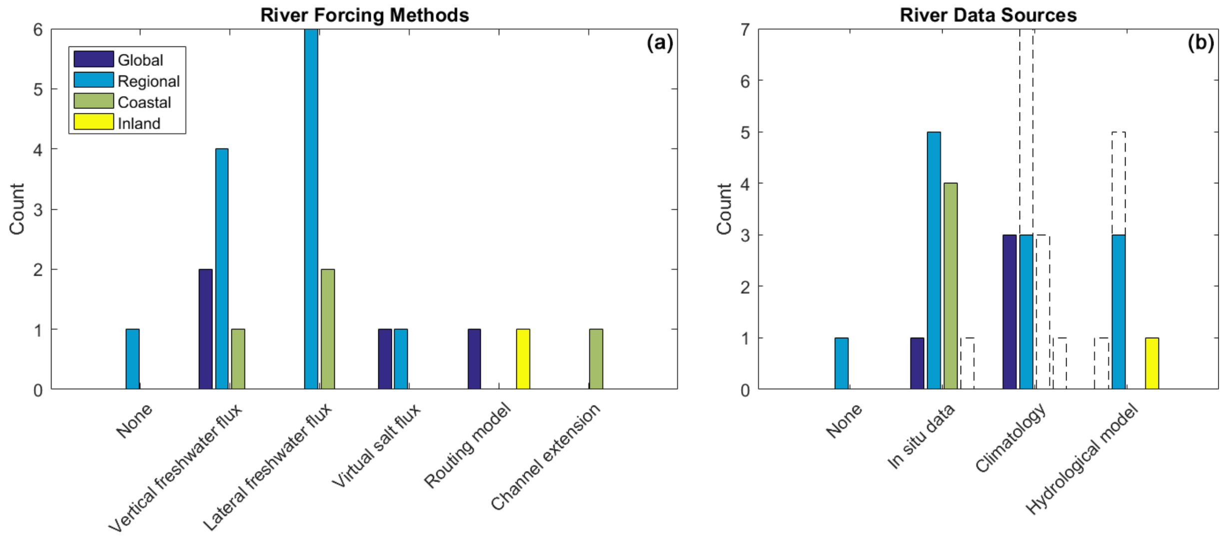


**Figure 3.** Graphical summary from a survey on river forcing methods **(a)** and data sources **(b)** used in global, regional, coastal, and inland OOFSs listed in Appendix A. Coloured bars indicate the primary data sources or methods, whereas dashed bars represent secondary data sources used as a fallback when primary sources are unavailable.

ducted among members of the OceanPredict community in May 2023. It is meant to illustrate the diversity of methods employed for treating freshwater fluxes in OOFSs and associated input data sources in 4 global, 12 regional, 4 coastal, and 1 inland systems. Although the survey covers a limited number of systems, the literature review in previous sections offers additional examples to complete the picture.

Figure 3 provides a graphical summary of the six river forcing methods and four data sources used in the OOFSs listed in Appendix A. In terms of river forcing methods, most systems specify vertical or lateral freshwater fluxes to account for riverine inputs. Only a few of them rely on more sophisticated approaches that use channel extensions within the ocean model or routing schemes from hydrological models to transport the water from the watershed to the coast. Furthermore, none of the global systems surveyed use lateral boundary conditions, likely due to insufficient spatial resolution near river mouths.

In terms of the data sources used in OOFSs, what stands out from the survey is the use of in situ data as a primary source in most systems and climatology as either a primary or a fallback source of freshwater discharge. Global systems tend to opt for climatologies in comparison with regional or coastal systems that favour observed data when available, which allows both seasonal and non-seasonal events and their potential local or regional impacts to be captured. Only a few regional and inland systems use hydrological models or reanalyses as primary data sources.

Additional considerations were also highlighted by the respondents, essential for appropriately representing river inflow in ocean models and addressing challenges such as numerical instabilities and data limitations. For example, spatial smoothing around the river source or, equivalently, optimizing the integration distance for equivalent coastal precipitation may be required to prevent numerical instabilities. Similarly, an increased diffusivity within the surface mixing layer can be implemented to simulate the effects of river inflow. Salinity and temperature of the input freshwater can be set either to zero and to the local SST, respectively, or derived from a combination of real-time gauge data and monthly averages when available. For ungauged areas, river gauge data can be scaled, or additional coastal runoff can be incorporated. In contrast, some systems directly convert precipitation data into river discharges, disregarding hydrological processes and assuming an instantaneous response.

In sum, the representation of rivers in OOFSs requires careful consideration of various numerical methods, data sources, and modelling approaches. However, some simplifications may limit accuracy in applications requiring high regional precision.

## 5 Summary and recommendations

The assessment of river forcing implementation in OOFSs highlights the complexity and challenges of accurately integrating riverine freshwater discharges into ocean models. Despite the growing demand for operational oceanographic products, especially in coastal areas (Ciliberti et al., 2023), OOFS river forcing still faces shortcomings related to the representation of physical processes, data availability, and data quality. The parameterization of river inputs and the interaction between model components, often nonlinear, remain unresolved issues, underscoring the absence of standardized practices for river forcing. Addressing these gaps requires advancements in model physics; improved spatial and temporal resolution; and enhanced coupling between land, ocean, and atmosphere. Furthermore, the incorporation of river flow varies regionally, largely due to differences in the availability and quality of river discharge, salinity, and bathymetric datasets, and is further influenced by model scale and resolution. As the demand for reliable coastal forecasts grows, real-time, high-quality river discharge data become increasingly pressing. Standardized methodologies and improved integration of riverine parameters – including salinity, temperature, and biogeochemical components – will facilitate seamless watershed–ocean coupling and improve predictions of coastal dynamics, particularly under extreme conditions.

Service evolution roadmaps, such as those outlined by CMEMS, emphasize the need for a better characterization of coastal freshwater exchanges to improve forecasts, especially during severe weather events (Sotillo et al., 2021b). A key step forward involves the progressive replacement of static climatologies with real-time, updated time series (past, present, and forecasts) of river inputs, covering both major and minor or ephemeral streams. Recommendations have been made towards standardized freshwater inputs (and associated river inputs of nutrients and sediment loading), harmonized river forcing approaches, and a more integrated watershed–ocean strategy (Campuzano et al., 2016; Capet et al., 2020; Sobrinho et al., 2021). Additionally, ensuring validated observational error estimates for estuary-mouth forcing, including river discharge and auxiliary variables such as coastal salinity, is crucial for model accuracy (De Mey-Frémaux et al., 2019; Polton et al., 2023). Improved interfaces between coastal monitoring and modelling systems are therefore essential. The FOCCUS project exemplifies progress in addressing these challenges through advancements in hydrological and estuarine modelling, dynamic freshwater inputs, and the integration of AI-driven tools to refine river discharge estimations and coastal system forecasts.

Future efforts must focus on refining model physics, resolution, and coupling strategies to better integrate the land–ocean continuum. Standardized methodologies and integrated high-quality data sources, together with continued interdisciplinary collaboration and technological advancements, will be key to overcoming existing limitations and ensuring more accurate and reliable ocean predictions. Such efforts are critical for improving predictions of coastal dynamics and for fostering a deeper understanding of their implications on global climate and ecosystem functioning.

## Appendix A: Survey on river forcing methods and data sources in current OOFSs

This appendix presents results of a survey conducted among members of the OceanPredict community in May 2023. The responses are reported in the following tables as given by the participants; nearly no changes were made to each contributed entry, except for a few added references and acronym definitions.

## A1 Global systems

**Table A1.** Examples of river forcing methods and data sources in global OOFSs.

| System | Institution | Domain(s) | Resolution | Circulation model | Method for river forcing | Data sources |
|---|---|---|---|---|---|---|
| MOVE/MRI.COM-G3[a] (Multivariate Ocean Variational Estimation/Meteorological Research Institute Community Ocean Model – Global version 3) | Japan Meteorological Agency's (JMA) Meteorological Research Institute | Global | 1/4° | MRI.COM Ver. 4 | River discharge is expressed as a part of the surface freshwater. | Climatology of JRA55-do river runoff data. |
| GEOS[b] (NASA Goddard Earth Observing System) | NASA's Global Modeling and Assimilation Office | Global | 4–25 km | MOM6 | GEOS-land component runoff, routed to catchments. | In situ data, land/catchment model. |
| RTOFSv2[c] (Real-Time Ocean Forecast System) | NOAA's National Centers for Environmental Prediction | Global | 0.08° | HYCOMv2.2 | Rivers are implemented as virtual salt flux at the ocean surface. River runoff is distributed over several ocean grid points around the river source by applying spatial smoothing to spread out the effect of the river and prevent negative salinities due to numerical overshooting. To mimic the river inflow, river freshwater is mixed from the surface down to a depth specified by the user (set to 6 m in RTOFS). In the grid cells with not-zero river runoff and in the upper layers, river freshwater is mixed within increased vertical diffusivity. Alternatively, rivers can be added directly to the input precipitation fields, which is a better option for higher-frequency (than monthly) river flow data. It is possible to treat rivers (as well as evaporation minus precipitation, $E-P$) as a mass exchange (not activated in RTOFS). | RTOFS uses the global climatology of monthly mean river discharge created at the Naval Research Laboratory (NRL) (Barron and Smedstad, 2002). It provides monthly runoff for 986 rivers. The dataset is based on the Perry et al. (1996) data with corrections and additions derived from (1) monthly mean streamflow over all years, accessible from the USGS (Wahl et al., 1995); (2) the Global River Discharge (RivDIS) database (Vörösmarty et al., 1998); and (3) the Regional, Hydrometeorological Data Network (R-Arcticnet[d]) database providing most of the information ultimately used on rivers flowing into the Arctic, primarily rivers in Russia and Canada. |
| FOAM-CPL-NWP[e] (Forecast Ocean Assimilation Model, Coupled Numerical Weather Prediction | UK Met Office | Global | 1/4° | NEMO v3.6 | Freshwater runoff from land is input in the surface layer of the ocean with the assumption that the runoff is fresh and at the same temperature as the local sea surface temperature. An enhanced vertical mixing of $2\times10^{-3}\,m^2\,s^{-1}$ is added over the top 10 m of the water column at runoff points to mix the runoff vertically and avoid instabilities associated with very shallow fresh layers at the surface (Storkey et al., 2018). | Climatological river runoff fields were derived by Bourdallé-Badie and Treguier (2006) based on estimates given in Dai and Trenbert (2002; Blockley et al., 2014). |

[a] https://ds.data.jma.go.jp/wmc/products/elnino/move_mricom-g3_doc.html (last access: 2 May 2025). [b] https://gmao.gsfc.nasa.gov/GEOS_systems/ (last access: 2 May 2025).
[c] https://polar.ncep.noaa.gov/global/about/ (last access: 2 May 2025). [d] http://www.r-arcticnet.sr.unh.edu/ (last access: 2 May 2025). [e] https://www.metoffice.gov.uk/services/data/met-office-data-for-reuse/model (last access: 2 May 2025).

## A2 Regional systems

**Table A2.** Examples of river forcing methods and data sources in regional OOFSs.

| System | Institution | Domain(s) | Resolution | Circulation model | Method for river forcing | Data sources |
|---|---|---|---|---|---|---|
| MOVE/MRI.COM-NP/JPN[a] (Multivariate Ocean Variational Estimation/ Meteorological Research Institute Community Ocean Model – North Pacific/ Japan) | Japan Meteorological Agency (JMA)'s Meteorological Research Institute | North Pacific | 2–10 km | MRI.COM Ver. 5 | River discharge is expressed as a part of the surface freshwater | Climatology of JRA55-do river runoff data |
| TOPAZ[b] | Norwegian's Nansen Environmental and Remote Sensing Center (NERSC) | Arctic and Nordic seas | 12 km | HYCOM | Removal of salt from the surface (an ellipse around the river mouth) and barotropic water flux. We use nutrients (N, P and Si) from the globalNEWS model and scale them by river discharge. | Swedish Meteorological and Hydrological Institute (SMHI) (Arctic-HYPE and E-HYPE), GRACE satellite for Greenland mass loss and a homemade climatology for Greenland surface mass balance. |
| eSA-Marine[c] | South Australian Research and Development Institute | South Australian gulfs and shelf | 2.5 and 0.5 km | ROMS | None, intermittent river input is usually weak to non-existent. | None. |
| DMI HYCOM-CICE[d] | Danish Meteorological Institute (DMI) | Arctic and Atlantic oceans | 4–10 km: $\sim$ 5 km throughout Arctic and northern Atlantic | HYCOM + CICE fully coupled using Earth System Modeling Framework (ESMF) coupler. CICE runs on a subset of the full HYCOM domain | River forcing is converted to monthly mean precipitation equivalents [$m\,s^{-1}$] for $\sim$ 50 000 river runoff outlets and distributed to the nearest coastal model grid point(s) (Ponsoni et al., 2023). | River forcing is taken from various sources using a dataset from the Geological Survey of Denmark and Greenland (Mankoff et al., 2020), converted to monthly mean precipitation equivalents [$m\,s^{-1}$]. |
| DKSS[e] (Danish Storm Surge System) | Danish Meteorological Institute | North Sea–Baltic Sea, with multiple nested subdomains | 3 nmi (nautical miles; coarsest) to 0.1 nmi (finest) | HBM (HIROMB Baltic Model) | River forcing is treated as a freshwater flux into coastal grid cells. Water temperature equal to receiving cell (river temperature data not used) with 0 °C as lower limit to avoid instantaneous freezing. | European hydrological model E-HYPE3, from which an annual plus a calendar day $\sim$ 30-year climatology has been derived and used as a back-up for a daily forecast. The forecast model is run by the Swedish Hydrological and Meteorological Institute, and the day-to-day service comes with an annual fee. |
| IBI Near-Real-Time[f] | Iberia Biscay Irish (IBI) Sea – Monitoring Forecasting Center | European Atlantic façade (the Iberia–Biscay–Ireland zone). Lat: from 26 to 56° N; long: from 19° W to 5° E | 1/36°, surface and 3D fields (50 vertical levels) | NEMO v3.6 | Freshwater river discharge inputs are implemented as lateral open boundary conditions for the main 33 rivers of the IBI area. The system also incorporates an extra coastal runoff rate (derived from the Dai and Trenberth, 2002, climatology, on a monthly basis), which makes the IBI forcing consistent with the ones imposed in the parent Copernicus Marine GLOBAL system. | Data come from different sources, depending on their availability, in the following order: (1) model data taken from the SMHI hydrologic model; (2) monthly climatological data taken from GRDC, French "Banque Hydro"[g] dataset, Copernicus Marine Service, and EMODnet. |

**Table A2.** Continued

| System | Institution | Domain(s) | Resolution | Circulation Model | Method for river forcing | Data sources |
|---|---|---|---|---|---|---|
| IBI Multi-Year[h] | Iberia Biscay Irish (IBI) Sea – Monitoring Forecasting Center | European Atlantic façade (the Iberia–Biscay–Ireland zone). Lat: from 26 to 56° N; long: from 19° W to 5° E | 1/12°, surface and 3D fields (50 vertical levels) | NEMO v3.6 | Same as IBI-NRT, but with an additional river (LAGAN) | Data come from different sources, depending on their availability, in the following order: (1) in situ data – daily measurements from Copernicus Marine Service, EMODnet, or national web sites; (2) model data – SMHI hydrologic model. |
| CBEFS[i] (Chesapeake Bay Environmental Forecast System) | Virginia Institute of Marine Science | Chesapeake Bay | 600 m × 600 m | ROMS | Freshwater: real-time USGS river gauge data are scaled to better represent total freshwater inflows over a larger area based on a watershed model. The scaled discharge is then disaggregated into the main river inflow and smaller streams based on proportions developed from the watershed model. The forecast is a simple autoregressive model based on the past few days.<br>Riverine biogeochemistry: inputs are specified using artificial neural network AI models based on the discharge and date, which recreate what the watershed model would have predicted had the current and forecast conditions been simulated by the watershed model.<br>Temperature: water temperature is specified using a combination of real time gauge data and monthly averages depending on what is available. | In situ gauge data. Hindcast watershed model information. Artificial neural networks. |
| DREAMS[j] (RIAM Real-Time Ocean Forecasting) | Kyushu University's Research Institute for Applied Mechanics (RIAM) | East Asian marginal seas | 0.3–22 km | RIAM Ocean Model | Coastal precipitation is directly converted into the amount of river discharges. The integration distance was optimized by using model Green's functions (Hirose, 2011). | Grid point value (GPV) precipitation data of Japan Meteorological Agency (JMA) |

**Table A2.** Continued

| System | Institution | Domain(s) | Resolution | Circulation Model | Method for river forcing | Data sources |
|---|---|---|---|---|---|---|
| FOAM-AMM15[k] (Forecast Ocean Assimilation Model – Atlantic Margin model 1.5 km) | UK Met Office | Northwest European shelf seas | 1.5 km | NEMO v3.6 | For each river input location, a daily freshwater flux is assigned, with depth determined by the average ratio of runoff to tidal range (as per the estuary classifications of Cameron and Pritchard, 1963). The runoff temperature is assumed to align with the local sea surface temperature (SST), as the climatology does not include temperature data (Graham et al., 2018). | River runoff is primarily derived from a daily climatology of gauge measurements averaged for 1980–2014. UK data were processed from raw data provided by the Environment Agency, the Scottish Environment Protection Agency, the Rivers Agency (Northern Ireland), and the National River Flow Archive (gauge data were provided by Sonja M. van Leeuwen, CEFAS, Lowestoft, UK, personal communication, 2016). For major rivers that were missing from this dataset (e.g. along the French and Norwegian coasts), data have been provided from an earlier climatology (Vörösmarty et al., 2020; Young and Holt, 2007), based on a daily climatology of gauge data averaged for the period 1950–2005 (Tonani et al., 2019). |
| FOAM-AMM7[l] (Forecast Ocean Assimilation Model– Atlantic Margin model 7 km) | UK Met Office | Northwest European shelf seas | 7 km | NEMO v3.6 (coupled to ERSEM 20.10 for biogeochemistry) | For each river input location, a daily freshwater flux is assigned, with depth determined by the average ratio of runoff to tidal range (as per the estuary classifications of Cameron and Pritchard, 1963). The runoff temperature is assumed to align with the local sea surface temperature (SST), as the climatology does not include temperature data (Graham et al., 2018). | Daily time series of river discharge, nutrient loads (nitrate, phosphate, silicate, ammonia), alkalinity (bioalkalinity, dissolved organic carbon), and oxygen were produced from an updated version of the river dataset used in Lenhart et al. (2010), combined with climatology of daily discharge data from the Global River Discharge Database (Vörösmarty et al., 2020) and from data prepared by the Centre for Ecology and Hydrology as used by Young and Holt (2007). The climatology has an annually varying component until 2018 to account for historic changes in nutrient loads, and values for 2018 are used as a climatology in the operational system (Kay et al., 2020). |
| DOPPIO[m] and MARACOOS[n] (Mid-Atlantic Regional Association Coastal Ocean Observing System) | Rutgers University | Northeast USA and Nova Scotia, Canada | 7 km | ROMS | Discharge is introduced as volume flux divergence (method LwSrc in ROMS) at 27 point sources in model cells adjacent to the coast. | Daily USGS discharge data are scaled for ungauged portions of the watershed based on the statistics of a 10-year hydrological model analysis. |

[a] https://www.data.jma.go.jp/kaiyou/data/db/kaikyo/knowledge/move_jpn/system.html (last access: 2 May 2025). [b] https://nersc.no/en/products-and-services/analysis-tools-and-models/ocean-models/ (last access: 2 May 2025).
[c] https://pir.sa.gov.au/research/services/esa_marine/about_esa-marine (last access: 2 May 2025). [d] https://ocean.dmi.dk/models/hycom.uk.php (last access: 2 May 2025).
[e] https://opendatadocs.dmi.govcloud.dk/Data/Forecast_Data_Storm_Surge_Model_DKSS#:~:text=DKSS%20is%20DMI%27s%20forecast%20model,ice%20thickness%20and%20ice%20concentration (last access: 2 May 2025).
[f] https://marine.copernicus.eu/about/producers/ibi-mfc (last access: 2 May 2025). [g] http://www.hydro.eaufrance.fr/ (last access: 2 May 2025). [h] https://marine.copernicus.eu/about/producers/ibi-mfc.
[i] https://www.vims.edu/research/products/cbefs/ (last access: 2 May 2025). [j] https://dreams-c1.riam.kyushu-u.ac.jp/vwp/ (last access: 2 May 2025).
[k] https://www.metoffice.gov.uk/services/data/met-office-data-for-reuse/model. [l] https://www.metoffice.gov.uk/services/data/met-office-data-for-reuse/model. [m] López et al. (2020).
[n] https://maracoos.org/ (last access: 2 May 2025).

## A3 Coastal systems

**Table A3.** Examples of river forcing methods and data sources in coastal OOFSs.

| System | Institution | Domain(s) | Resolution | Circulation model | Method for river forcing | Data sources |
|---|---|---|---|---|---|---|
| DFO's Port Ocean Prediction Systems[a] | Government of Canada's Department of Fisheries and Oceans (DFO) | Kitimat Fjord, Vancouver Harbour, lower Fraser River, St. Lawrence Estuary, Port of Canso, Saint John Harbour | 20–200 m | NEMO 3.6 | NEMO's runoff feature for some rivers, and a SSH open boundary condition for others | Gauge data (from Environment and Climate Change Canada, ECCC) where available, climatology elsewhere |
| CIOPS[b] (Coastal Ice-Ocean Prediction System) | Environment and Climate Change Canada (ECCC) | Canadian East and West coasts (CIOPS-E, CIOPS-W), Salish Sea (SalishSea500) | $1/36° +$ 500 m for Salish-Sea500 | NEMO 3.6 | Same as DFO port models | Gauge data for Fraser River, climatology elsewhere |
| FANGAR BAY[c] | Universitat Politècnica de Catalunya | Ebro Delta | 350 m/70 m | COAWST (ROMS/SWAN) | Climatological freshwater from Ebro River | In situ data |
| NARF[d] (Northern Adriatic Reanalysis and Forecasting system) | Istituto Nazionale di Oceanografia e di Geofisica Sperimentale | Northern Adriatic Sea (Mediterranean Sea) | $1/128°$ ($\sim 750$ m) | MITgcm-BFM (coupled hydrodynamic–biogeochemical) | The downstream end of the rivers flowing into the basin is simulated as a narrow channel: one or two cells in the horizontal direction and a few vertical levels. Freshwater discharge rates from NRT data or climatologies are converted into horizontal velocities (the section of the riverbed is known) and applied as lateral open boundary conditions. Salinity is constant (5 PSU), temperature has a yearly sinusoidal cycle (maxima and minima in summer and winter, respectively), and biogeochemical concentrations are derived from the literature/climatologies. | In situ NRT discharge data for the Po River (main contributor) and climatologies for the others (with sinusoidal modulation: maxima in spring and fall, minima in summer and winter). Daily frequency. |

[a] https://publications.gc.ca/site/eng/9.905464/publication.html (last access: 2 May 2025). [b] https://eccc-msc.github.io/open-data/msc-data/nwp_ciops/readme_ciops_en/ (last access: 2 May 2025).
[c] López et al. (2024). [d] https://medeaf.ogs.it/got (last access: 2 May 2025).

## A4 Inland systems

**Table A4.** Example of river forcing methods and data sources in inland OOFSs.

| System | Institution | Domain(s) | Resolution | Circulation Model | Method for river forcing | Data sources |
|---|---|---|---|---|---|---|
| WCPS* (Water Cycle Prediction System) | Environment and Climate Change Canada (ECCC) | Great Lakes and northwest Atlantic (NWA) | 1/36° + 1 km | NEMO 3.6 | Fully coupled hydrologic model for Great Lakes, climatology for NWA | Hydrological model uses gauge data |

* https://eccc-msc.github.io/open-data/msc-data/nwp_wcps/readme_wcps_en/ (last access: 2 May 2025).

**Data availability.** No datasets were used in this article.

**Author contributions.** PM: conceptualization, investigation, writing (original draft preparation), writing (review and editing). JW: writing (review and editing). JS: writing (review and editing).

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** The authors wish to thank Kristen Wilmer-Becker and members of the OceanPredict community who participated in the survey conducted in May 2023 on the status of the implementation of river forcing in current OOFSs, as well as three anonymous reviewers for their constructive comments on this paper.

**Review statement.** This paper was edited by Stefania Angela Ciliberti and reviewed by three anonymous referees.

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State Planet, 5-opsr, 20, 2025
https://doi.org/10.5194/sp-5-opsr-20-2025






# Towards Earth system modelling: coupled ocean forecasting

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Received: 13 September 2024 – Discussion started: 27 September 2024
Revised: 25 January 2025 – Accepted: 28 January 2025 – Published: 2 June 2025

**Abstract.** Forecasting across different Earth system components has initially been achieved independently, but increasing computer power, increasing model accuracy, increasing connectivity between experts, and increasing need for multi-hazard weather warning is changing the scene. Coupling methods, which involve exchanging information between discrete modelling systems, enable us to gain accuracy and consistency across Earth system components. This paper explains the principles of two-way coupling, where models run simultaneously and exchange information both ways. As individual models reach better accuracy, coupling becomes a key factor to improve forecasting capability because it reproduces the natural complexity of the environment: a wealth of literature shows the benefits of coupling. However, coupling is still limited in operational oceanography by its large demands on computational resources, by data assimilation techniques (currently not very well harmonised between the different models), and by administrative separation of forecasts across different Earth system components. Overcoming these barriers will support ocean predictions towards a multi-hazard approach and a more accurate representation of the Earth system component interactions and improve collaborations between multidisciplinary forecasting communities.

## 1 Introduction

Coupling can be loosely defined as the process of exchanging information between discrete modelling systems, generally of components of the Earth system, to better represent exchange processes (Shapiro et al., 2010). The number of components of a coupled system, and indeed the level of coupling between the components, varies depending on the application. Coupled global climate models (GCMs) generally include the ocean, ice, atmosphere, and land surface. Increasingly, surface waves are included to represent the exchange between the ocean and the atmosphere better, especially for applications that require representation of natural hazards such as storms. For Earth system models which need to include predictions of the biogenic components to predict carbon and other nutrient transfers, the components are often extended to include ocean biogeochemistry and atmospheric chemistry (Mulcahy et al., 2023).

There are a number of solutions to how this coupling may be achieved, and which is preferred will depend both on the scientific importance of the exchanges and the timescales on which they occur and on technical limitations. In the "traditional" way of working, the models are run independently, with a flux of information from adjacent components of the Earth system being calculated based on independent and non-interactive models. This implies that the winds, precipitation, and air temperatures ("forcing") used to drive the exchanges at the ocean's surface do not respond to changes in the ocean conditions themselves. The forcing is not calculated on a time step basis but over a period generally somewhere between 1 h and 1 d. Forecasts run in this mode are termed forced or one-way coupled.

Coupled systems exist with varying complexity of exchanges between models. For example, a common approach for the coupling of hydrodynamics and sea ice is to run both systems at the same time and exchange information both ways. These are termed fully or two-way coupled systems. In these two-way coupled systems, the independent models often communicate with each other through an interface code ("coupler") which allows the independent models to operate on different grids and with different time steps (Larson et al., 2005; Valcke, 2013; Hanke et al., 2016). As the number of components interacting with each other increases, the flexibility of including a coupler becomes increasingly attractive. A coupling software creates a computational interface between separate systems that allows the passing of information between them without undue intrusion into the code of the modelling systems. This approach is widely used (e.g. Lewis et al., 2019a; Pianezze et al., 2022; Wahle et al., 2017), but other approaches exist. ECMWF (Wedi et al., 2015) has integrated its various modelling components into a single executable, with the passing of information being done internally within the code rather than through a separate coupling software. Figure 1 illustrates the Regional Environmental Prediction system under development in the United Kingdom, with complex exchanges between five different models, using three different coupling approaches (Best et al., 2004; Valcke, 2013; Bruggeman and Bolding, 2014).

## 2 Why is coupling important for ocean prediction?

Atmosphere–ocean coupling is common practice at seasonal and decadal timescales. At these scales, most of the memory is contained in the ocean and in coupled interactions, such as for the El Niño Southern Oscillation (ENSO). Indeed, both the ocean and the atmosphere can propagate an anomaly in the other component to remote places. For example, oceanic equatorial waves generated by wind anomalies can propagate to the whole tropical Pacific and generate an El Niño event, and, in turn, the atmosphere may generate teleconnections from the tropics to the mid-latitudes through upper-level Rossby wave trains in the troposphere or planetary waves in the stratosphere and influence the ocean back in remote ocean basins (Hardiman et al., 2019; Kim et al., 2012). These may take longer than 10 d to propagate and are therefore sources of seasonal and multi-annual forecast signals. For short-term marine prediction, coupling is emerging as a new potential for improving both atmospheric and oceanic predictions (Brassington et al., 2015).

A clear and extremely well documented weather situation when air–sea coupling is key for both the atmosphere and the ocean is tropical cyclone forecasts: the strength of tropical cyclones is decreased through large decreases in sea surface temperature (SST) caused by intense turbulent fluxes, by deepening of the surface mixed layer by entrainment (Vellinga et al., 2020; Mogensen et al., 2017; Castillo et al., 2022; Feng et al., 2019), and (if the cyclone translation speed is slow) by upwelling (Corale et al., 2023; Yablonsky and Ginis, 2009). In more general situations, coupling reduces the lifetime of mesoscale eddies and dampens submesoscale currents through dampening of the wind stress curl and heat fluxes (Yang et al.,2019; Renault et al., 2016, 2018; Dawe and Thompson, 2006). Coupling also sometimes involves a higher-resolution atmosphere than forcing, which then results in more turbulent eddy kinetic energy in the ocean (Storto et al., 2023). In the tropics, dynamical waves in the atmosphere and ocean can influence each other. For example, Madden–Julian Oscillation (MJO) atmospheric events in the Indian Ocean can be modulated by coupling (Fu et al., 2017) or simply by the diurnal cycle of SST (Karlowska et al., 2023). Convectively coupled Kelvin waves also generate a strong signal in the Indian Ocean (Azaneu et al., 2021).

At the coastal scale, coupling also becomes interesting, since the assumptions of equilibrium between Earth system components often break down (e.g. wave state is not in equilibrium with winds in the sheltered North Sea; Grayek et al., 2023; Wiese et al., 2019; Wahle et al., 2017). Some examples in the literature include better near-surface currents and upwelling forecasting with the inclusion of the Stokes–Coriolis drift by a wave model, which induce an extra term of advection in the direction of wave group speed (Alari et al., 2016; Bruciaferri et al., 2021). Coupling also benefits wave modelling, for example, where tidal currents modulate wave and wind activity (Renault and Marchesiello, 2022; Valiente et al., 2021). Coupling an ocean with waves can have considerable impacts on SSTs, which can go in either direction, depending on the difference in momentum stress passed to the ocean (more momentum input by the waves in the case of Lewis et al. (2019b), resulting in a near-surface cooling, but less momentum in Alari et al. (2016), resulting in warming) through modulation of the ocean stratification. Coupling a wave model with an atmospheric model will tend to decrease wind speed over young seas and increase ocean momentum flux, which is especially important during storms (Gentile et al., 2022; Bouin and Lebeaupin Brossier, 2020b). In general, coupling will tend to dampen air–sea fluxes because components will tend to adjust to one another, so this may decrease ocean spread at the start of ensemble forecasts (Lea et al., 2022). However, the spread in SST will increase rapidly in regions which have a shallow surface mixed layer, which respond quickly to atmospheric spread (Lea et al., 2022). Precipitation and river flow can also have a local influence on near-surface temperatures and salinity in the ocean, especially during extreme precipitation events (Bouin and Lebeaupin Brossier, 2020a; Sauvage et al., 2018). The ocean can finally act as a memory between two intense atmospheric events (e.g strong winds and strong precipitation; Berthou et

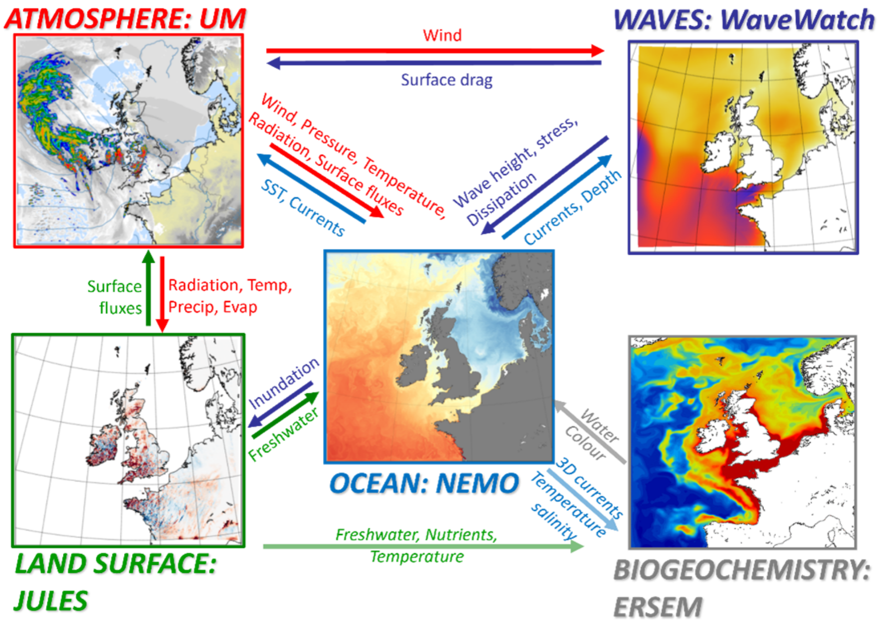


**Figure 1.** Regional coupled system under development in the United Kingdom for the Regional Environmental Prediction project (Lewis et al., 2019a), bringing together all the models run by the Met Office for short-term predictions and climate projections. Arrows represent exchanges between models, either as integrated coupling at the time step (Best et al., 2004) (UM/JULES), 2D coupling through the OASIS coupler (Valcke, 2013) (UM/WaveWatch III/NEMO), or 3D coupling through the FABM coupler (Bruggeman and Bolding, 2014) (NEMO/ERSEM).

al., 2018; Lebeaupin Brossier et al., 2012) or in the case of marine heatwaves and extreme temperature or precipitation events (Berthou et al., 2024; Martín et al., 2024), in which case a coupled system is beneficial for longer-range forecasting (3–7 d). In regional atmospheric forecasts, using a predicted SST (obtained through either coupling or forcing) is beneficial for variables such as near-surface temperature (Mahmood et al., 2021), fog (Fallmann et al., 2019) or snow (Yamamoto et al., 2011).

However, it is worth noting that differences in near-surface parameterisations can also generate differences which are as large as or larger than coupling differences (Gentile et al., 2022), indicating the need for continuous research and investment in observation systems of near-surface characteristics. Coupling is most successful when the water, heat, and momentum budgets are closed, which can be challenging when model parameterisations are designed in forced mode. Recent parameterisation improvements taking into account coupled variables include wave coupling in the NEMO turbulent kinetic energy scheme (Couvelard et al., 2020), current feedback taken into account in atmospheric turbulence (Renault et al., 2019), and the new wave-age-dependent stress parameterisation (Bouin et al., 2024). In some situations, increasing the complexity of air–sea exchanges can be beneficial, for example, including sea spray effects on moisture and heat fluxes (Yang et al., 2019; Xu et al., 2021; Zhang et al., 2011; Bianco et al., 2011).

Coupling with land and river models is also attractive to provide river flow forecasts, especially as the coupling interface gets more complex, and include back-water effects into rivers and coastal wetting and drying (Bianco et al., 2011). Finally, coupling with biogeochemistry and sediment transport models can provide interesting feedback on the ocean colour, with a feedback loop between thermal stratification and phytoplankton bloom, through the modulation of depth penetration of the solar heat flux (Skákala et al., 2022). Other feedbacks include chemistry and aerosols, where the atmosphere can then provide deposition fluxes (e.g. iron, nitrogen) to the ocean, and the phytoplankton sends back chemicals which can affect low-level cloud cover (Mulcahy et al., 2023).

The potential benefits of using a coupled framework are also reinforced by the move towards a multi-hazard approach to predictions. Natural hazards from multiple sources may combine or occur concurrently. Large waves, storm surges, high wind speeds, and extreme precipitation are all hazards that are likely to co-occur and influence each other through coupled feedback and compound each other through, for example, over-topping. Coupled systems that predict this feedback may enable an improvement in the range and consistency of actionable information provided through hazard warnings and guidance.

## 3 How extended is the use of coupled modelling for ocean prediction?

Many centres and research groups have developed monitoring and prediction tools independently for individual Earth components (e.g. atmosphere, ocean, land, waves). This is natural based on the historical context of their development and limitations on computing capabilities, but it has created an infrastructure within and across institutions that adds complexity to the task of unifying prediction systems. The major prediction centres are making progress towards an integrated approach by unifying software infrastructure for models and data assimilation capabilities and by providing opportunities to increase interactions among the development teams of each system component. At the global scale, the use of a coupled atmosphere–ocean–sea–ice model has increased rapidly in the past few years, usually starting with deterministic and then ensemble-coupled capability, and has been used by the following authors: Allard et al. (2012) and Komaromi et al. (2021) (Naval Research Laboratory), Mogensen et al. (2017) (European Centre for Medium-Range Weather Forecasts), Smith et al. (2018) and Peterson et al. (2022) (Environment and Climate Change Canada), and Guiavarc'h et al. (2019) (Met Office). In parallel, the perspective of seamless predictive capability (Ruti et al., 2020), especially important during impactful extreme cyclonic or convective events, means kilometre-scale regional coupled systems are either operational (Durnford et al., 2018, for the Great Lakes and Saint Lawrence river; Komaromi et al., 2021, for tropical cyclone regions) or are actively being developed in several centres or research groups. Examples include western Europe (Sauvage et al., 2021), the southwestern Indian Ocean (Corale et al., 2023), the northwest European shelf (Lewis et al., 2019a), the northern Indian Ocean (Castillo et al., 2022), and the Red Sea (Sun et al., 2019, 2024). Finally, coupled river–ocean models, including two-way coupling between rivers and oceans, are used for operational forecasting of compound flooding during hurricanes in the Gulf of Mexico (Bao et al., 2024, using the COWAST system; Warner et al., 2010).

The extent of the uptake of coupled modelling is still limited, however, by several barriers. Firstly, it places extreme demands on computational resources: the cost of running an extra model is often prohibitive for agencies with limited forecasting remits (e.g. only ocean forecasting). However, recognising the benefits acknowledged above, these agencies are exploring alternatives, such as coupling with a single-column mixed-layer model, either in the atmosphere or in the ocean (Voldoire et al., 2017; Lemarié et al., 2021). For the agencies with several remits (e.g. weather, marine, hydrology, air quality forecasting), coupled modelling is more attractive and has the potential to reduce the complexity of the modelling chains and to prevent large data transfers between platforms.

A second major barrier is data assimilation, which requires the processing of environmental observations. It is itself a technically challenging problem which is made harder if one tries to harmonise it across all the Earth system components. Data assimilation requires the calculation of an innovation (difference between the modelled and observed value) and then appropriately adjusting the model parameter space to create a state estimate that is optimised to best reflect understanding of model and observation errors. In coupled systems, there are correlations between parameters in the different systems that need to be respected: for example, sea surface and air surface temperature are closely correlated. This creates an additional scientific and technical challenge that needs to be addressed in coupled forecasting systems (Penny and Hamill, 2017). The differing timescales inherent in ocean forecasting and atmospheric NWP are also problematic, though Lea et al. (2022) suggest that using the shorter NWP-based windows does allow the retention of the longer oceanic timescales, as long as the memory inherited with cycling the system in time remains intact. Nevertheless, strongly coupled data assimilation means an observation in one model can be beneficial for both models (Fu et al., 2021; Phillipson et al., 2021) and allows coupled observation operators. Indeed, remote-sensed observations of the ocean (remote-sensed SST, radiances, colour, ice freeboard) require filtering out an atmospheric signal, a task which could be dealt with by a coupled assimilation system instead of externally, which potentially introduces contradictory biases from other systems.

Weaker barriers include the need for different frequency of running forecasts: ocean forecasts often run daily with a single deterministic member, but the atmospheric and the wave forecasts require sub-daily ensembles with several members. In ensemble modelling, inflated spread schemes are often employed (e.g. in the SST) to generate a much larger spread than the ocean uncertainty and must be modified in coupled systems (Lea et al., 2022). Nevertheless, the ocean and sea ice uncertainty needs thorough quantification against independent observational datasets for these schemes to be effective. Finally, simple bureaucratic barriers, such as the constraint of a common forcing model in international projects, can also prevent the adoption of coupled modelling.

## 4 Conclusion

Coupling models of different Earth system components is a technical task which requires scientific software engineering expertise and high-performance computing resources. Whilst common for seasonal and climate prediction, a handful of operational centres have achieved this for NWP timescales, most of them in the past 5 years. Coupling enables better treatment of air–sea interactions, especially important in the tropics, for intense events (tropical cyclones); for regions of strong SST gradients, eddies, and tidal influence; or for complex coastlines. The cost is affordable for centres which have the responsibility for forecasting across different Earth system components. In these cases, in addition to the benefits of coupled feedback, coupled forecasting allows forecast consistency, essential for impact-based forecasting of multi-hazard events. For other centres, cheaper solutions exist, such as only treating the boundary layer of the other Earth system component, which is the most important part for coupling at short timescales.

Coupling models also increases knowledge exchange between researchers in different Earth system components, which helps build our understanding of the Earth system as a whole. Novel methods, such as machine learning and artificial intelligence, offer great hope in overcoming some of the barriers faced by traditional NWP. At a time of greater coupling between traditional numerical forecasting systems, the use of machine learning and AI should cut across Earth system components and avoid the pitfalls of parameterisations designed with a single component in mind. This can only be achieved by a strong and organised coupling research community.

**Code availability.** Figure 1 was generated using Scitools/Iris (https://scitools.org.uk/, last access: 27 March 2025; https://doi.org/10.5281/zenodo.15077277, Iris contributors, 2025) and Matplotlib (https://matplotlib.org/, last access: 27 March 2025, https://doi.org/10.5281/zenodo.573577, Droettboom et al., 2017).

**Data availability.** The authors have used data from the Regional Environmental Prediction system in the UK (UKC4), successor of the UKC3 system (Lewis et al., 2019a), to draw the illustrative picture of this article (Fig. 1). The underlying data can be requested from the main author of this article if needed.

**Author contributions.** JS started a draft of this document. SB took over and completed the article, helped by a literature review completed by VFL. PYLT and IH reviewed the text.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.



**Acknowledgements.** The authors would like to acknowledge the two reviewers for their suggestions of improvements to the article.

**Review statement.** This paper was edited by Kirsten Wilmer-Becker and reviewed by K. Andrew Peterson and one anonymous referee.

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# Improving accuracy and providing uncertainty estimations: ensemble methodologies for ocean forecasting

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Received: 15 August 2024 – Discussion started: 1 October 2024
Revised: 30 January 2025 – Accepted: 4 February 2025 – Published: 2 June 2025

**Abstract.** Ensemble forecasting has emerged as an essential approach for addressing the uncertainties inherent in ocean prediction, offering a probabilistic framework that enhances accuracy of both short-term and long-range forecasts. By more effectively addressing the intrinsic chaotic nature of mesoscale and submesoscale variability, ensemble methods offer critical insights into forecast errors and improve the reliability of predictions. This paper reviews the ensemble methodologies currently used in ocean forecasting, including techniques borrowed from weather prediction, such as virtual ensembles and Monte Carlo (MC) methods. It also explores the latest advancements in ensemble data assimilation (DA), which have been successfully integrated into both ocean general circulation models (OGCMs) and operational forecasting systems. These advancements enable more accurate representation of forecast uncertainties (error of the day) by sampling perturbations conditioned on available observations. Despite the progress made, challenges remain in fully realizing the potential of ensemble forecasting, particularly in developing tools for analyzing results and incorporating them into decision-making processes. This paper highlights the crucial role of ensemble forecasting in improving ocean predictions and advocates for its wider adoption in operational systems.

## 1 Introduction to ensemble forecasting

Forecasts of the ocean state generated by numerical models are inherently uncertain owing to the nonlinear chaotic nature and imperfect internal physics of the ocean models and to inevitable uncertainties in their inputs, such as initial and boundary conditions, atmospheric forcing, and bathymetry (e.g., Lorenz, 1996; Pinardi et al., 2008; Sandery et al., 2014; Vandenbulcke and Barth, 2015; Kwon et al., 2016; Sanikommu et al., 2020). Thus, the future ocean cannot be completely described by a single forecast model run and is better described by a set, or ensemble, of forecasts that provides an indication of the range of possible future ocean states and that represents the uncertainty in the forecasts, also known as errors of the day (Houtekamer and Zhang, 2016; Hoteit et al., 2018) (Fig. 1).

Ensemble forecasting has increasingly become a key aspect of weather and climate predictions – see Du et al. (2018) for a review – as it provides a basis to communicate forecast confidence to end users for better decision-making. Similarly, it should become an integral part of ocean forecasts. Ensemble forecasting was indeed proven to provide extended ocean prediction skills compared to deterministic forecasts, especially for extended timescale predictions (Mullen and Buizza, 2002; Ryan et al., 2015). This ensemble probabilistic framework is also needed for short-range forecasting to better describe the intrinsic chaotic nature of the mesoscale and submesoscale variability resolved by the new generation

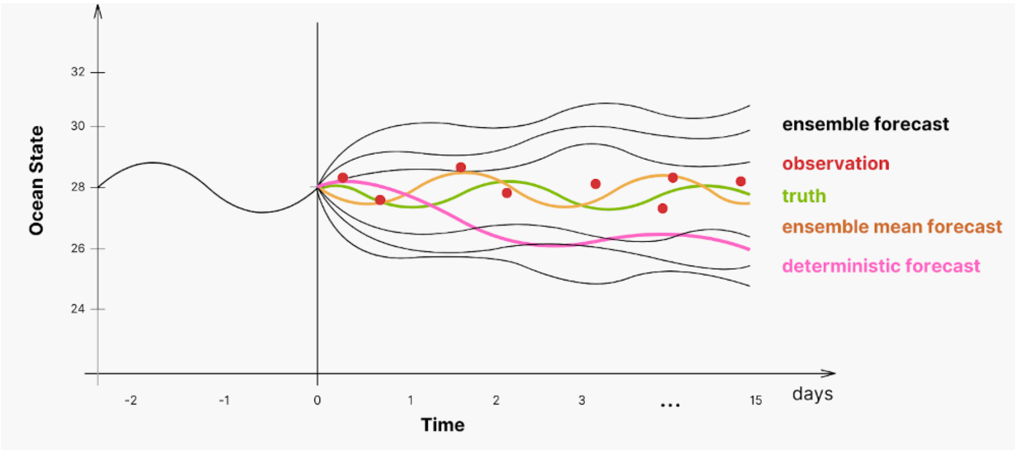


**Figure 1.** Schematic illustration of deterministic hindcast (black line at the forecast date 0), forecast (pink line after day 0), and ensemble forecasts (black lines after day 0) of the ocean state. The ensemble forecasts were driven by various sources of uncertainties, including initial conditions, atmospheric forcing, model physics, and bathymetry. The ensemble forecast mean and the unknown truth are represented by the orange and green lines, respectively. Solid red dots denote observations.

of high-resolution ocean models (Thoppil et al., 2021). Information about forecast uncertainty can be used in many ways. For instance, the probabilistic information that ensembles provide is particularly valuable for early warnings of hazardous conditions in the ocean and can be integrated into the decision-making process based on economic values (Richardson, 2000; Fundel et al., 2019). On short timescales, the probabilistic information is useful for triggering the deployment of environmental protection measures in the event of an oil spill (Barker et al., 2020), for advising fishers about the most probable regions of fishing zones, for helping coastguards find the probable areas to focus on for search and rescue operations (Melsom et al., 2012), and for advising on path planning for autonomous marine vehicles (e.g., Albarakati et al., 2021). On climate timescales, ensemble forecasting is useful for providing probabilistic information on climate indices such as El Niño and the Indian Ocean Dipole (Schiller et al., 2020).

## 2 Methods

Ensemble forecasts find their roots in weather forecasting and can be generated (i) as virtual ensembles whose members are selected from deterministic forecasts and/or historical runs (e.g., Hoffman and Kalnay, 1983; Ebert, 2001; Schwartz and Sobash, 2017) or (ii) by applying some form of Monte Carlo (MC) analysis in which a set of forecasts is produced by perturbing the model physics and/or inputs as a way to account for their inherent uncertainties (e.g., Martin et al., 2015; Houtekamer and Zhang, 2016; Hoteit et al., 2018). Ensemble forecasts may also be generated following a multi-model approach as the forecasts of different ocean models or from their combination with MC forecasts (Fig. 2). Ideally, the actual future oceanic state should fall within the predicted ensemble range.

- *Virtual ensemble forecasts.* The lower-cost virtual ensembles can be used to quantitatively estimate forecast uncertainties based on existing forecasts through various techniques, including (a) the time-lagged ensemble, which automatically creates a forecast ensemble by pulling multiple forecasts that have been initiated at different times; (b) the poor-man ensemble, which gathers single-model forecasts from different sources and is thus a multi-model ensemble from existing forecasts; and (c) the analog ensemble, made of past forecasts matching up with the current forecast. These methods are straightforward but may result in restricted ensembles due to the limited available sources of existing forecasts. They are also not designed to capture the flow-dependent error of the day (Du et al., 2018).

- *Monte Carlo (MC) ensemble forecasts*. This kind can be generated by perturbing the ocean model physics and/or inputs (Du et al., 2018). Uncertainties in the ocean model could be accounted for by perturbing its internal sources of uncertainties which could come from the missing physics, parameterization schemes, and numerical errors. Different approaches were suggested, such as (a) the multi-physics approach, which uses a different parameterization scheme for each ensemble member (Sanikommu et al., 2020); (b) the perturbed parameters approach of a selected parameterization scheme; and (c) the stochastic parameterizations approach, which injects stochastic perturbations into the physical parameterization schemes (Brankart et al., 2015; Storto and Andriopoulos, 2021). Additionally, given that the short-term predictability of the atmosphere and the ocean

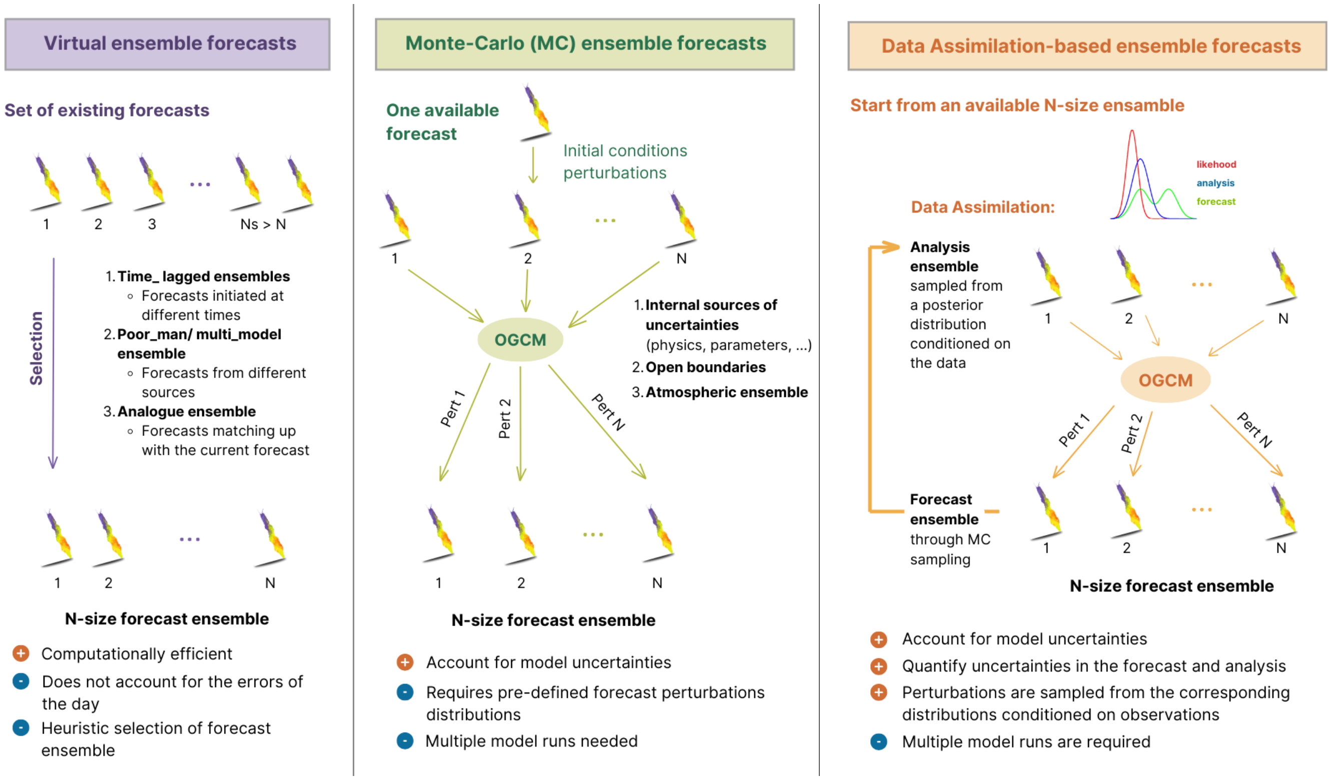


**Figure 2.** Schematic diagram illustrating the steps involved in various ensemble forecasting methods. Characteristics of each method are also listed.

is dominated by their initial conditions (ICs), various methods to perturb the initial model state have been proposed to generate ensembles. These include (i) random perturbations sampled from some available error statistics; (ii) the singular vectors and their variants designed to represent the perturbations with the fastest error growth; and (iii) the vector breeding approach, which computes the initial perturbations as the differences between a pair of past concurrent forecasts. Different approaches were also suggested to perturb the bathymetry, open boundaries, and atmospheric and river forcing (Lima et al., 2019; Storto and Yang, 2023; Zedler et al., 2023), but ensembles of atmospheric and oceanic forecasts are now available from the global operational prediction centers and can be readily used to generate ocean forecast ensembles.

– *Data-assimilation-based ensemble forecasts*. Ensemble forecasts in data assimilation (DA) are typically generated by introducing multiple, slightly different estimates of the current system state to capture uncertainties in observations and model parameters while accounting for the error of the day. For example, in an ensemble Kalman filter (EnKF), observations can be perturbed (or not) (Whitaker and Hamill, 2002; Hoteit et al., 2015), and the model is then integrated from these perturbed initial states, sampled according to the estimated initial-state statistics derived from previous forecasts and the most recent observations, resulting in an ensemble of forecasts. Additional perturbations may be introduced to the model physics or inputs to represent other sources of uncertainty, as demonstrated in Monte Carlo (MC) ensemble forecast methods (Whitaker and Hamill, 2012; Hoteit et al., 2018; Sanikommu et al., 2020). This collection of forecasts provides a probabilistic picture of future conditions, reflecting both initial conditions and model uncertainties.

Virtual ensemble forecasts were traditionally more common for operational purposes, as they do not require major extra computations, although their large ensemble spread was perceived as a disadvantage. The multi-model approach involves the tedious task of running and maintaining different ocean general circulation models (OGCMs), but it can be facilitated by combining the forecasts from different operational centers (e.g., Ren et al., 2019). Ensemble forecasts generated by an MC approach are increasingly adopted operationally. Despite their demonstrated skill, the MC ensemble forecasts require that the ensemble truly represents the probability distribution of the underlying dynamical system (Leith, 1974). Designing perturbation schemes that accurately capture all sources of uncertainty (e.g., initial conditions, forcing, model physics) remains a significant challenge, as does determining how to vary these perturbations in time.

Recent advances in ensemble data assimilation approaches now provide robust frameworks to represent the error of the day, for both initial conditions and inputs or parameters, by sampling perturbations directly from (approximate) error distributions conditioned on observations (Hoteit et al., 2018; Carrassi et al., 2022). Nevertheless, obstacles persist, particularly in high-dimensional ocean forecasting systems, where the ensemble size is often limited by computational costs. Methods such as localization and inflation are commonly used to mitigate sampling errors and maintain adequate ensemble spread (Brankart et al., 2015; Storto and Andriopoulos, 2021). Hybrid ensemble–variational approaches and other advanced techniques can further alleviate these issues by blending flow-dependent ensemble covariances with multi-year or climatological statistics (Song et al., 2013). However, each solution carries its own computational demands and assumptions, highlighting the ongoing need to balance accuracy, efficiency, and complexity in operational ocean forecasting systems (OOFSs).

## 3 Probabilistic assessment

Forecast ensembles are evaluated through their sample statistics, mainly the ensemble mean and its spread (the standard deviation with respect to the ensemble mean). The mean can be directly compared with available observations, while the spread indicates the confidence in the forecast: a smaller spread implies lower uncertainty and vice versa. High-order moments, such as skewness and kurtosis, help characterize the shape of the ensemble distribution (Groeneveld and Meeden, 1984). In addition, probabilistic validation and verification methods, including reliability, resolution, sharpness, and rank histograms, are frequently employed (Johnson and Bowler, 2009). An ensemble is deemed reliable if the predicted probability of an event aligns with the observed frequency. Resolution assesses how far the forecast deviates from the climatological event frequency; increasing this deviation enhances the reliability of the forecast. In the same context, sharpness measures the ability of an ensemble forecast to spread away from the climatological average. Ideally, an ensemble forecast needs to be reliable, with as many forecasts as possible away from the climatological average. Rank histograms, which tally the position of the observation among sorted ensemble values, are used to test reliability and diagnose errors in the ensemble mean or spread (Hamill, 2001). Another commonly used metric is the continuous ranked probability score (CRPS), which evaluates both accuracy and reliability by comparing the forecast distribution with the observed value across all possible outcomes. A lower CRPS indicates a closer match to reality and thus better overall probabilistic forecasts (Leutbecher and Haiden, 2021).

## 4 Current status of ensemble forecasts in operational ocean forecasting systems (OOFSs)

Despite the early establishment of ensemble methods for ocean data assimilation and forecasting (Evensen, 1994), ensemble forecasts, particularly the global systems, only recently found their way to the operational centers. This is mostly because the centers prioritized using the available computational resources to increase the resolution of ocean models. This was due to the need to resolve the mesoscale to submesoscale processes to better describe the energy cascade in the ocean and to meet user demands for higher-resolution forecasts (e.g., D'Addezio et al., 2019; Davidson, 2021). Recent developments in ocean ensemble forecasting followed the improved coverage in ocean observations that provided increased information to accurately constrain the initial ocean state for extended forecast horizons, the better coordination between ocean forecasting groups, the ease of access to atmospheric ensembles, and the ever-increasing availability of computational power (Metzger et al., 2010; Strohmaier et al., 2015; Bauer et al., 2021). Ocean ensemble forecasts are now routinely generated at several operational ocean centers on both global and regional scales to cater to different needs, as summarized in Table 1.

## 5 Role of ensemble forecasts in next-generation OOFSs

Recognizing the importance of representing uncertainties in ocean forecasts to meet the need of future demands in probabilistic predictions, ensemble forecasts are expected to become a standard output of any operational ocean product. Although high-resolution observations of some surface variables are now more accessible, the lack of dense, three-dimensional coverage, especially at subsurface levels, still leaves mesoscale and submesoscale processes poorly constrained by ocean analysis systems. Uncertainties from the unconstrained scales might lead to larger forecast errors due to growing dynamical instabilities (Sandery and Sakov, 2017), which limit the forecasting skills of high-resolution ocean models (e.g., Thoppil et al., 2021). Ensemble forecasting has been proven efficient to extend ocean forecasting horizons when model uncertainties in the initial conditions, inputs, and physics are accounted for (Mullen and Buizza 2002; Ryan et al., 2015; Sanikommu et al., 2020). Ensemble forecasts are also essential for providing the error statistics required by ocean analysis systems, thereby enabling better use of high-density observations from recently launched and upcoming satellite missions, such as Surface Water and Ocean Topography (SWOT) (Fu and Ubelmann, 2014). Long delayed by the desire of the community to increase the resolution of the ocean models to improve their realism, the ever-increasing computing resources will provide more and more power to integrate these within ensemble forecasting frameworks.

**Table 1.** Summary of selected operational ensemble forecasting systems worldwide.

| Institution | Forecasting system | Domain (resolution) | Ensemble perturbations (size) | Type of forecast | Reference |
|---|---|---|---|---|---|
| Met Office, UK | FOAM | Global (9 km) | Observations + internal physics + atmosphere (36) | Short-range ocean state | Lea et al. (2022) |
| NRL, USA | Navy-ESPC | Global (9 km) | Observations (16) | Days to subseasonal ocean state | Barton et al. (2021) |
| Bluelink, Australia | OceanMAPS | Global (10 km) | Initial conditions + time-lagged (48) | Short-range ocean state | Brassington et al. (2023) |
| ECMWF | NEMO | Global (25 km) | Initial conditions + forcing + observations (5) | Near-real-time ocean state | Zuo et al. (2019) |
| NERSC, Norway | TOPAZ5 | North Atlantic and Arctic (6 km) | Atmosphere (100) | Short-range ocean state | Nakanowatari et al. (2022) |
| KAUST, Saudi Arabia | MITgcm | Red Sea (4 km) | Atmosphere + internal physics (50) | Short-range ocean state | Sanikommu et al. (2020) |
| INCOIS, India | ROMS | Indian Ocean (8 km) | Atmosphere + internal physics (80) | Short-range ocean state | Francis et al. (2020) |
| Bureau of Meteorology, Australia | ACCESS-S | Global (4 km) | Internal physics + time-lagged (30) | Multi-week to seasonal El Niño/IOD | Wedd et al. (2022) |
| CMA, China | CMMEv1 | Global (100 km) | Multi-model + initial conditions (90) | Multi-week to seasonal El Niño/IOD | Ren et al. (2019) |
| CMCC | CMCC-SPS3.5 | Global (25 km) | Initial conditions + model physics (50) | 184 d | Gualdi et al. (2020) |
| ECMWF | SEAS5 | Global (25 km) | Initial conditions + model physics + observations (51) | 6 months | Johnson et al. (2019) |
| Meteo-France | Meteo-France System 8 | Global (25 km) | Model dynamics (51) | 7 months | Pianezze et al. (2022) |
| DWD | GCFS 2.1 | Global (25 km) | Initial conditions + model physics (50) | 215 d | Fröhlich et al. (2021) |
| ECMWF | IFS | Global (10 km) | Internal physics (51) | Short-range waves | Browne et al. (2019) |
| NCEP | GWES | Global (25 km) | Wind (30) | Short-range waves | Penny et al. (2015) |
| UK Metoffice | Wavewatch-III | Atlantic-UK (3 km) | Wind (22) | Short-range waves | Bunney and Saulter (2015) |
| MET-Norway | Barotropic version of ROMS | Norway (4 km) | Atmosphere (51) | Short-range storm surge | Kristensen et al. (2022) |

Ocean forecasts have long been produced by data assimilation (DA) systems and are now routinely used operationally. Ensemble forecasts could be generated from deterministic DA systems, which produce one single forecast, by simply perturbing the observations (or other parameters of the assimilation system) or during the forecasting step using an ensemble forecasting method. Ensemble DA methods, on the other hand, readily produce ensemble ocean perturbations that (approximately) represent the error of the day and can be directly used to generate ensemble forecasts. These could also be combined with standard ensemble forecasting methods to further represent the missing information about the error growth in the computationally restricted DA ensembles. To fully exploit the benefits from ocean ensemble forecasts, new tools to analyze, visualize, and also integrate these probabilistic products in decision-making and management of ocean services need to be developed and made available for the end users.

**Data availability.** No data sets were used in this article.

**Author contributions.** IH conceptualized and prepared the article. EC and MB provided critical reviews and valuable feedback. All authors read and approved the final version of the article.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** The authors gratefully acknowledge Siva Reddy and Naila Raboudi from KAUST for their invaluable insights and significant contributions to this article.

**Financial support.** This study has been supported by the King Abdullah University of Science and Technology (grant no. REP/1/3268-01-01).

**Review statement.** This paper was edited by Stefania Angela Ciliberti and reviewed by two anonymous referees.

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# Crafting the Future: Machine learning for ocean forecasting

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Received: 4 September 2024 – Discussion started: 20 September 2024
Revised: 9 December 2024 – Accepted: 18 December 2024 – Published: 2 June 2025

**Abstract.** Artificial intelligence and machine learning are accelerating research in Earth system science, with huge potential for impact and challenges in ocean prediction. Such algorithms are being deployed on different aspects of the forecasting workflow with the aim of improving its speed and skill. They include pattern classification and anomaly detection; regression and diagnostics; and state prediction from nowcasting to synoptic, sub-seasonal, and seasonal forecasting. This brief review emphasizes scientific machine learning methods that have the capacity to embed domain knowledge; to ensure interpretability through causal explanation, to be robust and reliable; to involve effectively high-dimensional statistical methods, supporting multi-scale and multi-physics simulations aimed at improving parameterization; and to drive intelligent automation, as well as decision support. An overview of recent numerical developments is discussed, highlighting the importance of fully data-driven ocean models for future expansion of ocean forecasting capabilities.

## 1 Introduction

Research into applications of artificial intelligence (AI) and machine learning (ML) in ocean, atmospheric, and climate sciences has accelerated at a breathtaking pace over the last 5 years or so (e.g., Schneider et al., 2023; Eyring et al., 2024). With essentially all of these applications concerned with ML, we will drop the more broadly defined "AI" term in most of the following, except when used by references cited. We will also take the perspective of scientific machine learning (SciML), defined in a 2019 U.S. Department of Energy report on "Basic Research Needs for Scientific Machine Learning" (Baker et al., 2019), which emphasizes six key elements of SciML algorithms: (i) ML approaches that incorporate domain knowledge, such as physical principles, symmetries, constraints, expert feedback, computational simulations, and formal uncertainties; (ii) ML approaches that are interpretable, such that a user's confidence in ML-based model predictions may be bolstered by causal explanations based on a user's domain knowledge; (iii) ML approaches that are robust and reliable as a prerequisite for making high-stakes and high-regret decisions; (iv) ML approaches that are data-intensive, i.e., that ingest high-dimensional, noisy, and uncertain input data which contain complex structures and which require statistical and probabilistic methods to deal with ill-conditioning, non-uniqueness, and over-fitting; (v) ML approaches that enhance modeling and simulation to support, e.g., multi-scale and multi-physics simulations in terms of improved model parameterization or model acceleration; and (vi) ML approaches to support intelligent automa-

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tion and decision support, which can range from quality control to application-oriented post-processing workflows. Arguably, all of these criteria are fundamental to the uses of ML in ocean prediction.

Next, following the review by Reichstein et al. (2019), it is useful to distinguish different categories of ML applications, namely (A) classification and anomaly detection, which is concerned with, e.g., finding extreme event patterns or the classification of important structures or regimes; (B) regression, which is concerned with state reconstruction of important state variables, parameters, or diagnostics (metrics) from available data; and (C) state prediction, ranging from nowcasting to operational forecasting and sub-seasonal to seasonal prediction. A comprehensive collection of review articles on deep learning in Earth sciences is Camps-Valls et al. (2021), covering algorithmic foundations and examples of all three categories.

Because the subject of this document is ocean prediction, we will focus the following on the third category, namely state prediction or forecasting. To keep this review manageable, we will not review the interesting subjects of ML applications for state reconstruction, downscaling, or classification.

## 2 State prediction

The workflow of operational ocean prediction largely follows that of numerical weather prediction (NWP). Its core engine is a data assimilation (DA) framework, consisting of a physical model (i.e., a complex algorithm for solving a set of partial differential equations, PDEs), a workflow for quality-controlling and ingesting diverse observational data streams into the DA system (ideally in near-real time), and an optimal estimation algorithm that combines models and data in a formal manner that produces statistically optimal forecasts (e.g., Park and Zupanski, 2022). As pointed out by Stephen Penny in a 2022 U.S. National Academy of Sciences workshop on Machine Learning and Artificial Intelligence to Advance Earth System Science (NASEM, 2022), machine learning (ML) approaches hold the prospect for accelerating various elements of the DA workflow. We briefly summarize ML approaches targeting the physical model and the DA algorithm. Opportunities in the application of ML for partial differential equation (PDE)-based models fall into two main categories, where one is concerned with targeted insertion of ML within a physical model, and the other is concerned with the complete replacement of the physical model by a surrogate model. In the former, certain elements or subcomponents of a physical model are replaced by a surrogate model (e.g., a neural network), whereas in the latter, the entire model is emulated. Chantry et al. (2021) have used the terms "soft AI" versus "hard AI". We avoid the somewhat non-descriptive or ambiguous terminology to avoid giving a false sense of which of these approaches is "harder" to realize.

### 2.1 Hybrid physics–ML models: enhancing forecast models and data assimilation with ML algorithms

A major source of model uncertainty is the parameterization of subgrid-scale (SGS) processes in terms of structural errors (formulation of functional representations of parameterizations) and parametric uncertainties (calibrating empirical parameters in the functional representations). Exciting efforts are underway to apply machine learning to replace conventional functional representation subgrid-scale (SGS) turbulent oceanic processes with surrogate models that are based on machine learning and that have been trained either offline or online (Bolton and Zanna, 2019; Frezat et al., 2021, 2022; Zhang et al., 2023; Sane et al., 2023; Perezhogin et al., 2023). This follows on early ideas in the context of climate model parameterization (e.g., Schneider et al., 2017; Rasp et al., 2018). Similarly, equation discovery has proven successful to infer the functional form of such SGS ocean parameterization schemes (Zanna and Bolton, 2020, 2021; Perezhogin et al., 2024). A longer list of related efforts exists for numerical weather prediction and has been reviewed by Dueben et al. (2021) and Bouallègue et al. (2024). These surrogates, mostly some form of neural networks, have been trained on (i.e., fit to) what are considered simulations of much higher fidelity and where these processes are resolved (e.g., large-eddy simulations). Related efforts aim at learning improved parameterizations from online bias correction or analysis increments incurred in sequential data assimilation (e.g., Gregory et al., 2023, 2024; Storto et al., 2024). Rapid progress is expected on this front in the coming years.

A second important application of hybrid approaches is the desire to replace specific numerical algorithms within PDE-based models with surrogate models to accelerate the simulation's time to solution. Studies exist within the generic field of computational fluid dynamics (Kochkov et al., 2021) and atmospheric modeling (Arcomano et al., 2023; Kochkov et al., 2024), and there are ocean-specific applications currently underway. Most of these take advantage of the concept of differentiable programming (Gelbrecht et al., 2023; Shen et al., 2023; Zhang et al., 2023; Sapienza et al., 2024). The underlying idea is to eventually be able to generate code for the derivative of the physical model, in particular the adjoint model that enables efficient "online" (or "full model") learning of the model parameters (or neural network weights).

There is a strong conceptual correspondence between machine learning and data assimilation (e.g., Abarbanel et al., 2018). This provides various opportunities for embedding ML approaches within operational data assimilation workflows deployed in ocean prediction. Examples in ocean modeling so far are largely restricted to "toy problems" (such as the "Lorenz 96 model") or reduced-order versions of Earth system models that target eventual applications for ocean prediction (Bocquet et al., 2020; Brajard et al., 2021; Penny et al., 2022; Irrgang et al., 2021). The use of hybrid DA/ML approaches, whether in the context of ensemble DA or adjoint-based methods (e.g., 4DVar), presents substantial algorithmic hurdles (e.g., availability of a differentiable dynamical core in the context of adjoint-based DA), which explains the relative paucity of such studies to date compared to purely data-driven methods.

### 2.2 Purely data-driven models: replacing numerical simulations with surrogate models

Over the last decade, with the acceleration in AI-based solutions in other fields, a number of approaches to model the atmosphere and ocean using different purely data-driven ML techniques have been developed. The overwhelming majority of these cases have so far been realized in weather prediction or computational fluid dynamics.

#### 2.2.1 Deterministic applications in weather prediction

Arguably, the field of data-driven weather forecasting has seen the strongest advances over the last 5 years or so (Schneider et al., 2022). This is a strong incentive for providing a very brief review that is organized in terms of approaches as a function of underlying "blocks" of the ML architectures employed. In a number of cases, these architectural blocks are being combined. For example, the European Centre for Medium-Range Weather Forecast's AIFS system (Lang et al., 2024) uses an overall "encode–process–decode" architecture, with a graph-based encoder and decoder but a sliding window transformer as the processor.

- *Convolutional neural networks (CNNs)*. Perhaps among the first serious endeavors using ML for emulating weather forecast models have been the CNNs used by Weyn et al. (2019, 2020, 2021) and Karlbauer et al. (2024). CNNs use a mathematical operation called convolution to compress information, learning features, or patterns in the input. Most recently, CNNs have been used by Cresswell-Clay et al. (2024) to create a coupled atmosphere–ocean emulator which produces a stable climate for 1000-year periods and appears to be competitive with many CMIP6 models.
- *Graph neural networks*. Among the leading emulators for medium-range weather forecasts is the work by Lam et al. (2023). Based on graph neural networks, the GraphCast model was trained on atmospheric reanalysis data to produce autoregressive forecasts for up to 10 d.
- *Transformers*. These have been revolutionary in other ML/AI fields, such as natural language processing and image recognition/generation. They serve as the backbone of some of the leading atmospheric emulators, including Pangu-Weather (Bi et al., 2023), FuXi (L. Chen et al., 2023), and FengWu (K. Chen et al., 2023).
- *Fourier neural operators (FNOs)*. FNOs have been designed to move toward mesh-independent operators using Fourier bases (Li et al., 2020). FourCastNet (Pathak et al., 2022; Kurth et al., 2023) is based on a variant called the Adaptive FNO (AFNO). Another variant, the Spherical FNO (SFNO; Bonev et al., 2023; Watt-Meyer et al., 2023) seeks to take advantage of the spherical geometry (and underlying symmetries) in representing operator kernels for global-scale applications. Very recently, the use of SFNOs has been extended to coupled atmosphere–ocean modeling targeting seasonal prediction (C. Wang et al., 2024).
- *Recurrent neural networks (including long short-term memory, LSTM, and reservoir computing)*. Recurrent neural networks (RNNs) are well suited for sequential data processing, such as time series. Among special cases of RNNs, LSTM networks use a special type of neuron that keeps track of previous inputs (short-term memory) and are especially useful for predicting time series with memory, such as the case for the atmosphere and ocean. Reservoir computing (RC), another method based on RNNs with a pool of interconnected neurons forming the "reservoir", is particularly well adapted to the emulation of time series (e.g., Arcomano et al., 2020; Penny et al., 2022; Platt et al., 2023; Smith et al., 2023).

#### 2.2.2 Probabilistic approaches – generative models

Most examples sketched in Sect. 2.2.1 describe emulators that are trained to be deterministic forecast models. Recent developments in ML have considered generative frameworks, i.e., models that are designed to be probabilistic. Such frameworks would include variational autoencoders, generative adversarial networks (GANs), and diffusion models. However, we note that GANs can suffer from a lack of sample diversity (Bayat, 2023), and they are notoriously challenging to train, requiring a careful setup to avoid training instabilities (e.g., Miyato et al., 2018). Moreover, in recent years, diffusion models have started to outperform GANs in image classification (Dhariwal and Nichol, 2021). For these reasons, diffusion models have become popular in generative modeling, despite their relatively high computational cost. Recent examples of diffusion models include GenCast (Price et al., 2024). Finally, we note a very recently developed technique, DYffusion (Cachay et al., 2023, 2024), which is a generative framework that aims to reduce the computational cost of diffusion modeling by encoding the temporal evolution expected in physical systems into the generative process.

#### 2.2.3 Physics-informed machine learning

The results of purely data-driven solutions may potentially produce meaningless output as the training strategy of a neural network is to minimize a mathematical loss function, e.g., the mean squared error (i.e., L2 norm) between the prediction and the original target. Similar issues, e.g., producing overly blurred output, may arise with other choices of the loss function, such as an L1 norm. An evolution of this approach is to include some physical constraints in the loss function in order to force the ML algorithm to produce more consistent outputs, such as the Navier–Stokes equation (Ma et al., 2022; Daw et al., 2021). This class of methods is known as physics-informed neural networks (PINNs). However, the performance of PINNs for extrapolation remains subject to debate (e.g., Du et al., 2023, for a cautionary example). Recently, another approach, which tries to solve differential equations using neural networks, is under development. Although this method is mostly developed for other physics fields, the methodology and knowledge can be applied to ocean modeling (Zubov et al., 2021; Smets et al., 2023).

#### 2.2.4 Applications in ocean surface state forecasting

With previous examples mostly limited to weather prediction and computational fluid dynamics (in a few cases), we turn our attention to applications in the context of predicting ocean surface properties. They include the use of multilayer perceptrons (James et al., 2018; Gracia et al., 2021) and LSTMs (Minuzzi and Farina, 2023; Lawal et al., 2024) for surface wave prediction, surface wave–current interaction forecasting, storm surge forecasting (Xie et al., 2023), and sea surface temperature prediction via deep learning (Wolff et al., 2020; Xu et al., 2023) and the use of neural networks for accelerating resonant nonlinear wave–wave interaction in an ocean surface wave model (Puscasu, 2014), regional to coastal sea level prediction (Nieves et al., 2021), ocean color mapping (Chen et al., 2019), and statistical downscaling (Accarino et al., 2021). Other applications include estimating ocean surface circulation (Sinha and Abernathey, 2021; Subel and Zanna, 2024) and predicting dissolved oxygen across scales (O'Donncha et al., 2022).

### 2.3 ML-based ocean circulation prediction

Among the challenges of fully realizing the opportunities of ML approaches in ocean circulation prediction is the fact that, in the absence of adequate and densely sampled observational data, most ML applications rely on the use of data obtained from high-fidelity model simulations as training data sets. These data sets are very expensive to generate, limited in the temporal ranges that they can represent, remain subject to unquantified structural and parametric model uncertainty, require vast amounts of storage (on the order of petabytes), and are thus challenging to query. Cloud-based solutions are the most promising approach for ubiquitous data access and analysis capabilities "close to the data" (Abernathey et al., 2020).

Within the realm of machine learning (ML) applications for ocean forecasting, progress has been somewhat limited. Recent developments have marked a shift in this landscape, particularly with the introduction of Fourier neural operators for modeling oceanic processes, as suggested by Bire et al. (2023), Chattopadhyay et al. (2024), and Sun et al. (2024). These studies present fully data-driven ocean models that match the capabilities of traditional numerical ocean models in predicting high-resolution sea surface height (SSH) fields. FNOs are attractive for their performance in learning complex and high-dimensional mappings and their ability to incorporate physical laws and constraints, which are prominently observable in the spectral domain. A drawback of FNOs applied to ocean (unlike atmospheric) modeling is the existence of land-covered portions of the domain, which renders the use of periodic basis functions challenging and may create artifacts near land–ocean boundaries.

Concurrently, X. Wang et al. (2024) introduced a transformer-based model tailored for oceanic applications, demonstrating performance that rivals that of leading operational global ocean forecasting systems. Similar advances are being made in the data-driven prediction of sea ice cover in the polar oceans (Andersson et al., 2021; see also Bertino et al., 2025, in this report). This body of work signifies the emergence of a promising research avenue in fully data-driven ocean modeling, despite it still lagging considerably behind the advancements seen in weather forecasting. We posit that the drive of fully data-driven solutions in NWP by private sector companies is related to the prospect of high-stakes and high-reward applications. Such applications for ocean predictions should be better articulated to attract similar research efforts. Careful evaluation of skill, such as that now being discussed more comprehensively in NWP (e.g., Bonavita, 2023; Charlton-Perez et al., 2024), will also be required for operational ocean prediction.

Another challenge presents the extension of ML applications to seasonal, inter-annual, and multi-decadal – i.e., climate – timescales (see, e.g., the discussion in Gentine et al., 2021; Beucler et al., 2024; Subel and Zanna, 2024). Here, the increased need for models or invariant operators (physics-based or surrogates) to conserve fundamental properties (mass, energy, momentum, and active tracers) puts severe demands on ML approaches. Arguably, as these approaches increasingly incorporate physical knowledge, they will converge to the realm of classical inverse methods (Willcox et al., 2021).

### 2.4 Benchmarking forecast models

Data-driven forecasting in meteorology – and to some extent in oceanography – is proceeding at a breathtaking pace. The use of different approaches, different training data, and different performance metrics complicates objective assessment of the different works at the present time. Recognizing the need for standardized evaluation has led to the proposition of common evaluation benchmarks that encompass both data-driven and "traditional" forecasting in weather prediction (Dueben et al., 2022; Rasp et al., 2020, 2024), as well as climate model emulation (Yu et al., 2023). These benchmarks comprise common data sets, open-source evaluation workflows, and common evaluation metrics. Similar benchmarking efforts in ML-driven ocean circulation and surface wave forecasting will be equally important to advance the field and establish standardized evaluation metrics.

## 3 The role of surrogate models in digital twins

The concept of digital twins (DTs) is rapidly gaining traction within the ocean science community and Earth system science more broadly (e.g., Bauer et al., 2021a, b). Because of the differing view of what constitutes a DT in the recent literature, we here adopt and emphasize the definition from NASEM (2022) (see also Niederer et al., 2021; NASEM, 2023), which states that a DT is

> a set of virtual information constructs that mimics the structure, context and behavior of an individual/unique physical asset, or a group of physical assets, is dynamically updated with data from its physical twin throughout its life cycle and informs decisions that realize value. A digital twin is highly dynamical, mimicking the time evolution of its physical asset (PA) via advanced simulation and emulation capabilities; it is updated by ingesting vast amounts of observational data of diverse types; and it enables WHAT-IF queries and multiple realizations to support prediction of responses of the PA to hypothetical perturbations with quantified uncertainties.

Virtually all aspects of ocean forecasting – and ML opportunities therein – may be viewed through the DT lens from the need to generate high-fidelity simulations or digital representations, ingesting, i.e., assimilating, large and heterogeneous data streams, and the development of fast surrogates or emulators to either accelerate simulations or provide comprehensive uncertainty estimates, to the generation of diagnostic data that create value for (possibly rapid) decision support.

**Data availability.** No data sets were used in this article.

**Author contributions.** PH and FO'D conceptualized the paper. The original draft was prepared by PH, FO'D, and JMGV. All authors contributed to reviewing and editing the paper.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** We would like to thank Enrique Alvarez Fanjul at the OceanPrediction Decade Collaborative Center for initiating this review.

**Financial support.** The authors have been supported in part by the U.S. National Science Foundation (grant no. 2103942), the U.S. Office of Naval Research (grant no. N00014-20-1-2772), the U.S. Department of Energy (grant no. DE-SC002317), the NOAA Physical Sciences Laboratory, and a JPL/Caltech subcontract.

**Review statement.** This paper was edited by Swadhin Behera and reviewed by two anonymous referees.

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# Unlocking the power of parallel computing: GPU technologies for ocean forecasting

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Received: 17 September 2024 – Discussion started: 26 September 2024
Revised: 4 February 2025 – Accepted: 10 February 2025 – Published: 2 June 2025

**Abstract.** Operational ocean forecasting systems (OOFSs) are complex engines that must execute ocean models with high performance to provide timely products and datasets. Significant computational resources are then needed to run high-fidelity models, and, historically, the technological evolution of microprocessors has constrained data-parallel scientific computation. Today, graphics processing units (GPUs) offer a rapidly growing and valuable source of computing power rivaling the traditional CPU-based machines: the exploitation of thousands of threads can significantly accelerate the execution of many models, ranging from traditional HPC workloads of finite difference, finite volume, and finite element modelling through to the training of deep neural networks used in machine learning (ML) and artificial intelligence. Despite the advantages, GPU usage in ocean forecasting is still limited due to the legacy of CPU-based model implementations and the intrinsic complexity of porting core models to GPU architectures. This review explores the potential use of GPU in ocean forecasting and how the computational characteristics of ocean models can influence the suitability of GPU architectures for the execution of the overall value chain: it discusses the current approaches to code (and performance) portability, from CPU to GPU, including tools that perform code transformation, easing the adaptation of Fortran code for GPU execution (like PSyclone), the direct use of OpenACC directives (like ICON-O), the adoption of specific frameworks that facilitate the management of parallel execution across different architectures, and the use of new programming languages and paradigms.

## 1 Introduction

Operational ocean forecasting systems (OOFSs) are computationally demanding, and large computing resources are required in order to run models of useful fidelity. However, this is a time of great upheaval in the development of computer architectures. The ever-shrinking size of transistors means that current leakage (and the resulting heat generated) now presents a significant challenge to chip designers. This breakdown of Dennard scaling (transistor power consumption is proportional to area as in Dennard et al., 1974) began in about 2006 and means that it is no longer straightforward to continually increase the clock frequency of processors. Historically, this has been the main source of performance improvement from one generation of processor to the next (Fig. 1). Although the number of transistors per device continues to rise, they are increasingly being used to implement larger numbers of execution cores. It is then the job of the application to make use of these additional cores to achieve a performance improvement. Graphics processing units (GPUs) are a natural consequence of this evolution. Originally developed to accelerate the rendering of computer-generated images (a naturally data-parallel task thanks to the division of an image into pixels), scientists were quick to seize on their potential to accelerate data-parallel scientific computation. Therefore, manufacturers today produce HPC-specific "GPUs" that are purely intended for computation. The suitability of this hardware for the training of deep neural networks used in machine learning (ML) and artificial intelligence has stimulated massive development and competition amongst GPU vendors. Because of the exploding interest of AI applications in virtually all sectors of industry, the commercial HPC market is undergoing a seismic shift toward GPU-based hardware, with serious implications for available HPC architectures in the future, to which OOFS will have to adapt.

Unlike CPUs, which tend to have relatively few but powerful (general purpose) processor cores, GPUs support hundreds of simpler cores running thousands of threads which can obtain data from memory very efficiently. The simplicity of these cores makes them more energy-efficient; therefore GPUs tend to offer significantly greater performance per watt. With the energy consumption of large computing facilities now the key design criterion, GPUs are an important part of the technology being used in the push towards exascale performance and beyond (e.g. Draeger and Siegel, 2023). As an illustration, in the November 2024 incarnation of the TOP500 list (Strohmaier et al., 2024), 9 of the machines in the top 10 are equipped with GPU accelerators from NVIDIA, Intel, or AMD. Although CPUs are present in these machines, their primary role is to host the GPUs which provide the bulk of the computing performance. GPUs are therefore a major feature of the current HPC landscape, and their importance and pervasiveness are only set to increase.

## 2 Computational characteristics of ocean models

To understand why GPUs are well suited to running OOFSs, it is important to consider their computational characteristics. The equations describing ocean evolution form a system of partial differential equations that are solved numerically by discretising the model domain and then using a finite difference, finite volume, or finite element scheme. In these forms, the bulk of the computational work takes the form of stencil computations, where the update of a field at a given grid location requires that many other field values be read from neighbouring locations. This means that the limiting factor in the rate at which these computations can be done is how quickly all these values can be fetched from memory (so-called "memory bandwidth"). Finite element schemes do have the advantage of shifting the balance in favour of doing more arithmetic operations, but memory bandwidth still tends to dominate. These computations are, of course, repeated across the entire model grid, meaning that it is a single instruction, multiple data (SIMD) problem. OOFSs are therefore a very good fit for GPU architectures, which naturally support massively data-parallel problems and typically provide much higher memory bandwidth than CPUs.

For execution on distributed-memory computers, OOFSs typically use a geographical domain decomposition where each processor is assigned a part of the model domain. In order to handle stencil updates at the boundaries of a processor's sub-domain, it must exchange information with those processors operating on neighbouring sub-domains. Obviously, there is a cost associated with performing these exchanges, which high-performance processor interconnects can only do so much to mitigate. As more processors are thrown at a problem in order to reduce the time to solution, the size of their sub-domains decreases and so does the amount of computation that each must perform. Consequently, the relative cost of inter-processor communication becomes more significant and, after a certain point (the "strong-scaling limit"), will begin to dominate. At this point, using further processors will bring only limited performance improvements, if any.

Inter-processor communication on a GPU-based machine can be more costly, as messages may have to go via the CPUs hosting the GPUs, unless a machine has both hardware and software support for direct GPU–GPU communication. Communication-avoiding/minimising strategies are therefore more important on these architectures. These can include algorithmic design (e.g. Silvestri et al., 2024) to allow the overlap of communication and computation or simply the use of wider halo regions to reduce the frequency of halo exchanges.

## 3 The use of GPUs in ocean forecasting

Although GPUs are now a well-established HPC technology with potentially significant performance advantages for OOFSs, they are not yet widely adopted in the ocean-forecasting community. For example, in Europe, NEMO (Madec et al., 2024) is the most important ocean-modelling framework; it is used operationally by Mercator Ocean International, the European Centre for Medium-Range Weather Forecasts (ECMWF), the UK Met Office, the Euro-Mediterranean Center on Climate Change, and other institutes worldwide. NEMO is implemented in Fortran and parallelised with MPI and, as such, is limited to running on CPUs only. The German Weather Service (DWD) uses ICON-O (Korn, 2017), which is also a Fortran model. Experiments are in progress with the use of OpenACC directives to extend this code to make use of GPUs, but this functionality is not used operationally.

In the US, NOAA's Real-Time Ocean Forecast System (https://polar.ncep.noaa.gov/global/, last access: 14 April 2025) is based on the Hybrid Coordinate Ocean Model (HYCOM; Chassignet et al., 2009). HYCOM is also a Fortran code, parallelised using a combination of OpenMP and MPI. Although not used operationally, the Energy Exascale Earth System Model (E3SM) is also significant. It utilises the ocean, sea ice, and land ice versions of the Model for Prediction Across Scales (MPAS; Ringler et al., 2013), which again is implemented in Fortran with MPI. Although a port of this was attempted through the addition of OpenACC directives, it has been abandoned due to poor GPU performance (Mark R. Petersen, personal communication, 2024). Instead,

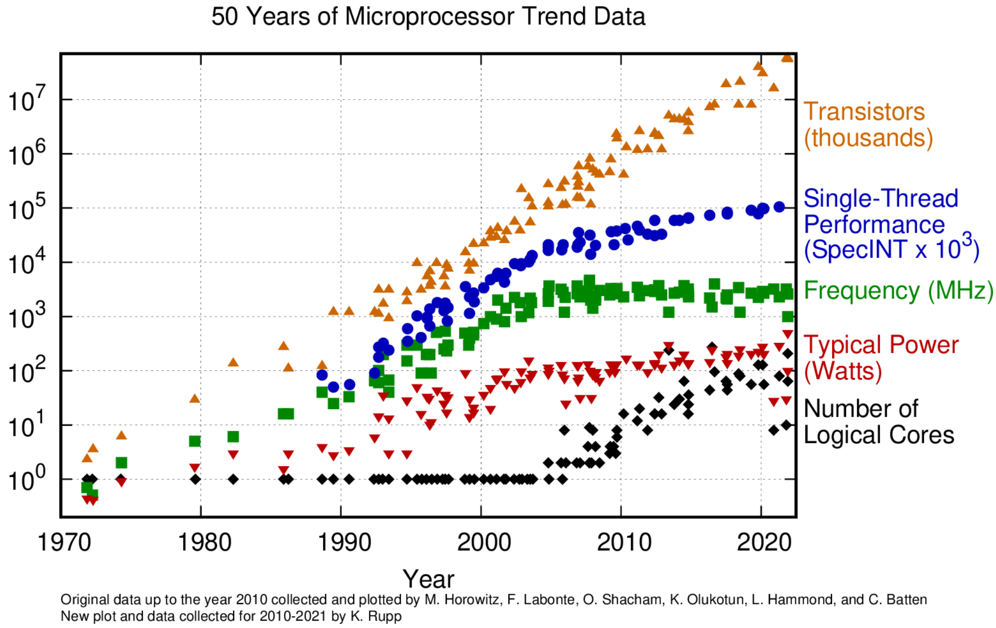


**Figure 1.** The breakdown of Dennard scaling, shown by 50 years of microprocessor (CPU) evolution (Rupp, 2022).

a new ocean model on unstructured meshes named Omega is being developed in C++ from the ground up. Other widely used ocean general circulation models include the MIT General Circulation Model (MITgcm; Marshall et al., 1997) and the Modular Ocean Model, version 6 (MOM6; Adcroft et al., 2019), both of which again are Fortran codes with support for distributed- and shared-memory parallelism on CPU.

The Japanese Meteorological Agency runs operational forecasts using the Meteorological Research Institute Community Ocean Model (MRI.COM) (Tsujino et al., 2010). As with the previous models, this is also implemented in Fortran with MPI and thus only runs on CPU.

For regional (as opposed to global) forecasts, the Rutgers Regional Ocean Modeling System (ROMS) (Shchepetkin and McWilliams, 2003) is used by centres worldwide, including the Japan Fisheries Research and Education Agency, the Australian Bureau of Meteorology, and the Irish Marine Institute. ROMS is also a Fortran code parallelised using either MPI or OpenMP (but not both combined) and is thus restricted to CPU execution. Although various projects have ported the code to different architectures (including the Sunway architecture for China's Tianhe machine; Liu et al., 2019), these are all standalone pieces of work that have not made it back into the main code base.

## 4 Discussion

From the preceding section, it is clear that OOFSs are currently largely implemented in Fortran with no or limited support for execution on GPU devices. The problem here is that OOFSs comprise large and complex codes which typically have a lifetime of decades and are constantly being updated with new science by multiple developers. Maintainability, allowing for the fact that the majority of developers will be specialists in their scientific domain rather than in HPC, is therefore of vital importance. Given that such codes are often shared between organisations, they must also run with good performance on different types of architecture (i.e. be "performance-portable").

Previously, one generation of supercomputers looked much like the last; therefore the evolution of these computer models was not a significant problem. However, the proliferation of computer hardware (and, crucially, the programming models needed to target them) that has resulted from the breakdown of Dennard scaling has changed this (Balaji, 2021). With the average supercomputer having a lifetime of just some 5 years, OOFSs are now facing the problem of adapting to future supercomputer architectures, and this is difficult because the aims of performance, performance portability, and code maintainability often conflict with each other (Lawrence et al., 2018).

*Transformation of existing codes*. To date there have been various approaches to this problem. NEMO v.5.0 (Madec et al., 2024) has adopted the PSyclone code transformation tool (Adams et al., 2019), which enables an HPC expert to transform Fortran source code such that it may be executed on GPUs using whichever programming model (i.e. OpenACC or OpenMP) is required. Previous, unpublished work found that, for a low-resolution (1°) global mesh, a single NVIDIA V100 GPU performed some 3.6 × better than an HPC-class Intel socket. For a high-resolution (1/12th°) global mesh, ∼90 A100 GPUs gave the same performance as ∼270 Intel sockets. In both cases, this is an ocean-only configuration, with virtually all computing being performed on the GPUs. This is important, since any computation happening on the CPU incurs substantial data transfer costs as data are moved from the GPU to the CPU, updated, and then transferred back to the GPU. The advent of hardware support for unified CPU/GPU memory should reduce the cost of this. As noted earlier, ICON-O is being extended manually with OpenACC directives. There are examples of recent (i.e. experimental) models that have moved away from Fortran in favour of higher-level programming approaches. Thetis (Kärnä et al., 2018) implements a discontinuous Galerkin method for solving the 3D hydrostatic equations using the Firedrake framework. This permits the scientist to express their scheme in the Python implementation of Unified Form Language (Alnæs et al., 2014). The necessary code is then generated automatically. The Veros model (Häfner et al., 2021) takes a slightly different approach: its dynamical core is a direct Python translation of a Fortran code and thus retains explicit MPI parallelisation. The JAX system (http://github.com/google/jax, last access: 14 April 2025) for Python is then used to generate performant code for both CPU and GPU. The authors report that the Python version running on 16 A100 GPUs gives the same performance as 2000 CPU cores for the Fortran version (although this comparison is slightly unfair, as the CPUs used are several generations older than the GPUs).

*Performance portability tools*. Another popular approach to performance portability is to implement a model using a framework that takes care of parallel execution on a target platform. Frameworks such as Kokkos (Carter Edwards et al., 2014), SYCL, and OpenMP are good examples, and the new Omega ocean component of E3SM mentioned previously is being developed to use Kokkos. In principle, this approach retains single-source science code while enabling portability to a variety of different hardware. However, it is hard to insulate the oceanographer from the syntax of the framework (which is often only available in C++), and, while the framework may be portable, obtaining good performance often requires that it be used in a different way from one platform to another. In OpenMP, for instance, the directives needed to parallelise a code for a multi-core CPU are not the same as those needed to offload code to an accelerator.

*New programming languages*. The Climate Modeling Alliance (CliMA) has adopted a radically new approach by rewriting ocean and atmospheric models from scratch using the programming language Julia (Perkel, 2019; Sridhar et al., 2022). Designed to overcome the "two-language problem" (Churavy et al., 2022), Julia is ideally suited to harness emerging HPC architectures based on GPUs (Besard et al., 2017; Bezanson et al., 2017). First results with CliMA's ocean model, Oceananigans.jl (Ramadhan et al., 2020), run on 64 NVIDIA A100 GPUs exhibit 10 simulated years per day (SYPD) at 8 km horizontal resolution (Silverstri et al., 2024). This performance is similar to current-generation CPU-based ocean climate models run at much coarser resolution (order of 25–50 km resolution). Similarly promising benchmarks have been obtained with a barotropic configuration of a prototype of MPAS-Ocean, rewritten in Julia (Bishnu et al., 2023). Such performance gains hold great promise for accelerating operational ocean prediction at high spatial resolution run on emerging HPC hardware.

*Toward energy-efficient simulations*. Increased resolution, process representation, and data intensity in ocean and climate modelling is vastly expanding the need for compute cycles (more cores and smaller time steps). As a result, the ocean, atmosphere, and climate modelling community has recognised the need for their simulations to become more energy-efficient and to reduce their carbon footprint (Loft, 2020; Acosta et al., 2024; Voosen, 2024). Owing to their architecture, GPUs can play a significant role in reducing energy requirements. A related research frontier being spearheaded by the atmospheric modelling community is the use of mixed or reduced precision to speed up simulations (Freytag et al., 2022; Klöwer et al., 2022; Paxton et al., 2022), with a potentially desirable side effect of natively capturing stochastic parameterisations (Kimpson et al., 2023). GPUs are ideally suited for such approaches, but successful implementation depends heavily on the model's numerical algorithms.

*Data-driven operational ocean forecasting*. Operational weather and ocean forecasting are facing the potential of a paradigm shift with the advent of powerful, purely data-driven methods. The numerical weather prediction (NWP) community has spearheaded the development of machine-learning-based emulators that perform several orders of magnitude faster than physics-based models (e.g. Bouallègue et al., 2024; Rasp et al., 2024). Such emulators have the potential to revolutionise probabilistic forecasting and uncertainty quantification, among others. The computational patterns underlying the ML algorithms, such as parallel matrix multiplication, are ideally suited for general-purpose GPU architectures. While these methods have been driven to a large extent by private sector entities and require access to increasingly large GPU-based HPC systems for training, corresponding efforts in operational ocean forecasting are only now beginning to catch up. A review of the rapidly changing landscape of AI methods in the context of ocean forecasting is attempted in Heimbach et al. (2025; in this report).

**Data availability.** No datasets were used in this article.

**Author contributions.** ARP created the first draft of this work. PH assisted with updating the text in light of the reviews received.

**Competing interests.** Andrew R. Porter has declared that he is an author of the PSyclone package and a co-chair of the NEMO HPC Working Group.

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**Acknowledgements.** The authors would like to thank the reviewers for bringing the E3SM work to their attention.

**Review statement.** This paper was edited by Jay Pearlman and reviewed by Mark R. Petersen and one anonymous referee.

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# Distributed environments for ocean forecasting: the role of cloud computing

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Received: 19 September 2024 – Discussion started: 30 September 2024
Revised: 7 March 2025 – Accepted: 16 March 2025 – Published: 2 June 2025

**Abstract.** Cloud computing offers an opportunity to innovate traditional methods for provisioning of scalable and measurable computed resources as needed by operational forecasting systems. It offers solutions for more flexible and adaptable computing architecture, for developing and running models, and for managing and disseminating data to finally deploy services and applications. The review discusses the key characteristic of cloud-computing-related on-demand self-service, network access, resource pooling, elasticity, and measured services. Additionally, it provides an overview of existing service models and deployments methods (e.g., private cloud, public cloud, community cloud, and hybrid cloud). A series of examples from the weather and ocean community are also briefly outlined, demonstrating how specific tasks can be mapped on specific cloud patterns and which methods are needed to be implemented depending on the specific adopted service model.

## 1 Introduction

Cloud computing presents an opportunity to rethink traditional approaches used in operational oceanography (Vance et al., 2016), since it can enable a more flexible and adaptable computing architecture for observations and predictions, offering new ways for scientists to observe and predict the state of the ocean and, consequently, to build innovative downstream services for end users and policy makers. Operational ocean forecasting systems (OOFSs) are sustained by a solid backbone composed of satellite and marine observation networks for Earth observations (i.e., data) and state-of-the-art numerical models (i.e., tools) that deliver products according to agreed standards (i.e., ocean predictions, indicators, etc.): the workflow is well represented by the ocean value chain, as described in Bahurel et al. (2010) and Alvarez Fanjul et al. (2022). OOFSs massively use high-performance computing (HPC) to process data and run tools, whose results are shared and validated according to agreed data standards and methodologies, which can result in a remarkable computational cost, not always affordable for research institutes and organizations. Additionally, when building services, it is also important to guarantee lower latency, cost efficiency, and scalability, together with reliability and efficiency. In such framework, cloud computing can represent an opportunity for expanding the capabilities of forecasting centers in managing, producing, processing, and sharing ocean data. It implies adopting, evolving, and sustaining standards and best practices to enhance management of the ocean value chain, to optimize the OOFS processes, and to allow rationalization of requirements and specifications to properly account for operating a forecasting system (Pearlman et al., 2019).

Cloud technology has dramatically evolved in the last decades: the private sector has extensively used cloud computing for enabling scalability and security, leveraging it for artificial intelligence (AI) and machine learning (ML) frameworks, Internet of Things (IoT) integration, and HPC to optimize and innovate operations. It plays also a crucial role in enhancing data interoperability and FAIR (findable, accessible, interoperable, and reusable; Wilkinson et al., 2016) principles, through standardization of formats, APIs, and access protocols, ensuring that datasets can be easily shared, accessed, and reused by researchers globally.

Considering OOFSs, the computational and programming models offered by cloud computing can largely support real-time data processing, scalable model runs, data sharing, and elastic operations, facilitating the integration of AI/ML techniques (Heimbach et al., 2025, in this report) and the development of applications for the blue economy and society (Veitch et al., 2025, in this report) in operational frameworks. More in detail, cloud computing can provide a powerful and collaborative platform for the development and running of operational models, for management and dissemination of data, for building and deploying services to downstream business and applications, and finally for analyses and visualization of oceanographic products, enabling researchers to tackle larger and more complex problems without the burden of building and maintaining computing and storage infrastructures. However, challenges such as data transfer latency, security, and potential vendor lock-in must be addressed, including the high costs for running complex modeling systems.

This paper explores today's capabilities in cloud computing technology with an outlook on the benefit and challenges in adopting this paradigm in OOFSs. The remainder of this paper is organized as follows: Sect. 2 presents cloud computing foundational key concepts, highlighting some existing initiatives from the private sector; Sect. 3 discusses opportunities and challenges for ocean prediction in adopting cloud technologies, presenting existing international initiatives worldwide as examples; and Sect. 4 concludes this paper.

## 2 Key concepts of cloud computing

### 2.1 A brief history of cloud computing

Cloud computing is a specialized form of distributed computing that introduces utilization models for remotely provisioning scalable and measured computing resources (e.g., networks, servers, storage, applications, and services) (Mahmood et al., 2013), offering organizations different benefits for their business services and applications: scalability, cost savings, flexibility and agility, reliability and availability, collaboration and accessibility, innovation and experimentation, and sustainability.

The term "cloud computing" originated as a metaphor for the Internet, which is, in essence, a network of networks providing remote access to a set of decentralized IT resources. In the early 1960s, John McCarthy introduced the concept of computing as a utility:

> If computers of the kind I have advocated become the computers of the future, then computing may someday be organized as a public utility just as the telephone system is a public utility. … The computer utility could become the basis of a new and important industry.

This idea opened the concept of having services on the Internet so users could benefit of them for their applications. In the same period, Joseph Carl Robnett Licklider envisioned a world where interconnected systems of computers could communicate and interoperate: that was the milestone of the modern cloud computing. In the late 1990s, Ramnath Chellappa introduced for the first time the term "cloud computing" as a new computing paradigm (Chellappa, 1997), "where the boundaries of computing will be determined by economic rationale rather than technical limits alone", dealing with concepts such as expandable and allocatable resources that can ensure cost efficiency, scalability, and business value. In the same period, Compaq Computer Corporation adopted the concept of the "cloud" in its business plan as a term for evolving the technological capacity of the company itself in offering new scalable and expandable services to customers over the Internet. The last 2 decades have been characterized by a rapid expansion of cloud computing: while the general public has been leveraging forms of Internet-based computer utilities since the mid-1990s as form of search engines, e-mail services, social media platforms, etc., it was not until 2006 that the term "cloud computing" emerged, when Amazon launched its Simple Storage Service (Amazon S3) followed by the Elastic Compute Cloud (Amazon EC2) service, enabling organizations to lease computing capacity and storage to run their business applications. In 2008, Google launched the Google App Engine, a cloud computing platform used as a service for developing and hosting web applications; then, in 2010 Microsoft launched Azure as a cloud computing platform and service provider that provides scalable, on-demand resources to customers to build applications globally; in 2012, Google launched the Google Compute Engine which enables users to launch virtual machines (VMs) on demand.

To understand the framework over which cloud computing is built, it is fundamental to refer to the standards and best practices provided by the North American National Institute of Standard and Technology (NIST) (Mell and Grance, 2011):

> cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction.

NIST further elaborates on cloud computing providing a cloud computing reference architecture based on five essential characteristics, three service models, and four deployment models.

### 2.2 An outlook to NIST definitions

Cloud computing essential characteristics defined by NIST can be considered reference guidelines for both providers and clients to ensure scalable, cost-effective, and accessible resources to fit specific needs. Table 1 shows a summary of the essential characteristics' definitions as provided in Mell and Grance (2011), offering the client and provider's perspectives with some examples that show how cloud solutions ensure scalability, flexibility, and efficiency.

NIST specifies three possible cloud services models: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). They define the foundational cloud services' characteristic client needs to ensure adequate levels of management, flexibility, and control. Table 2 presents service models' definitions as provided in Mell and Grance (2011), discussing examples where they are used.

Besides the NIST definitions, similar to PaaS another service model is the serverless model (or Function as a Service – FaaS), which is the capability provided to the user to abstract infrastructure concerns away from applications, where developers can implement application functionality as invocable functions/services whilst providers automatically provision, deploy, and scale these services based on a range of criteria, including efficiency, cost, and load balancing. Examples of serverless/FaaS services are AWS Lambda (https://aws.amazon.com/lambda, last access: 29 April 2025) and Fargate (https://aws.amazon.com/fargate, last access: 29 April 2025), Microsoft Azure Functions (https://azure.microsoft.com/en-us/products/functions, last access: 29 April 2025), Google Cloud Functions (https://cloud.google.com/functions, last access: 29 April 2025), and Scaleway Serverless Functions (https://www.scaleway.com/en/serverless-functions, last access: 29 April 2025).

Cloud computing deployment models can be based on different approaches, offering organizations options for workload placement, application development, and resource allocation to optimize their cloud strategy based on their needs, cost considerations, performance requirements, compliance regulations, and desired level of control. The four cloud computing deployment models identified by NIST are reported in Table 3 with a description and some examples.

Besides the cloud deployment models identified by NIST, there are few other approaches that are worth mentioning that provide further capabilities to the organizations that decide to embrace cloud technology.

Multi-cloud computing refers to the strategy of using multiple cloud service providers, allowing organizations leveraging the services of two or more public/private cloud providers or a of combination public–private cloud providers, combining their offerings to build and manage their applications and infrastructure. This approach allows businesses to take advantage of the strengths and capabilities of different cloud providers, such as cost effectiveness, performance, geographic coverage, or specialized services. It also offers increased flexibility and redundancy, and it mitigates the risk of vendor lock-in (Hong et al., 2019). Multi-cloud solutions, which can be based on open-source technologies such as Kubernetes, offer the possibility to ease migration of applications, improving portability since they support containerization and microservices. Major challenges include the complexity in the management of the infrastructure, issues with integration and interoperability, and security. The edge-computing paradigm enables data analyzing, storage, and offloading computations near the edge devices (such as Internet of Things – IoT – devices, sensors, and mobile devices) to improve response time and save bandwidth (Pushpa and Kalyani, 2020). This approach aims at minimizing the data volume to process in the cloud, reducing network costs and bandwidth utilization, and increasing reliability and scalability. Major challenges include the complexity in the management of the edge devices, security potentially affected by devices' vulnerability, and synchronization of communications between edge devices and cloud infrastructure.

Distributed cloud-edge computing, one of the main innovation streams for cloud computing, combines elements of cloud computing with edge computing, extending the capabilities of the traditional centralized cloud infrastructure by distributing cloud services closer to the edge of the network, where data are generated and consumed, rather than relying solely on centralized data centers. By moving cloud services closer to where data are generated, latency (defined as the delay in network communication) is reduced, allowing fast response times, and real-time or time-sensitive applications (e.g., collection of observations from automated sensors and systems for guaranteeing efficiency in operations; early warning systems for disaster management and safety) can benefit from faster response times and improved performance. This is especially crucial for applications requiring immediate data processing and low latency. Recently, public cloud providers started to offer pre-configured appliances (e.g., AWS Outpost, Azure Stack) that bring the power of the public cloud to the private and edge cloud and have defined collaborations with telcos (e.g., AWS and Vodafone, Google and AT&T) to create 5G edge services. Furthermore, the main open-source cloud management platforms provide extensions (OpenNebula ONEedge, OpenStack StarlingX, Kubernetes KubeEdge) for enhancing private clouds with capabilities for automated provisioning of computing, storage, and networking resources and/or orchestrate virtualized and containerized application on the edge. Major challenges include ensuring data security across the distributed locations, for a safe communication between cloud and edge, and resource management and network reliability.

Based on NIST's definitions as discussed before, Table 4 summarizes how the five essential characteristics apply across the four deployment models (public, private, hybrid, and community cloud) to support the selection of the right cloud model with respect to efficiency in costs and performances, security, and management.

**Table 1.** NIST cloud computing essential characteristics: client/provider perspectives and examples.

| Characteristics | Primary focus | Client perspective | Cloud provider perspective | Example |
|---|---|---|---|---|
| On-demand self-service | Users can provision computing resources (e.g., storage, VMs) automatically, without requiring human interaction with the service provider. | Users can request and configure resources like virtual machines, storage, or applications when needed, directly from a web interface or API. | Automatically provide resources in response to user requests without manual intervention. | A developer launches a virtual machine on a cloud platform using a dashboard or API in minutes, without needing to contact support. |
| Broad network access | Cloud resources are available over a network and accessible through standard mechanisms from various devices. | Users can access cloud services from a range of devices (e.g., mobiles and PCs) through standard protocols like HTTP/HTTPS and APIs. | Ensure cloud services can be accessed consistently and securely from different client devices. | A user edits a document stored in the cloud from a laptop at home and then continues editing from a smartphone while commuting. |
| Resource pooling | Cloud providers pool resources to serve multiple users (tenants) dynamically, with no fixed assignment to any one user. | Users do not know the exact physical location of the resources they are using, but they get what they need as required. | Dynamically allocate physical and virtual resources across many customers to maximize efficiency and utilization. | Multiple customers use the same set of servers and storage, but their workloads are isolated through virtualization technologies for security. |
| Rapid elasticity | Cloud resources can be quickly scaled up or down to meet demand, often appearing limitless to the user. | Users can automatically scale their resources up or down based on their needs, without delays. | Automatically add or remove resources in response to changing demand, ensuring that the user has sufficient capacity. | An e-commerce website automatically scales up its computing resources during a flash sale and then scales down when the traffic subsides. |
| Measured service | Cloud systems automatically control and optimize resource usage by tracking it and charging based on actual consumption. | Users only pay for the amount of resources (e.g., storage, CPU, bandwidth) they actually use, with detailed reporting. | Track resource consumption at various levels (e.g., storage, CPU usage) and optimize based on real-time monitoring. | A company receives a monthly bill detailing how much computing power and storage they used, ensuring that they are billed accurately based on consumption. |

Cloud-native applications – which are built, run, and maintained using tools, techniques, and technologies for cloud computing – provide abstraction from underlying infrastructure and enhanced scalability, flexibility, and reliability, which are strongest in public and hybrid cloud models. Cloud-native application development is driven by new software models, such as microservices and serverless, and is made possible through technologies such as containers (i.e., Docker, https://www.docker.com/, last access: 29 April 2025) and container orchestration tools (i.e., Kubernetes), which are becoming the de facto leading standards for packaging, deployment, scaling, and management of enterprise and business applications on cloud computing infrastructures.

Following the rise of containerization in enterprise environments, the adoption of container technologies has gained momentum in technical and scientific computing, including high-performance computing (HPC). Containers can address many HPC problems (Mancini and Aloisio, 2015): however, security and performance overhead represent some current limits in using containerization in HPC environment (Chung et al., 2016; Abraham et al., 2020). Several container platforms have been created to address the needs of the HPC community, such as Shifter (Jacobsen and Canon, 2015), Singularity (Kurtzer et al., 2017) (now Apptainer), Charliecloud (Priedhorsky and Randles, 2017), and Sarus (Benedicic et al., 2019). Recently, Podman (https://podman.io/, last access: 29 April 2025) has been analyzed to investigate its suitability in the context of HPC (Gantikow et al., 2020), showing some promise in bringing a standard-based, multi-architecture enabled container engine to HPC.

**Table 2.** NIST cloud computing service models.

| Service model | Primary focus (from Mell and Grance, 2011) | Client perspective | Provider perspective | Use cases |
|---|---|---|---|---|
| Infrastructure as a Service (IaaS) | The capability provided to the consumer is to provision processing, storage, networks, and other fundamental computing resources where the consumer can deploy and run arbitrary software. | Renting and managing computing resources in a virtualized infrastructure. | Provisioning of computing resources in a virtualized infrastructure. | Suitable for organizations that want full control over their infrastructure resources (virtual machines, networks, storage) and want their flexibility in customizing software stack and applications, including data processing and backup. Examples: Amazon EC2 and Microsoft Azure. |
| Platform as a Service (PaaS) | The capability provided to the consumer is to deploy onto the cloud infrastructure consumer-created or acquired applications created using programming languages, libraries, services, and tools supported by the provider. | Easing application deployment without taking care of the infrastructure and middleware. Dependency on provider's platform. | Provisioning and management of the platform. | Suitable for developers and organizations that want to develop, deploy and maintain applications without the burden of managing the underlying infrastructure (virtual machines, network and storage), which is provisioned and deployed by the providers. Examples: Google App Engine and Microsoft Azure App Service. |
| Software as a Service (SaaS) | The capability provided to the consumer is to use the provider's applications running on a cloud infrastructure. | Using software applications directly via the Internet (e.g., web browser or using a client), decreasing costs related to licenses. | Provisioning and management of the software applications, including customer support. | It enables organizations to focus on their core business activities while relying on the expertise and infrastructure provided by the SaaS provider. Examples: Google Drive, Dropbox, and Microsoft 365. |

## 3 Cloud technology landscape in oceanography

Technological advancements in cloud computing and its foundational characteristics, services, and models can provide enormous advantages for operational oceanography across the ocean architectures.

Vance et al. (2019) explored uses of the cloud for managing and analyzing observational data and models workflows: for instance, they show how cloud platforms can be supportive during the collection and the quality control of observations, reducing the risk of power outages, network connectivity, or other issues related to weather conditions at sea that can compromise transmissions from sensors to the base station. Large-scale datasets related to forecast and observational oceanographic products can be stored in cloud-native storages (e.g., S3 Object Storage) and accessed from any location with public connectivity, enabling data-proximate computations (Ramamurthy, 2018). This approach facilitates data-proximate computations (Ramamurthy, 2018), allowing analysis to be performed near the data source using remote resources rather than requiring extensive local downloads and infrastructure (Zhao et al., 2015).

Nowadays, the Digital Twin of the Ocean (DTO) framework is revolutionizing ocean services, acting as a bridge between the current digitalization of processes and the future intelligence. DTO is empowering the use of advanced technologies, such as artificial intelligence (AI) and cloud computing, for industrializing and informatizing the marine sector while supporting operations from data pooling to data processing, with a final direct benefit for applications (Chen et al., 2023). It is then of paramount importance to understand how modern computing technologies can support scientific investigation, enhance ocean forecasting services, and contribute to the evolution of such systems.

To achieve this goal, analysis patterns theorized by Fowler (1997) and described for e-science by Butler and Merati (2016) can be applied, in a simplified way, to the ocean value chain (Alvarez Fanjul et al., 2022) explaining the added value of adopting cloud-based solutions to improve operational forecasting workflows.

**Table 3.** NIST cloud computing deployment models.

| Deployment model | Description | Examples |
|---|---|---|
| Private cloud | Deployment of cloud infrastructure and services exclusively for a single organization or entity. In a private cloud, the computing resources, such as servers, storage, networking, and virtualization technologies, are dedicated to and managed by the organization itself. The infrastructure can be hosted on premises within the organization's own data centers or in a dedicated off-site facility. | Open-source software solutions such as CloudStack[a], OpenNebula[b], and OpenStack[c] allow organizations to build their own private cloud computing solutions. |
| Public cloud | Use of cloud services provided by third-party vendors over the Internet. The infrastructure and resources in the public cloud are shared among multiple customers, and the cloud service provider is responsible for managing and maintaining the underlying hardware, software, and infrastructure. Users can access and utilize the services on a pay-as-you-go basis, typically through a subscription or usage-based pricing model. | Examples of public cloud providers are Alibaba[d], Amazon Web Services[e], Google Cloud Platform[f], Hetzner[g], Microsoft Azure[h], and Scaleway[i]. |
| Community cloud | Cloud infrastructure and resources are shared among organizations with common interests, such as industry-specific regulations, security requirements, or collaborative projects. In a community cloud, the infrastructure is designed and managed for the specific needs of the community members, and it allows organizations within the community to share costs, resources, and expertise while maintaining a higher level of control and customization compared to public cloud services. | EGI[j] is a federation of different European data centers providing a cloud infrastructure for research communities. The European Open Science Cloud (EOSC[k]) is an environment for hosting and processing research data to support EU science, built on top of EGI cloud infrastructure. The European Weather Cloud[l] will deliver data access and cloud-based processing capabilities for the European Meteorological Infrastructure (EMI) and their users. The D4Science[m] e-infrastructure (Assante et al., 2019) is the core of the Blue-Cloud[n] virtual research environments (VREs): it implements proven solutions for connecting to external services and orchestrates distributed services, which will be instrumental for smart connections to other e-infrastructures in Blue-Cloud, including EUDAT and DIAS (WEkEO). |
| Hybrid cloud | It combines both public and private cloud environments to create a unified computing infrastructure, allowing organizations to host some applications or data in a private cloud (i.e., greater control, security, and compliance), while utilizing public cloud services for other applications or workloads (i.e., scalability, cost effectiveness, and flexibility for workload burst/on-demand peaks). The hybrid approach provides the ability to address specific requirements, such as regulatory compliance or data sovereignty, by keeping sensitive data within a private infrastructure while utilizing the public cloud for less sensitive workloads. | Netflix[o] uses a hybrid cloud storage solution in order to store and move assets across Amazon AWS S3 and multiple on-premises storage systems. |

[a] https://cloudstack.apache.org (last access: 29 April 2025). [b] https://opennebula.io (last access: 29 April 2025). [c] https://www.openstack.org (last access: 29 April 2025). [d] https://www.alibabacloud.com (last access: 29 April 2025). [e] https://aws.amazon.com (last access: 29 April 2025). [f] https://cloud.google.com (last access: 29 April 2025). [g] https://www.hetzner.com/cloud (last access: 29 April 2025). [h] https://azure.microsoft.com (last access: 29 April 2025). [i] https://www.scaleway.com/en (last access: 29 April 2025). [j] https://www.egi.eu (last access: 29 April 2025). [k] https://eosc.eu (last access: 29 April 2025). [l] https://www.europeanweather.cloud (last access: 29 April 2025). [m] https://www.d4science.org/ (last access: 29 April 2025). [n] https://www.blue-cloud.org/e-infrastructures/d4science (last access: 29 April 2025). [o] https://aws.amazon.com/solutions/case-studies/netflix-storage-reinvent22 (last access: 29 April 2025).

**Table 4.** Mapping essential characteristics on the type of cloud deployment models.

| Essential characteristic | Deployment model | | | |
|---|---|---|---|---|
| | Private cloud | Public cloud | Community cloud | Hybrid cloud |
| On-demand self-service | Managed internally, self-service for internal teams | Users provision services via public provider's API or portal | Self-service for community members, often through secure portals | Self-service across both public and private clouds, with potential for complex management |
| Broad network access | Limited to internal users or authorized external users (VPN, private network) | Accessible over the public Internet via standard protocols (e.g., HTTP) | Restricted to community members with specific access | Accessible over both public and private networks, often with encrypted or dedicated connections |
| Resource pooling | Resources are pooled internally for organizational needs | Resources are pooled and shared across multiple tenants | Resources are pooled among members of a specific community | Resources are pooled across private and public clouds, with dynamic allocation based on workload |
| Rapid elasticity | Elasticity may be constrained by internal resources | High elasticity with near-unlimited scalability based on demand | Elasticity exists but is constrained by the community's shared resources | Public cloud provides high elasticity, with private cloud handling more stable, predictable workloads |
| Measured service | Internal measurement and chargeback to departments | Public provider measures and bills based on usage (e.g., compute hours, storage) | Resource usage is tracked across community members for cost sharing | Both private and public clouds measure usage, with different billing models (internal and public) |

The term "analysis pattern" focuses on organizational aspects of a system since they are crucial for requirement analysis. Geyer-Schulz and Hahsler (2001) designed a specific template for analysis patterns: starting from that and the examples proposed by Butler and Merati (2016) for e-science, we propose an initial analysis of cloud patterns (CPs) for the cloud-based OOFS processes, taking the ocean value chain components as a reference framework.

The following are some initial identified cloud patterns, which are mapped in Fig. 1.

- *CP1: cloud-based management of ocean data for OOFSs*. This is devoted to the integration into forecasting services of the cloud-based approach, facilitating the access to large volumes of diverse, current, and authoritative data. It addresses challenges related to locating and using large amounts of scientific data. It is particularly useful for data managers that needs to provide upstream data to forecasters for running one or more models, or for performing validation of the numerical results. It can be implemented on the hybrid/public cloud, and the design can be based on PaaS or SaaS (data access as a service). It enables seamless integration of upstream data from multiple sources (including observations and forcings data used in model applications).
- *CP2: cloud-based computing infrastructure for OOFSs*. It explores cloud-based platforms and tools for running computationally intensive numerical models and procedures used for forecasting services. It benefits numerical modelers and forecasters that require high-performance computing (HPC) to run a model application that can include AI/ML pre-/post-processing. It can be implemented on a private cloud, adopting IaaS service models. It enhances the execution of the Marine Core Service by optimizing computing resources such as CPU/GPU, networking, and storage.
- *CP3: cloud-based management of ocean data produced by OOFSs.* Designed for storing and managing geospatial ocean data in the cloud, this component addresses the challenge of the growing data volume with limited budgets dedicated to data management. It is valuable for data managers that need to store forecast products, including model results in native format, for further analysis and processing. Data can be stored in dedicated file systems or databases and accessible through APIs (including GIS-based ones). It can be implemented on a private cloud, using the PaaS service model. It ensures efficient storage and accessibility of data produced by the Marine Core Service, made available for dissemination to users.

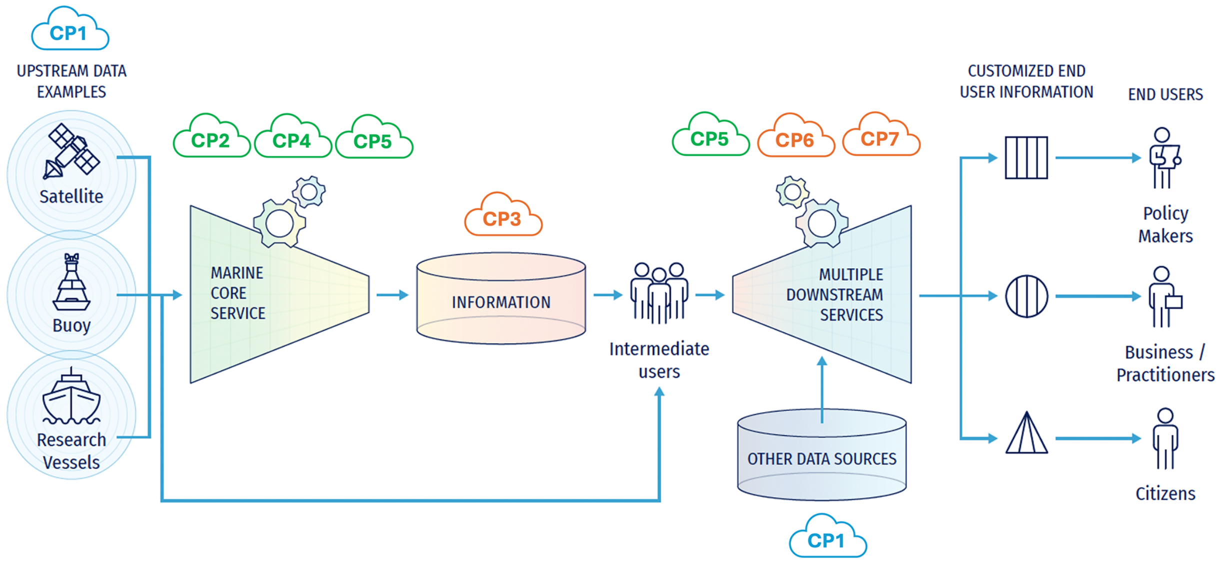


**Figure 1.** The ocean value chain and associated cloud patterns (adapted from Alvarez Fanjul et al., 2022).

- *CP4: cloud-based computing infrastructure for OOFS disaster recovery in the cloud.* Focused on leveraging cloud computing in the ocean forecast production pipeline to enhance robustness and meet the growing demand for scalable computational resources. It can be used by forecasters that need OOFSs on demand under unexpected situations (e.g., working as backup in case the nominal unit is down). A private/hybrid cloud can be used, and the design can be based on PaaS or IaaS. This approach enhances the Marine Core Service by ensuring operational continuity and timely dissemination of forecast products.

- *CP5: analysis of OOFS products in the cloud*. Focused on performing analysis and processing of ocean data in the cloud, facilitating multi-model intercomparisons and quality assessment, even in case of larger datasets and/or datasets from multiple sources. It is beneficial for product quality experts and data analysts in charge of quality control or for providing a private-cloud-based service for pre-qualification of ocean products. It can be implemented through a hybrid/private cloud, and the design can be based on SaaS. It supports the Marine Core Service quality assurance and downstream services through tailored user-oriented metrics or indicators for downstream applications.

- *CP6: visualization of OOFS in the cloud*. Devoted to integration of cloud-based visualization capabilities to process and publish ocean products via the (cloud) service. It also addresses the need for visualizing larger amounts of data. It can be useful for data engineers and forecasters that need to create user-friendly visualizations for end users and policy makers. It can be implemented using a private/public cloud, and the design can be based on SaaS. It supports downstream services by providing an interactive visualization service and tailored user-oriented visual bulletins for end users.

- *CP7: product dissemination and outreach in the cloud.* Devoted to the use cloud-based platforms and tools for dissemination of OOFS products to different audiences – scientific and non-scientific. This is useful for communication experts that need to use a cloud-based repository for sharing insights and digital material produced using OOFS products. It uses hybrid/private cloud solutions, and the design can be based on SaaS. It enhances multiple downstream services by providing customized and accessible end-user information for policy-making, business, society.

Most of the challenges generically introduced in Sect. 2 can be still pertinent when adopting cloud computing solutions for OOFS.

- *Data security.* Processing oceanographic data might generate sensible information that requires proper management. In addition, downstream services might require the use of data from governmental or research institutes that need to be preserved and possibly not shared.

- *Costs.* While cloud computing can reduce upfront infrastructure costs, it can become expensive for continuous, long-term use or for HPC tasks that require significant computational power.

- *Latency and bandwidth limitations.* Ingesting or assessing a large volume of ocean data on centralized cloud data centers might affect OOFSs' performances due to poor network connection.

- *Dependence on cloud providers (vendor lock-in).* Deployment of OOFS on specific cloud providers might lead to vendor lock-in, complicating migration to another cloud provider due to proprietary technologies, APIs, or data format.

- *Regulatory and compliance issues.* Cloud providers must comply with various regulatory frameworks, and using a public cloud for OOFS might complicate compliance with data protection laws or environmental regulations or even with licenses.

- *Limited control over hardware.* Cloud users do not have direct control over the underlying hardware, which may be a disadvantage when HPC resources need fine-tuned optimization to run OOFS.

- *Impact on code refactoring.* Adapting OOFS to a cloud environment may require significant code refactoring to optimize for distributed computing, cloud-native architectures, and specific provider APIs, potentially increasing development effort and complexity.

In the following, some US and EU programs, initiatives, and projects are reported as examples on how cloud computing technologies and patterns have been used to provide services to the oceanographic and scientific community in general.

### 3.1 NOAA Open Data Dissemination and Big Data Program

NOAA's Open Data Dissemination (NODD, https://www.noaa.gov/nodd, last access: 29 April 2025) Program is designed to facilitate public use of key environmental datasets by providing copies of NOAA's information in the cloud, allowing users to do analyses of data and extract information without having to transfer and store these massive datasets themselves. NODD started out as the Big Data Project in April 2015 (and then later became the Big Data Program); NODD currently works with three IaaS providers (Amazon Web Services (AWS), Google Cloud Platform, and Microsoft Azure) to broaden access to NOAA's data resources. These partnerships are designed to not only facilitate full and open data access at no net cost to the taxpayer but also foster innovation by bringing together the tools necessary to make NOAA's data more readily accessible. There are over 220 NOAA datasets on the cloud service provider (CSP) platforms. The datasets are organized by the NOAA organization that generated the original dataset (https://www.noaa.gov/nodd/datasets, last access: 29 April 2025).

### 3.2 Copernicus Service and Data and Information Access Services

Copernicus (https://www.copernicus.eu, last access: 29 April 2025) is the Earth observation component of the EU Space Programme, looking at the Earth and its environment to benefit all European citizens. Copernicus generates on a yearly basis petabytes of data and information that draw from satellite Earth observation and in situ (non-space) data. The up-to-date information provided by the core services (atmosphere, https://atmosphere.copernicus.eu/, last access: 29 April 2025; climate change, https://climate.copernicus.eu/, last access: 29 April 2025; marine, https://marine.copernicus.eu/, last access: 29 April 2025; land, https://land.copernicus.eu/en, last access: 29 April 2025; security, https://www.copernicus.eu/en/copernicus-services/security, last access: 29 April 2025; and emergency, https://emergency.copernicus.eu/, last access: 29 April 2025) is free and openly accessible to users. As the data archives grow, it becomes more convenient and efficient not to download the data anymore but to analyze them where they are originally stored.

To facilitate and standardize access to data, the European Commission has funded the deployment of five cloud-based platforms (CREODIAS, https://creodias.eu/, last access: 29 April 2025; Mundi, https://mundiwebservices.com/, last access: 29 April 2025; Onda, https://www.onda-dias.eu/cms/, last access: 29 April 2025; Sobloo, https://engage.certo-project.org/sobloo-overview/, last access: 29 April 2025; and WEkEO, https://www.wekeo.eu/, last access: 29 April 2025), known as Data and Information Access Services (DIAS; https://www.copernicus.eu/en/access-data/dias, last access: 29 April 2025) that provide centralized access to Copernicus data and information, as well as to processing tools. The DIAS platforms provide users with a large choice of options to benefit from the data generated by Copernicus: to search, visualize, and further process the Copernicus data and information through a fully maintained software environment while still having the possibility to download the data to their own computing infrastructure. All DIAS platforms provide access to Copernicus Sentinel data, as well as to the information products from the six operational services of Copernicus, together with cloud-based tools (open source and/or on a pay-per-use basis). Thanks to a single access point for all the Copernicus data and information, DIAS platforms allow the users to develop and host their own applications in the cloud, while removing the need to download bulky files from several access points and process them locally.

### 3.3 Blue-Cloud

The European Open Science Cloud (EOSC) provides a virtual environment with open and seamless access to services for storage, management, analysis, and reuse of research data, across borders and disciplines. Blue-

Cloud aims at developing a marine thematic EOSC to explore and demonstrate the potential of cloud-based open science for better understanding and managing the many aspects of ocean sustainability (https://blue-cloud.org/news/blue-clouds-position-paper-eosc, last access: 29 April 2025). The Blue-Cloud platform, federating European blue data management infrastructures (SeaDataNet, https://www.seadatanet.org/, last access: 29 April 2025; EurOBIS, https://www.eurobis.org/, last access: 29 April 2025; Euro-Argo ERIC, https://www.euro-argo.eu/, last access: 29 April 2025; Argo GDAC (Wong et al., 2020); EMODnet, https://emodnet.ec.europa.eu/en, last access: 29 April 2025; ELIXIR-ENA, https://elixir-europe.org/services/biodiversity, last access: 29 April 2025; Euro-BioImaging, https://www.eurobioimaging.eu/, last access: 29 April 2025; Copernicus Marine; Copernicus Climate Change; and ICOS-Marine, https://www.icos-cp.eu/observations/ocean/otc, last access: 29 April 2025) and horizontal e-infrastructures (EUDAT, https://www.eudat.eu/, last access: 29 April 2025; DIAS; D4Science), provides FAIR access to multidisciplinary data, analytical tools, and computing and storage facilities that support research. Blue-Cloud provides services through pilot demonstrators for oceans, seas, and freshwater bodies for ecosystems research, conservation, forecasting, and innovation in the blue economy, and it accelerates cross-discipline science, making innovative use of seamless access to multidisciplinary data, algorithms, and computing resources.

## 4 Conclusions

Cloud computing has been demonstrated to be a key driver in the digital evolution of the private sector, offering a baseline for expanding and scaling applications and services by enhancing scalability, cost efficiency, and data processing. Service models offer different layers for pushing technological evolution, where infrastructure/platform/software can be assimilated to services that can be deployed in different cloud models, depending on the specific needs of the users in keeping resources public or private or hybrid. By leveraging on-demand computing power, big data analytics, and global data accessibility and sharing, cloud computing improves business efficiency, scientific research, and innovation, benefiting society and business. Taking these concepts as granted, cloud computing can be seen as an opportunity for operational oceanography, for enhancing ocean prediction and monitoring by exploiting its collaborative framework to support blue economy, sustainable ocean management, and climate change mitigation actions. The simplified pattern analysis has revealed how OOFS architecture components can be implemented in a cloud environment without the burden of maintaining complex infrastructure: common tasks like processing and analyzing large datasets can be optimized in cloud-native storages, using software that can be integrated by AI/ML techniques for anomaly detection, or by means of specific APIs for data searching and retrieving. Cloud-based visualization and data delivery can ensure security especially for critical information that can impact decision-making, driving better-informed policies and responses in marine and coastal management.

Despite these advantages, several challenges remain, some of them partially solved with the implementation of existing deployments models (hybrid cloud, for instance): interoperability, which is one of the pillars for cloud-based environments, requires the definition of data standards and adoption of best practices. Security in data access/sharing as well as costs associated with running forecasting systems can raise constraints for vendor lock-in and long-term sustainability.

Promoting a collaborative framework among existing and new centers could be seen as one promising approach for fostering innovation, collaboration, and more efficient ocean prediction and monitoring: by leveraging shared cloud-based resources, forecasting centers can combine their expertise and share data and tools, supporting the creation of a "digital twin" of the ocean to use for a wide range of applications for managing and protecting our ocean.

**Data availability.** No datasets were used in this article.

**Author contributions.** SC contributed to the conceptualization, writing, and validation. GP contributed to the writing and validation.

**Competing interests.** At least one of the (co-)authors is a member of the editorial board of *State of the Planet*. The peer-review process was guided by an independent editor, and the authors also have no other competing interests to declare.

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**Acknowledgements.** The authors are grateful to Marco Mancini for sharing his expert view on cloud computing technology and to Enrique Alvarez Fanjul for analyzing Sect. 3 and sharing his expert view on the impact of using cloud computing in support of operational oceanography. The authors also extend their gratitude to the reviewers, Alvaro Lorenzo Lopez and Miguel Charcos-Llorens, and the to the topic editor, Jay Pearlman, for their valuable and insightful comments that significantly improved this paper.

**Review statement.** This paper was edited by Jay Pearlman and reviewed by Miguel Charcos-Llorens and Alvaro Lorenzo Lopez.

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State Planet, 5-opsr, 25, 2025
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STATE OF THE PLANET



# End-user applications for ocean forecasting: present status description

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Received: 13 September 2024 – Discussion started: 26 September 2024
Revised: 25 January 2025 – Accepted: 10 February 2025 – Published: 2 June 2025

**Abstract.** The direct benefits of developing ocean forecasting systems and of improving the accuracy of the predictions are practically demonstrated through downstream applications. These systems are considered pillars of the blue economy, offering potential for economy, environmental sustainability, the creation of new job opportunities, and actively supporting decision-making. In this paper, the authors outline the main sectors currently benefiting from ocean model products, reviewing the state of the art and potential use for societal activities, management, and planning.

## 1 Introduction

The blue economy is an increasing sector which includes, amongst other socio-economic sectors, marine living resources, marine non-living resources, marine renewable energy, port activities, shipbuilding and repair, maritime transport, naval activities, search and rescue operations, and coastal tourism. (Fig. 1). The associated economic activities have directly employed close to 4.45 million people and generated around EUR 667.2 billion in turnover and EUR 183.9 billion in gross value added (Rayner et al., 2019b). These sectors offer significant potential for economic growth, sustainability transition, and employment creation, and they ask for innovative, sound, and prompt decision-making support tools. A decision-making workflow needs to understand past and present ocean conditions and forecast future ocean conditions. Accurate predictive capabilities permit the implementation of services for real-time decision-making, multi-hazard warning systems, and anticipatory marine spatial planning. Once the ocean forecast model data are generated, they can be used in a variety of ways. For example, shipping companies can use the data to optimize their routes and avoid areas with dangerous weather or ocean conditions. Fisheries managers can use the data to predict fish populations and optimize their harvests. Environmental agencies can use the data to monitor water quality and detect the spread of pollution, etc. Notably, the Horizon Europe program (2021–2027) has a budget of EUR 95.5 billion (including EUR 5.4 billion from the NextGenerationEU recovery fund), of which at least 35 % will be devoted to support climate-related actions, such as supporting the transition of maritime industries to climate neutrality. Maritime spatial planning (MSP) is a policy framework for mediating between human uses of the ocean and managing their impact on the marine environment. It is considered a key pillar of the sustainable blue economy. Europe's coastal seas, particularly the North Sea and the Baltic Sea, host a highly competitive group of users, such as commercial and private shipping, oil and gas exploitation, pipelines, cables, sand extraction and disposal, wind farms, recreational activities, and fishing, as well as nature reserves and other marine and coastal protected areas (Buck et al., 2004).

The following paragraphs present some examples of how the blue economy is using model data and what its overall impact is.

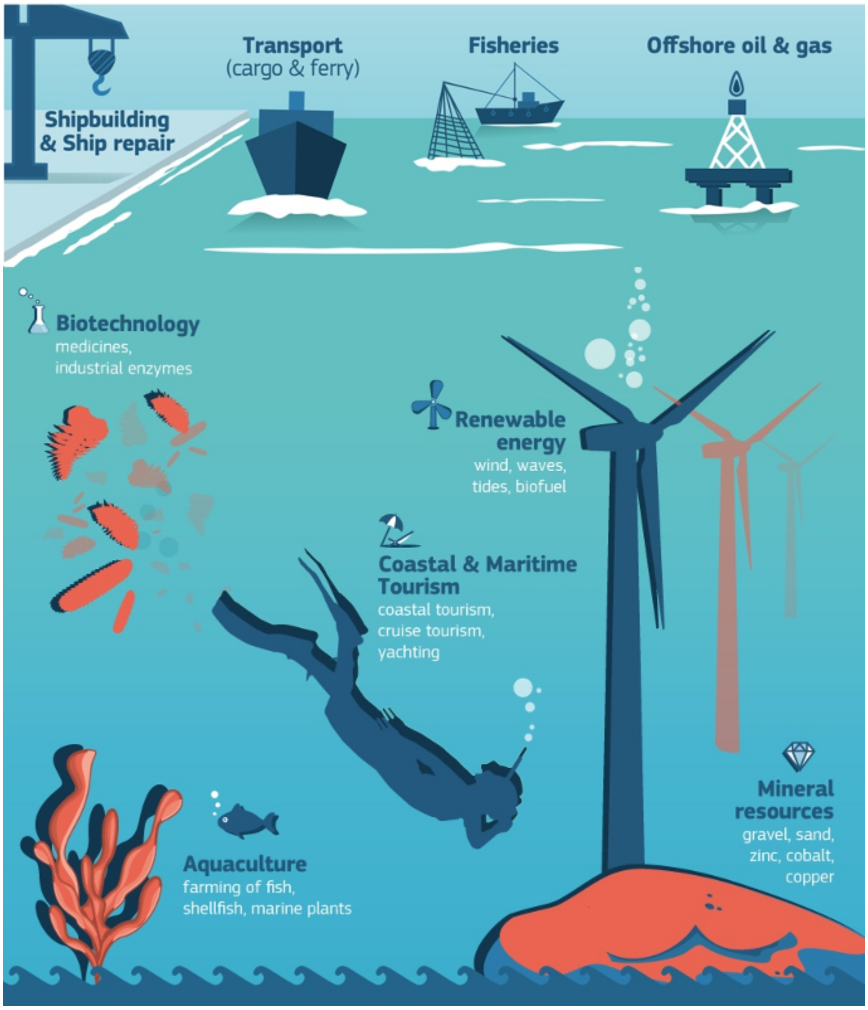


**Figure 1.** Blue growth, adapted from the EC infographics on blue growth (https://ec.europa.eu/assets/mare/infographics/, © European Union 2014, last access: 31 January 2025).

## 2 Model data applications in the blue economy

A good collection of examples of the application of ocean forecasting data in the blue economy can be found in the Expert Team on Operational Ocean Forecast Systems (ETOOFS) guide (https://www.mercator-ocean.eu/en/guide-etoofs/, last access: 24 April 2024). The following subsections briefly describe some of these application fields.

### 2.1 Operational Services for Ports and Cities (OSPAC)

Port and coastal cities need ocean forecasting data for several reasons. A good example of this kind of application can be found on the Operational Services for Ports and Cities (OSPAC) software system, consisting of an integrated set of tools and measuring instruments that provide an operational service to the city and the adjacent port in order to minimize risks and improve environmental management. In these systems, there are two main service layers: the first one includes forecast models of local sea conditions, and, based on these models, a second layer provides real-time alerts on extreme values of coastal variables, such as water quality, currents, and sea state, that are used for a variety of applications (Reboa et al., 2024; Gaughan et al., 2019; NOAA, 2021; OECD, 2016, 2022; Rayner et al., 2019a). The study on the trends and outlook of marine pollution (Regional Marine Pollution Emergency Response Centre for the Mediterranean Sea, 2021) reports that most ship-based environmental hazards, such as oil spills or slicks, occur close to city ports. While the situation has significantly improved over the years, the average number of spills per year in 1970 was approximately 79, which has now been reduced by over 90 % to as low as 6 per year (ITOPF, 2020). However, even a single spill can cause severe environmental damage. The extent of damage caused by an oil spill depends on several factors: the quantity of oil spilled, its behavior in the marine environment, the chemicals involved, the sensitivity of the affected marine area, and the wind and weather conditions at the time of the incident. For example, the clean-up and removal efforts following the break-up and sinking of the Bahamas-registered tanker *Prestige*, which spilled 63 200 t of oil on 13 November 2002, lasted more than 2 years. The pollution caused an estimated EUR 884.98 million in damages, with an additional EUR 554.10 million attributed to environmental and moral damages (Regional Marine Pollution Emergency Response Centre for the Mediterranean Sea, 2021) – amounting to an environmental cost of roughly EUR 2 million per day. Having OSPAC systems to plan and manage fast and effective responses is key to saving billions of euros in environmental and economic costs.

### 2.2 Marine transport, surveillance, naval operations, and marine search and rescue (SAR)

Maritime transport plays a key role in the EU economy and trade, estimated to represent between 75 % and 90 % (depending on the sources; EMSA, https://www.emsa.europa.eu/eumaritimeprofile.html, last access: 25 January 2025) of the EU's external trade and one-third of the intra-EU trade. EU passenger ships can carry up to 1.3 million passengers, representing 40 % of the world's passenger transport capacity. Marine surveillance and naval operations are critical to ensuring the security of marine operations. The sector consumes forecasting data on weather and ocean conditions to, for example, determine the optimal route and time of departure for a vessel, optimize the mission route, and minimize risks to personnel and equipment (Novellino et al., 2021; Życzkowski et al., 2019; Bitner-Gregersen et al., 2014; Schnurr and Walker, 2019). These models can help improve the safety and efficiency of marine transport while minimizing fuel consumption and environmental impacts (Wan et al., 2018). Related to naval operations, the search and rescue (SAR) operations use evidence-based methods to plan, execute, and evaluate SAR operations (Futch and Allen, 2019). SAR requires the gathering and processing of relevant data and information, such as weather and ocean forecasts, topography and geography of the area, and the real-time information of the nature of the incident and its evolution (Révelard et al., 2021; Coppini et al., 2016). This information is used, for example, to minimize the search areas.

### 2.3 Offshore operations

Offshore operations provide access to sources of energy and raw materials necessary for the economy. Ocean forecasting services are crucial for offshore operations: for oil and gas activities, they support oil spill trajectory modeling, data-driven approaches to forecasting production, maintenance support, and many other uses (Keramea et al., 2021); for offshore renewable energy production, they enable the accurate prediction of energy and operational yield efficiency (Uihlein and Magagna, 2016).

### 2.4 Aquaculture and fish stock management

The EU has highlighted the need for a new strategy for aquaculture to become sustainable and to enable future growth in this sector (COM/2021/236) and the new approach for a sustainable blue economy (COM/2021/240). Currently, the need for blue sector food products in the EU is mostly met through imports, around 60 %, ("The EU Fish Market" 2020 edition, EUMOFA), while EU aquaculture accounts for only 20 % of fish and shellfish supply. The rising population demands radical solutions towards food security, which cannot be solely met through land-based agriculture. Seaweed (macroalgae) aquaculture has the potential to supplement food supplies, enhance the maritime economy, and enable ecosystem services (Maar et al., 2023).

In this framework, forecasting services play an important role by providing valuable information to help improve production efficiency; reduce risks; and ensure sustainable practices, such as production planning. The services help to determine optimal production plans, e.g., size and timing of harvests, based on factors like water temperature, nutrient levels, and fish growth rates. These services also support the impact prediction of environmental factors, such as ocean extremes and pollution levels (Sangiuliano, 2018). Another component of the sustainable blue economy is balancing the need for productive fisheries with the preservation of marine biodiversity, i.e., the fish stock management and maintaining sustainable marine protected areas. By predicting environmental factors like water temperature, salinity, and ocean currents, models also help anticipate shifts in fish behavior and distribution and optimize daily operations. In addition to operational benefits, forecasting models support regulatory compliance by aiding fisheries in adhering to quotas, seasonal closures, and protected area guidelines set by organizations such as the International Council for the Exploration of the Sea (ICES) and regional fishery management bodies.

### 2.5 Coastal tourism

Coastal tourism plays an important role in many EU member state economies, with a wide-ranging impact on economic growth, employment, and social development. Coastal tourism is the largest blue economy sector, representing 44 % of the gross value added (GVA) and 63 % of the employment of the total EU blue economy. The value of models for coastal tourism extends from short-term weather forecasts to long-term forecasts, including climate change, sea level rise, and tourism demand; forecasting tourism demand using machine learning algorithms; and predicting coastal tourism vulnerability, from dangerous weather and ocean conditions (extreme events), including sea level (storm surge) events and their relevance in inundation and coastal destruction processes (Le Traon et al., 2015), to climate change and sea level rise (da Costa et al., 2024).

### 2.6 Education

Education and ocean literacy are integral to fostering a sustainable blue economy. By combining formal education with efforts to increase public understanding of the ocean's vital role in supporting life and economies, stakeholders can build a knowledgeable and engaged society. Academic institutions, vocational training centers, and research organizations are developing interdisciplinary programs that integrate technical expertise with environmental stewardship, preparing a workforce adept in ocean sciences, renewable energy, aquaculture, and maritime logistics (Novellino et al., 2022). Ocean literacy initiatives further complement these efforts by raising awareness about marine ecosystems; their resources; and the challenges they face, such as pollution and climate change (see, e.g., https://eurogoos.eu/ocean-literacy-resources/, last access: 25 January 2025). Public campaigns, community engagement projects, and educational outreach help individuals and communities understand the importance of sustainable practices.

## 3 Perspectives

The future of the blue economy is deeply intertwined with the ability to harness advanced scientific tools, such as ocean forecasting models, to address emerging challenges and seize new opportunities. The European Digital Twin of the Ocean, a cutting-edge initiative combining high-resolution ocean data with advanced simulation capabilities, represents a transformative leap in understanding and managing marine environments. This digital twin enables real-time modeling and prediction of ocean conditions, offering unprecedented opportunities for sectors such as maritime transport, renewable energy, fisheries, and coastal management to make data-driven decisions while aligning the needs and offerings of both the public and private sectors. The integration of on-demand access to computing resources and services further amplifies the potential of the digital twin by enabling scalability, real-time access, and computational efficiency. On-demand high-performance computing platforms make it feasible to process vast amounts of data, perform complex simulations, and deliver actionable insights to stakeholders across industries and regions. These technologies facilitate the democratization of ocean data, ensuring that even small-scale operators can leverage state-of-the-art tools to optimize their activities and align with sustainability goals. A key perspective is the integration of these advancements into a holistic framework that supports sustainable development, equitable resource distribution, and robust regulatory compliance. The transition to ocean-based renewable energy sources, the advancements in sustainable aquaculture, and the growing role of marine spatial planning highlight the need for interdisciplinary approaches that combine ecological stewardship with economic growth. Moreover, scaling solutions through the high-performance computing resources enables seamless collaboration across international borders, fostering knowledge exchange and ensuring that technological progress benefits all nations, particularly those heavily reliant on marine resources. Ultimately, the blue economy offers a pathway to achieving global sustainability goals, providing food security, clean energy, and economic resilience while preserving marine ecosystems.

**Data availability.** No data sets were used in this article.

**Author contributions.** AN developed the initial draft, which was reviewed and edited by the co-authors.

**Competing interests.** The contact author has declared that none of the authors has any competing interests.

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**Acknowledgements.** This activity was indirectly supported by the authors' activities under the Copernicus Marine Service and EMODnet programs and the following projects: EU H2020 NAUTILOS (ct. 101000825), HE OLAMUR (ct. 1011094065), HE EFFECTIVE (ct. 101112752), and HE BLUECLOUD2026 (ct. 101094227).

**Financial support.** This research has been supported by the EU Horizon 2020 NAUTILOS project (grant no. 101000825), the Horizon Europe OLAMUR project (grant no. 1011094065), the Horizon Europe EFFECTIVE project (grant no. 101112752), and the Horizon Europe BLUECLOUD2026 project (grant no. 101094227).

**Review statement.** This paper was edited by Jay Pearlman and reviewed by Laurent Delauney and one anonymous referee.

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# Capacity development for the future of ocean prediction

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Received: 19 August 2024 – Discussion started: 26 September 2024
Revised: 15 May 2025 – Accepted: 17 May 2025 – Published: 2 June 2025

**Abstract.** Capacity development in ocean prediction refers to the process of strengthening the abilities of individuals, institutions, and systems to generate, access, understand, and apply ocean prediction tools and information. This encompasses building human capital, enhancing technical skills, improving physical and digital infrastructure, reinforcing governance, fostering collaborative partnerships and networks, ensuring inclusive participation, and providing sustained support – both financial and human – to ensure that ocean prediction services are effective, inclusive, and sustainable, especially in developing and vulnerable regions. The first section of this paper provides an overview of key global frameworks for capacity development in ocean science, with a particular focus on ocean prediction. It also identifies existing gaps in current efforts. In the second part of the paper, we present the capacity development plans of the OceanPrediction Decade Collaborative Centre (DCC), developed within the context of the existing global framework. These plans are informed by the results of a dedicated survey (summarised in this paper) and are further supported by the regional project Ocean Prediction Enhancement in Regions of Africa (OPERA). This section emphasises the importance of integrating both technical and non-technical training, fostering community building, engaging stakeholders, and undertaking complementary actions to create an enabling environment for capacity development. It also highlights the value of a co-design approach and the need for continuous evaluation of the effectiveness and long-term impact of these initiatives. Finally, the discussion section offers recommendations for the future, drawing on the work carried out under the OPERA project and aligned with capacity development guidelines from the Intergovernmental Oceanographic Commission of UNESCO and the United Nations Decade of Ocean Science for Sustainable Development.

## 1 Introduction

Capacity development is defined by the Intergovernmental Oceanographic Commission of UNESCO (IOC-UNESCO) as "the process by which individuals and organisations obtain, strengthen, and maintain the capabilities to set and achieve their development objectives over time" (UNESCO-IOC, 2021a). The IOC Group of Experts on Capacity Development describes the goals of capacity development as "achieving evenly distributed capacity across the globe, across generations, and genders, thus reversing asymmetry in knowledge, skills, and access to technology" (IOC-UNESCO, 2020a). Capacity development is thus a polysemic notion, which shows its uncharted extent when considering that "components of capacity include knowledge, skills, systems, structures, processes, values, resources and powers that, taken together, confer a range of political, managerial and technical capabilities" (Shackeroff Theisen et al., 2016). In the context of ocean science, capacity development is described as a "multifaceted process aimed at building the human, institutional, technical, and financial abilities needed to conduct, understand, and apply ocean science for sustainable development" (Harden-Davies et al., 2022). Capacity development thus extends beyond knowledge dissemination and training and encompasses the strengthening of physical and digital infrastructure, advancement of technology, improvement of data accessibility, establishment of sustainable funding mechanisms, and fostering of collaborative networks and participatory decision-making. These priorities are underscored in the United Nations Decade of Ocean Science for Sustainable Development (Ocean Decade) White Paper Challenge 9: Skills, knowledge, technology and participatory decision-making for all (Arbic et al., 2024). Such a comprehensive approach is essential to empower all stakeholders to contribute meaningfully to ocean science and governance, crucial to achieve Ocean Decade Challenge 9 and underpinning progress across all other Ocean Decade challenges.

The Ocean Decade has made capacity development one of its main priorities, a key for delivering "the ocean we want" (IOC-UNESCO, 2020b). Strengthening countries' capacities in building and sustaining ocean observing systems is decisive to inform and guide policymaking and to develop and implement international agreements for a sustainable ocean (Miloslavich et al., 2018). Ocean Decade Challenge 9 thus seeks to "ensure comprehensive capacity development and equitable access to data, information, knowledge and technology across all aspects of ocean science and for all stakeholders" (UNESCO-IOC, 2021b). The equity principle is crucial, as the Global Ocean Science Report demonstrated over the years the extent to which inequalities persist in ocean science, whether in geographical, gender, or generational representations (IOC-UNESCO, 2017, 2020b). Indeed, studies tend to demonstrate that capacities are continuously larger in developed regions than in developing regions, as illustrated in Fig. 1 analysing the number of ocean science publications per country. Also, scientific cooperation across regions, despite intensifying, remains too limited within developed countries from Europe, North America, and Asia (IOC-UNESCO, 2020b). Strengthening the capacities of these groups while pursuing, to a larger extent, developing ocean science skills and knowledge of all is the twofold aim of capacity development in the Ocean Decade. When it comes to gender and generational imbalances, the Global Ocean Science Report demonstrated that women and young ocean scientists continue to be underrepresented in ocean science (Black, 2020; IOC-UNESCO, 2020b).

Given this situation, capacity development for ocean forecasting is more relevant than ever. This paper explores the actual status and the plans outlined in the framework of the OceanPrediction Decade Collaborative Centre (DCC). The first section provides an overview of the current capacity development landscape, including a review of global frameworks and platforms in ocean science that are relevant to ocean prediction. The second section summarises the findings of a survey conducted by the OceanPrediction DCC, which gathered insights into current practices and needs in the field. The analysis of these results informed the design of capacity development activities within the newly launched project Ocean Prediction Enhancement in Regions of Africa. This project is being implemented under the guidance of the OceanPrediction DCC's African regional team. The next section outlines a three-step approach to understanding capacity development, as framed by the OceanPrediction DCC. The discussion section presents recommendations based on the OPERA project's capacity development strategy and implementation plan. These are aligned with the guidelines of the IOC-UNESCO and Ocean Decade.

It should be noted that, while ocean literacy is an essential component of capacity development, it is beyond the scope of this paper and is therefore not addressed in this review.

## 2 Present status: main capacity development efforts in ocean science

### 2.1 IOC-UNESCO activities

In early 2023, IOC-UNESCO launched the Ocean CD-Hub (https://oceancd.org/, last access: 14 May 2025) to openly share worldwide ocean-related capacity development opportunities, posted by any stakeholder willing to contribute. The platform classifies the opportunities into different types, responding to the diversity of activities mentioned above. The Ocean CD-Hub also allows sorting the opportunities through regions and stakeholders. Out of 422 referenced opportunities currently, more than two-thirds are proposed by academic and research stakeholders or by international and intergovernmental agencies. The remaining activities are proposed by governmental parties, private sector stakeholders, and non-profit and philanthropic organisations. These results may evolve as the platform continues to develop, yet it still provides a clear indicator of the main actors involved in ocean science capacity development.

IOC-UNESCO is further advancing its capacity development objectives through the Ocean Teacher Global Academy (OTGA), a flagship initiative aimed at delivering high-quality training and education in ocean science and services, implemented by the International Oceanographic Data and Information Exchange (IODE) programme and through the IOC sub-commissions and regional committees (Claudet et al., 2020; Miloslavich et al., 2018). OTGA courses have a specific focus on IOC member states' training needs, with special attention to developing countries (but not only) and ensuring, during the applications' selection, a gender-balanced representation in its courses, as per UNESCO's gender policies. An endorsed project of the Ocean Decade, OTGA has developed a strong international network of local universities and research institutes, acting as regional training centres (Fig. 2). These centres develop courses addressing regional training needs, aligned with the IOC's policies and guidelines. Additionally, it enables training in the regionally relevant languages and resorting to in-field experts. OTGA, together with the European Copernicus Marine Service and EUMETSAT, also organises regular online courses to train future teachers (Supporting Marine Earth Observations Educators) and therefore multiply its impact over time.

The Ocean Decade Network (https://forum.oceandecade.org/, last access: 14 May 2025) is another global platform sharing numerous capacity development opportunities, as it references all Ocean Decade actions, contributions, programmes, and projects; for example, the above-mentioned OTGA initiative is an endorsed action under the Ocean Decade. The platform enables the sorting of activities by

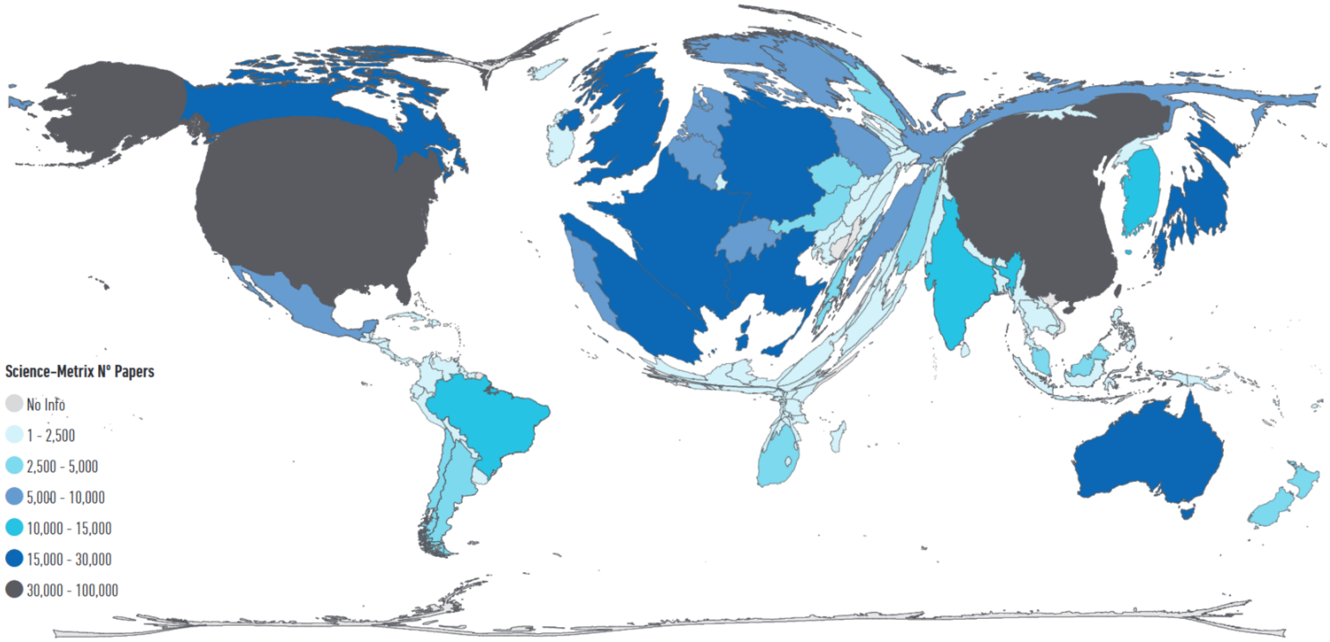


**Figure 1.** Distorted world map showing each country scaled in proportion to the number of ocean science publications. Different colours indicate different numbers of publications. Source: IOC-UNESCO (2017).

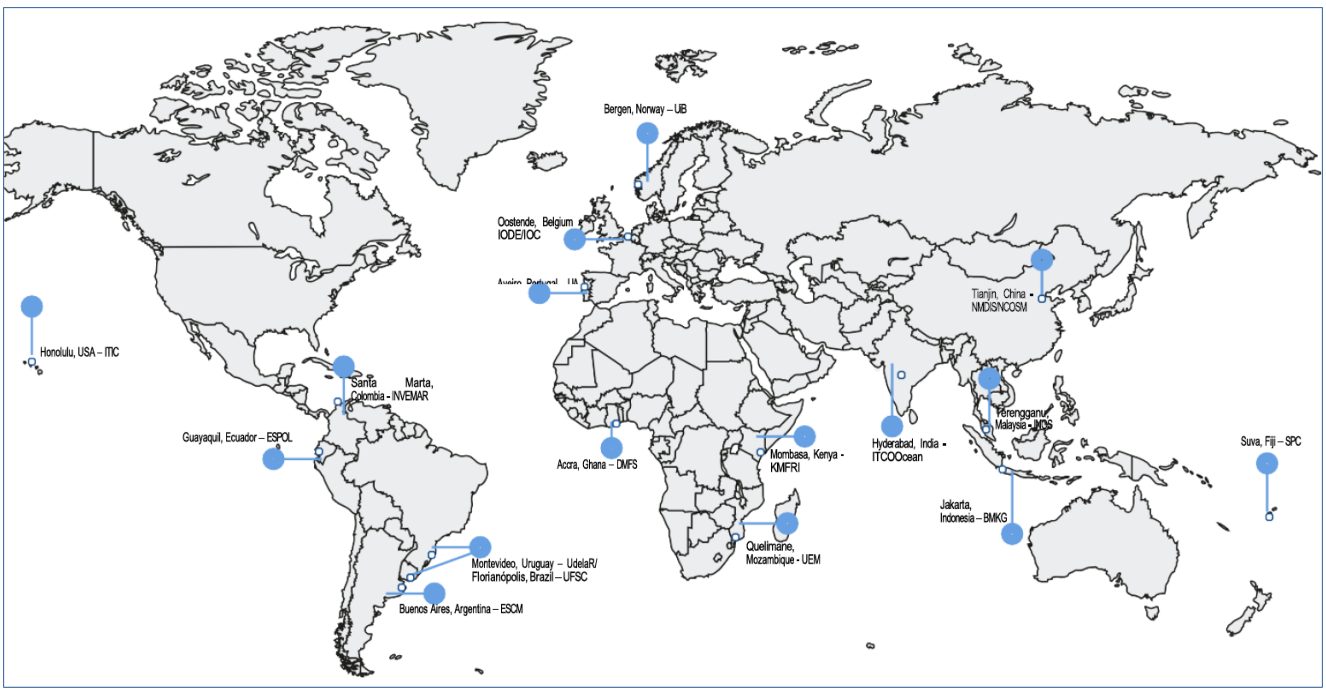


**Figure 2.** OTGA regional training centres and specialised training centres in 2020. Source: IOC-UNESCO (2020b).

Ocean Decade challenges, with the most relevant being Challenge 9 "Skills, knowledge and technology for all" and Challenge 7 "Expand the Global Ocean Observing System" working to "ensure a sustainable ocean observing system across all ocean basins that delivers accessible, timely, and actionable data and information to all users." The platform is further organised in thematic groups, including one on capacity development, to enable discussion and information exchange among peers.

The Global Ocean Observing System (GOOS) programme, which is coordinated by IOC-UNESCO, the World Meteorological Organisation (WMO), the UN Environment Programme (UNEP), and the International Science Council (ISC), comprises 15 regional alliances that play a key role in advancing ocean observing systems at the regional level. These alliances also lead and support targeted regional capacity development activities. Furthermore, the GOOS 2030 Strategy highlights capacity development as a top priority for strengthening in all countries, particularly those with limited resources, in order to achieve a truly integrated and inclusive global ocean observing system by 2030 (Fisher et al., 2019). In 2022, GOOS and its Expert Team on Operational Ocean Forecasting Systems (ETOOFS), with support from IOC-UNESCO, the WMO, and Mercator Ocean International, published the ETOOFS guide on "Implementing Operational Ocean Monitoring and Forecasting Systems". This reference guide aims to promote the global development, enhancement, and long-term sustainability of operational ocean monitoring and forecasting systems worldwide and delivers international standards and best practices (Alvarez Fanjul et al., 2022). WMO also supports capacity development in marine meteorology and ocean services through regional marine centres and dedicated training programmes.

## 2.2 Other capacity development initiatives

Numerous other actors are proposing activities at the global level. This section highlights key initiatives in capacity development, though it is not an exhaustive list. The initiatives primarily focus on enhancing skills and knowledge through training and education. However, as previously noted, capacity development encompasses a broader range of actions beyond these areas; it extends to addressing challenges such as inadequate infrastructure, funding limitations, restricted data accessibility, and inequitable participation:

- The European Copernicus Marine Service (https://marine.copernicus.eu/, last access: 14 May 2025) regularly organises online training workshops on how to access and use its data. Training workshops are dedicated to a specific region – or the European sea basins or the other continents – and provide use cases on local applications. Training is also tailored to different themes, known as the Copernicus blue markets, demonstrating how ocean data can inform and support decision-making across political/governance, socio-economic, or environmental fields. Each training workshop is evaluated and improved through feedback surveys. Copernicus Marine Service also actively contributes to external training initiatives, collaborating with partners such as EUMETSAT, EMODnet, GMES and Africa, and the Early Career Ocean Professional (ECOP) Ocean Decade programme. Through these partnerships, Copernicus Marine Service brings valuable expertise and resources related to ocean monitoring and forecasting, helping to build capacity in the effective use of marine data and services. As part of its efforts to support capacity development within the private sector, Copernicus Marine Service has organised and taken part in several ocean-data-related hackathon events designed to foster innovation, entrepreneurship, and the practical use of marine data. Lastly, Copernicus Marine Service also proposes on-demand mentoring initiatives, tailored to specific audiences, from a week-long course in 2023 for a master of science in "ocean, atmosphere, and climate sciences" ("oceanography and applications" track) in Cotonou, Benin, to on-demand mentoring.
- The Early Career Ocean Professional (ECOP) programme of the Ocean Decade aims to support young professionals by providing them with a global network and ensuring knowledge transfer, opportunities for sharing, and collective participation in the international ocean dialogue. In 2020, the programme launched a survey to which 1400 ECOPs replied, stating that network and information and training and mentoring were among their top needs and expectations. Organised in regional and national nodes and task teams, the ECOP programme intends to directly develop but also promote relevant training events and mentoring opportunities for ECOPs worldwide.
- The International Ocean Institute (IOI) has been active in ocean capacity development, and particularly ocean governance, since its creation in the 1970s; e.g. it organises (online) training courses, master programmes, summer schools, and tailored workshops and offers scholarships and sponsorships. The training mostly targets developing countries and focusses on regional perspectives; it is conducted at the national level through national training centres and partners in the respective country's main language.
- The Partnership for Observation of the Global Ocean (POGO) and the Scientific Committee on Oceanic Research (SCOR) are two international non-profit organisations with capacity development activities regarding ocean observation, particularly towards developing countries. Founded in 1999, POGO implements various training programmes for early career scientists from developing countries, especially the 10-month operational oceanography programme of the Nippon Foundation–POGO Centre of Excellence, dedicated each year to 10 postgraduate students, or the visiting fellowship programme – in partnership with the SCOR. The latter was founded in 1957 by the International Science Council (ISC) to foster interdisciplinary research related to the ocean. Among its capacity development activities, it particularly organises the visiting scholars programme, supporting ocean scientists to teach and provide men-

toring in developing countries' ocean science institutions. Such a partnership programme (also organised by POGO some years ago) revealed several long-term benefits, among which avoiding a "brain-drain" from early career scientists, enabling the visiting scientists to gain a better understanding of the existing gaps in the hosting countries and likely increasing their willingness to pursue their involvement (Urban and Seeyave, 2021).

- GEO Blue Planet, the ocean and coastal arm of the Group on Earth Observations (GEO), has capacity development as one of its core action areas with the aim to strengthen and transfer capabilities to ensure stakeholders can effectively use ocean and coastal observational data. The initiative organises training workshops around topics covered by its working groups, including ocean monitoring and prediction to support fisheries, coastal hazards, and Sargassum inundations. It also collaborates with stakeholders to co-design and co-develop adapted tools and services to meet specific information needs, such as the Sargassum Information Hub providing information on Sargassum monitoring and forecasting at the global, regional, and national levels.

- Universities and academic institutions are not addressed in this study since countless of them around the world organise some capacity development activities as part of their higher-education programmes; but they are, evidently, key players in training future professionals of ocean science or ocean governance (Miloslavich et al., 2018). Also, numerous capacity development activities exist at the local and regional levels, and it takes a strong knowledge of the regional organisation and its main stakeholders to thoroughly identify these structures and initiatives, similar to the analysis of marine studies programmes in the Pacific Islands conducted by Veitayaki and South (2001).

## 3 OceanPrediction DCC global survey on capacity development

The OceanPrediction DCC has established capacity development as one of the main tasks since its inception. To design a strategy for this objective, the OceanPrediction DCC launched a survey focusing on capacity development for ocean prediction. The survey served to assess awareness and knowledge of existing capacity development opportunities; to better understand needs, gaps, and interests; and to identify capacity development efforts around the globe.

The survey was completed by over 100 respondents, with 44 % representing governmental agencies, 40 % academic sector, 20 % the private sector, 11 % non-governmental organisations, and 3 % intergovernmental organisations. It is important to note that most responses came from technologically advanced countries in Europe and North America, which may bias the results toward more mature capacity development needs. Key findings from the survey analysis include the following.

- *Limited awareness of existing resources*. Overall, knowledge of current capacity development tools is low. Only 35 % of respondents were aware of the ETOOFS guide, and similarly low awareness was reported for other initiatives such as OTGA (52 %) and the Ocean CD platform (30 %). The most recognised initiative was the Ocean Decade Network (68 %). These results underscore the urgent need to raise awareness of existing tools and learning platforms.

- *Learning about downstream applications*. The most preferred approach is learning through success stories (59 %), followed by guidance on accessing relevant data (53 %) and hands-on training focused on specific applications and software (50 %), such as oil spill modelling or water quality forecasting.

- *Learning about building operational forecasting services.* The most in-demand topics (61 %) involve advanced techniques, including dynamic coupling, ensemble forecasting, and artificial intelligence. This is closely followed by interest in developing and operating full ocean forecasting service chains (60 %).

- *Expectations from capacity development activities*. The highest priority for participants (66 %) is networking (such as meeting experts, panellists, and fellow participants), followed by direct interaction with domain experts.

- *Preferred duration and format of educational activities.* Respondents showed a strong preference for short events (1 to 5 d, not necessarily consecutive). In terms of delivery format, 49 % preferred hybrid events, 33 % favoured online-only sessions, and 18 % preferred in-person formats.

Based on these findings, the following recommendations for future OceanPrediction DCC capacity development activities can be drawn:

- Activities should align with the foundational objectives of the OceanPrediction DCC, using the ETOOFS guide and system architecture as a central framework.

- Collaboration with Ocean Decade programmes will be essential for success.

- In the short-term, raising awareness of existing resources – particularly the ETOOFS guide and the best practices it offers – is a critical priority.

- Strategic partnerships with established platforms such as IOC's Ocean Teacher Global Academy and Ocean

Best Practices System (OBPS) are recommended, leveraging complementary strengths to amplify the impact of capacity development initiatives. Support from universities is also advised to provide academic grounding for new specialised courses and graduate programmes aimed at training a new generation of professional ocean forecasters.

Building on this survey, the OceanPrediction DCC is currently launching a new set of surveys to gather insights from experts and stakeholders on the current state, challenges, and prospects of ocean forecasting services specific to different regions. The pilot regional survey was launched in April 2024, focusing on the African marine community. A total of 134 responses were collected, with 60 % coming from experts and users affiliated with African institutions (OceanPrediction Decade Collaborative Centre, 2024). Although the survey did not solely focus on capacity development, it emerged as one of the key priorities for enhancing ocean forecasting and its application in Africa – alongside (and instrumental to) community building, development of new forecasting services, and applications and efforts to strengthen user uptake and societal engagement for long-term and meaningful impact. In the section on cross-cutting and additional needs, capacity development is the highest priority, even more so than dedicated funding for ocean forecasting and high-resolution services. In the elaboration of responses, this is linked to the need for a sustainable knowledge base and preparing a new generation of experts and scientists in ocean forecasting to provide African solutions for African problems. When analysed by region (north (coastal countries from Morocco to Egypt), west (Senegal to the Republic of the Congo), south (Angola to Mozambique), east (Tanzania to Eritrea)), the importance of capacity development is comparatively lower in the southern region than in other regions; nevertheless, it remains the top priority, as indicated in Fig. 3 extracted from the survey.

In the elaboration of responses, strong emphasis was placed on engaging students and young scientists through scholarships, training to build human capital in ocean forecasting. There is a need to focus training specifically on operational oceanography, from modelling to data assimilation and visualisations, which should also include "training of the trainers". Respondents highlighted the importance of democratising ocean science by actively including underrepresented groups (such as women, youth, and persons with disabilities) in capacity development efforts. Additionally, the need for improved technological infrastructure and robust data management practices was recognised as a critical component of sustainable capacity development. The results from the survey helped shape the project OPERA (Ocean Prediction Enhancement for Regions in Africa), which will be presented in the next section.

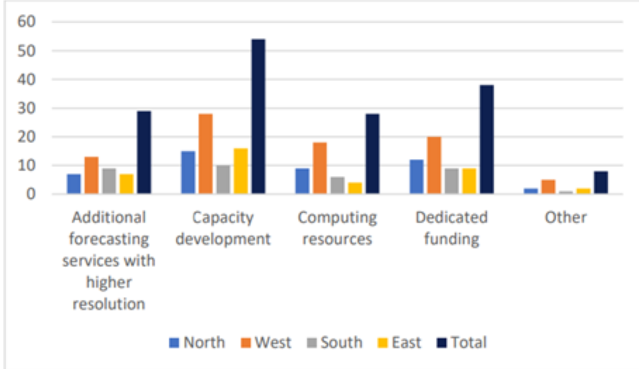


**Figure 3.** Additional needs related to ocean forecasting by region (north, west, south, east) and including the total for Africa (only replies coming from African institutions are considered). Source: summary results from the OceanPrediction Decade Collaborative Centre (2024).

## 4 Implementing capacity development activities in the OceanPrediction DCC: the OPERA project

In January 2025, a new project was launched, called OPERA (Ocean Prediction Enhancement in Regions of Africa), within the framework of the OceanPrediction DCC and its African regional team. Funded by the European Union, through its ArcX programme (Support to African Regional Centres of Excellence for the Green Transition), OPERA is implemented by Mercator Ocean International through its role as coordinator of the Ocean Prediction DCC and leveraging its expertise and leadership in Copernicus Marine Service and the European Digital Twin Ocean. At its core, OPERA will strengthen ocean prediction capabilities and cooperation in Africa by supporting the development of regional centres of excellence and digital ocean centres, organised in three consortia, each consisting of up to five African institutional partners. These centres will design, develop, deliver, and use fit-for-purpose ocean forecasting systems across a range of essential ocean variables and build innovative ocean knowledge-based solutions to serve the needs of decision makers, coastal communities, blue economy actors, and other beneficiaries.

Following recommendations from the IOC-UNESCO framework on capacity development, the Ocean Decade Africa Roadmap, the OceanPrediction DCC ocean forecasting surveys on capacity development and African ocean forecasting survey, and consultations with various stakeholders, the OPERA capacity development strategy was co-designed to be cross-cutting in the project. It encompasses community building, facilitates knowledge exchange, technological transfer to co-design innovative digital solutions, and targeted training for the consortia partners, as well as broader opportunities open to the wider African marine community. In addition, the project will support the acquisition of essential hardware for the consortia partners to strengthen their operational capabilities. This strategy will ensure not only engagement from the start but also the sustainability of the action and its long-lasting impact.

The OPERA capacity development strategy is twofold. The first component focuses on capacity development activities specifically tailored to the African partners in the three consortia involved in OPERA, while the second targets the broader African marine community, with opportunities open to all interested participants. This second component aims to grow the ocean forecasting community beyond the OPERA project, essential for scaling engagement and ensuring long-term impact. A blended approach will be carried out that combines in-person and remote training, ensuring accessibility and flexibility. Together, these activities respond to Ocean Decade Challenge 9 to ensure "comprehensive capacity development and equitable access to data, information, knowledge, technology, and participatory decision-making across all aspects of ocean science and for all stakeholders" (Arbic et al., 2024).

## 4.1 Capacity development targeting the African marine community at large and beyond

These capacity development activities will follow the OceanPrediction DCC's virtuous loop of ocean forecasting systems and will be implemented through OPERA (Fig. 4). These activities will be available online to ensure broad participation in Africa and on a global scale:

– In the first step of the loop is the Expert Team on Operational Ocean Forecast Systems (ETOOFS) guide, which will serve as a backbone to implement activities to provide a strong theoretical foundation on ocean forecasting and its applications (Alvarez-Fanjul et al., 2022).

– The second step focuses on the Ocean Forecasting Architecture Guide and develops activities on how to build an ocean forecasting system, describing the required tools and data standards and all the required "wiring" between the different components to ensure interoperability (Alvarez-Fanjul et al., 2024a).

– Third, the operational readiness level and its associated best practices serve to develop activities to train participants to operate, evaluate, and improve ocean forecasting services (Alvarez Fanjul et al., 2024b).

– Last, demonstrations via use cases and other approaches will be used to develop activities to train participants to apply ocean forecasting in real-world scenarios and integrate data into interoperable systems, with a focus on digital twins, particularly the European Digital Twin of the Ocean.

The activities target three audiences: (i) basic level – general public; (ii) intermediate level – technical audience with an interest in ocean forecasting; and (iii) advanced level – experts and practitioners developing and operating ocean forecasting systems, adapted for multi-stakeholder participation. The intermediate and advanced levels will have associated mentoring activities, providing participants opportunities for questions and exchange. There will also be an online dedicated OPERA forum on the OceanPrediction website to facilitate discussion and knowledge exchange among project participants which is also open to the African and global community at large.


**Figure 4.** OceanPrediction DCC virtuous loop for ocean forecasting (Alvarez-Fanjul et al., 2024a).

The capacity development activities derived from this loop, and oriented to the described levels, are summarised as follows:

– *Ocean literacy* is activities targeting non-experts to raise awareness and provide a general understanding on the importance of ocean forecasting and its applications in the context of the OPERA project and the OceanPrediction DCC.

– *Four massive online open courses (MOOCs) via the OTGA*, accompanied when required by additional online lectures and introductory-level data analysis workshops, focus on each part of the aforementioned OceanPrediction DCC's ocean forecasting virtuous loop, with increasing levels of difficulty. These courses will be available in French and English and adapted for the

African context with relevant use cases. There will be a certification on completion of each MOOC.

- *The development of an advanced interactive learning tool* – SEA-FORWARD (Simple Educational Access for Forecast and Warning Developers) – is designed to provide hands-on experience in setting up a basic ocean forecasting service. The software will serve as an educational tool, enabling users to explore forecasting methodologies, data integration, and operational workflows in a simplified yet realistic environment. There will be a certification on completion of the training.

### 4.2 Capacity development specifically for OPERA project participants

OPERA will establish three consortia of African centres led by African institutions through competitive and open calls open to coastal countries in sub-Saharan Africa. The first consortium will develop regional and coastal ocean forecasting systems. The other two consortia, which will be selected with attention to geographical balance, will concentrate on developing tailored applications and tools based on African priorities and regional needs. Through open calls, OPERA will establish technical expert teams to provide targeted assistance to the consortia, collaborating with them to co-design and co-develop software and digital solutions based on specific needs. The members of the technical expert team will provide tailored capacity development to the members of the consortia, so they will be able to understand, operate, and provide evolution to the ocean forecasting services and the applications developed at OPERA and implemented in Africa. The project will also organise two in-person technical training courses for consortium participants, along with annual workshops to bring together consortium members, with decision-makers, users of ocean forecasting systems, and other relevant stakeholders focused on raising awareness of the project, collecting feedback, and promoting the uptake of its results.

## 5 Discussion

During OPERA and after the project's implementation, it will be critical to evaluate the impact of capacity development activities – an essential cross-cutting component of the project – to assess whether they have effectively enhanced skills, knowledge, infrastructure, ocean governance, data accessibility, and participatory decision-making at institutional, national, regional, and pan-African levels. This will be carried out through impact surveys with project participants and stakeholders involved in the project:

- Concerning the ocean literacy activities, materials will first be piloted through selected user/stakeholder groups to test comprehension and engagement levels, making necessary adjustments based on feedback. At the end of each year, assessment tools, such as surveys and interactive quizzes, will be developed to evaluate the impact and effectiveness of the ocean literacy materials.

- Regarding the MOOCs and advanced training using the SEA-FORWARD education tool, all the interactive activities will be tested before launching with a subset of target users to refine the content, troubleshoot technical issues, and ensure the activities align with the intended skill development objectives. The project team will develop assessment methods tailored to interactive learning, such as project-based evaluations, live demonstrations, and peer-reviewed assignments.

However, the impact assessment will be time-bound, as support will not extend beyond the project's conclusion in December 2028, limiting opportunities for long-term feedback and evaluation of the effectiveness of capacity development activities.

The strategy and implementation plan for capacity development activities in the OPERA project serve as a pilot project that aims to be improved and adapted for other regions under the umbrella of the OceanPrediction DCC.

Based on guidelines from the existing literature, including the Ocean Decade White Paper Challenge 9, several initial recommendations can be made to strengthen capacity development efforts within and beyond the OPERA project.

- *Establish mechanisms for long-term impact assessment*. Ensure that project outcomes are measured beyond the project's duration to allow for a stronger assessment of impacts. This could include evaluating socio-economic impacts at the community level, particularly in areas such as disaster risk reduction, sustainable ocean-based economic activities, and efforts towards marine ecosystem health conservation.

- *Develop post-project capacity support structures*. Design and implement mechanisms to sustain capacity development after OPERA concludes. These may include mentoring schemes between consortium partners and technical assistance teams, long-term maintenance plans for hardware and software, and efforts to secure continued or additional funding.

- *Integrate "training of trainers"*. Embed a "train-the-trainer" approach within capacity development activities to enhance scalability and sustainability. This helps ensure knowledge transfer and skills development can continue independently within local contexts.

- *Integrating a maturity model for ocean practices*. Complement and strengthen the MOOC on the operational readiness level of ocean forecasting systems and its associated best practices with a module on measuring the maturity of practice descriptions and implementations, such as the model proposed by Mantovani et al. (2024).

- *Leverage regional networks and collaborations*. Engage with existing regional initiatives, institutions, and networks to develop more effective, locally relevant, and context-specific capacity development strategies. Collaborative approaches can help align efforts with regional priorities and amplify impact.
- *Foster interdisciplinary engagement*. Provide structured platforms that facilitate interdisciplinary collaboration. This supports the co-creation of solutions that address complex ocean challenges through integrated perspectives across natural and social sciences, technology, and policy.

## 6 Conclusion

This paper provides insights into capacity development for ocean science in the context of the Ocean Decade and more specifically the OceanPrediction DCC. Using the OPERA project as a concrete example, the paper explores the project's proposal design, which places capacity development at its core. It highlights important elements such as co-design, early stakeholder engagement, the implementation of diverse activities targeting and adapted for multiple stakeholder groups, and continuous evaluation of these activities' effectiveness – key prerequisites for generating long-term, meaningful impact.

However, the scope and depth of capacity development activities proposed by the OPERA project are constrained by limitations in funding and time. The paper thus puts forward recommendations grounded in existing literature to strengthen the capacity development approach in the context of OPERA for future projects in the OceanPrediction DCC.

A future version of this paper could be broadened to include global initiatives on ocean literacy related to ocean prediction, incorporating a mapping of existing activities, identification of gaps, and documentation of good practices. The mapping of the global capacity development efforts can be expanded beyond training and knowledge dissemination to encompass other important elements, such as data accessibility, infrastructure, funding, and equitable participation, which are integral to comprehensive capacity development. Specifically for the African continent, the paper could be expanded to include a mapping of capacity development, including education and training opportunities, in ocean forecasting and operational oceanography at both regional and national levels. An overview of current programmes and networks aimed at enhancing prediction capabilities in Africa would also add value. Furthermore, a more diverse group of co-authors will be invited to future works, particularly from countries with limited ocean forecasting capacity, to bring in their valuable perspective. To enhance the discussion on measuring impacts, the paper could include specific examples of capacity development activities in the ocean prediction field that have been effective in achieving intended outcomes, contrasted with those that have been less successful. This comparative approach could help identify factors that contribute to or hinder the effectiveness of capacity development activities.

**Data availability.** The data used in this study are produced from surveys launched by the OceanPrediction DCC and are not publicly available due to the General Data Protection Regulation.

**Author contributions.** LD redesigned the study and wrote the manuscript, originally initiated by RZ and CTC. AH contributed to final editing. EAF contributed to the writing and validation. All authors reviewed and edited final manuscript.

**Competing interests.** At least one of the (co-)authors is a member of the editorial board of *State of the Planet*. The peer-review process was guided by an independent editor, and the authors also have no other competing interests to declare.

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**Acknowledgements.** We thank Claudia Delgado (Ghent University), Anthony B. Ndah and Chris P. Nwachukwu (ECOP Africa network), and Stefania Ciliberti (Nologin) for their suggestions and ideas during the writing of the manuscript.

**Review statement.** This paper was edited by Jay Pearlman and reviewed by Alexis Valauri-Orton and two anonymous referees.

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