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

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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.

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.

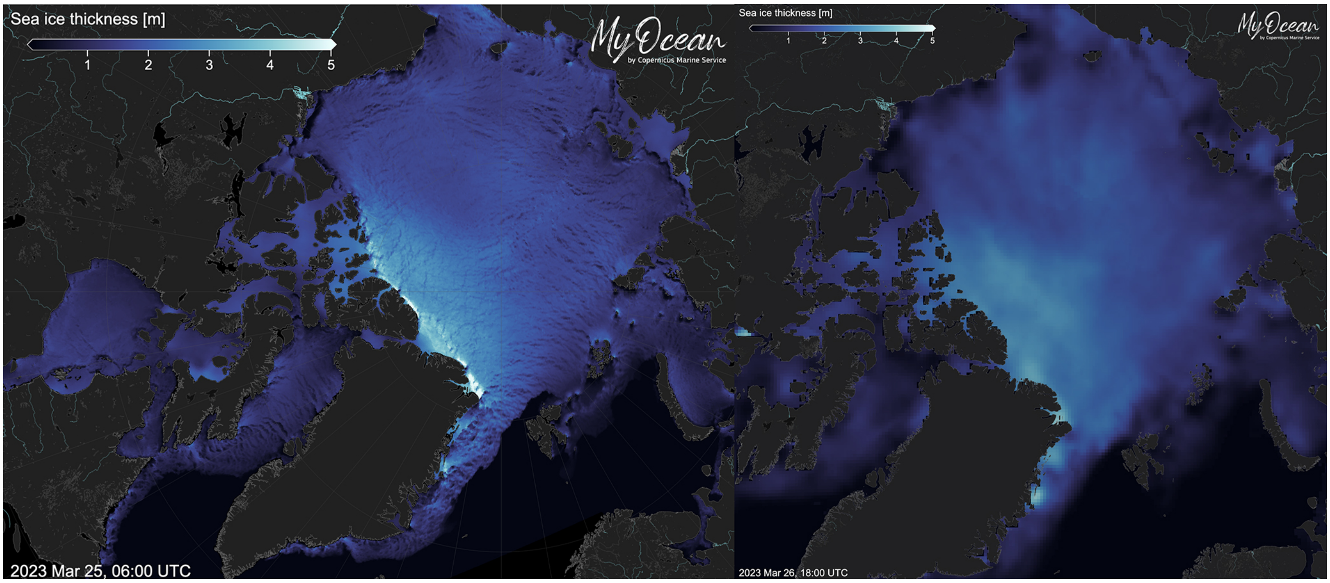

Figure 1. Example of sea-ice thickness analysis from the neXtSIM-F (left) system and the assimilated CS2SMOS data; visualisation from the Copernicus Marine Service (http://marine.copernicus.eu, last access: 24 March 2025).

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).

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