

Numerical Models for Monitoring and Forecasting Ocean Biogeochemistry: a short description of present status

Gianpiero Cossarini¹, Andy Moore², Stefano Ciavatta³, Katja Fennel⁴

¹Istituto Nazionale di Oceanografia e di Geofisica Sperimentale, Department of Oceanography, Trieste, Italy

²Physical & Biological Sciences Division, Ocean Sciences Department Institute of Marine Sciences, Institute of Marine Sciences, University of California Santa Cruz, Santa Cruz, California, USA

³Mercator Ocean International, Toulouse, France

⁴Department of Oceanography, Dalhousie University, Halifax, NS, Canada

10 *Correspondence to:* Gianpiero Cossarini, gcozzarini@ogs.it

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 15 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.

20 1 Introduction

Marine biogeochemistry refers to the cycling of chemical elements (e.g., carbon, nutrients, oxygen) resulting from physical transport, chemical reactions, 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 25 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 30 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, 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).

40 2.1 Formulations, processes and elements of biogeochemical models

In general, biogeochemical models solve a system of partial differential equations Eq. (1) describing 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 nonliving organic dissolved and particulate matter (Gutknecht et al., 2022; Fennel et al., 2022). The first three terms on the right side of Eq. (1) represent the physical terms: advection (first term), diffusion (second - horizontal - and third - vertical - terms) of biogeochemical tracers, where K_H and K_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).

$$\frac{\partial C}{\partial t} = -\nu \cdot \nabla(C) + \nabla_H(K_H \nabla_H(C)) + \frac{\partial}{\partial z} \left(K_V \frac{\partial C}{\partial z} \right) + w_{sink} \frac{\partial C}{\partial z} + R_{bio}(T, light, \rho, C) \quad (Eq. 1)$$

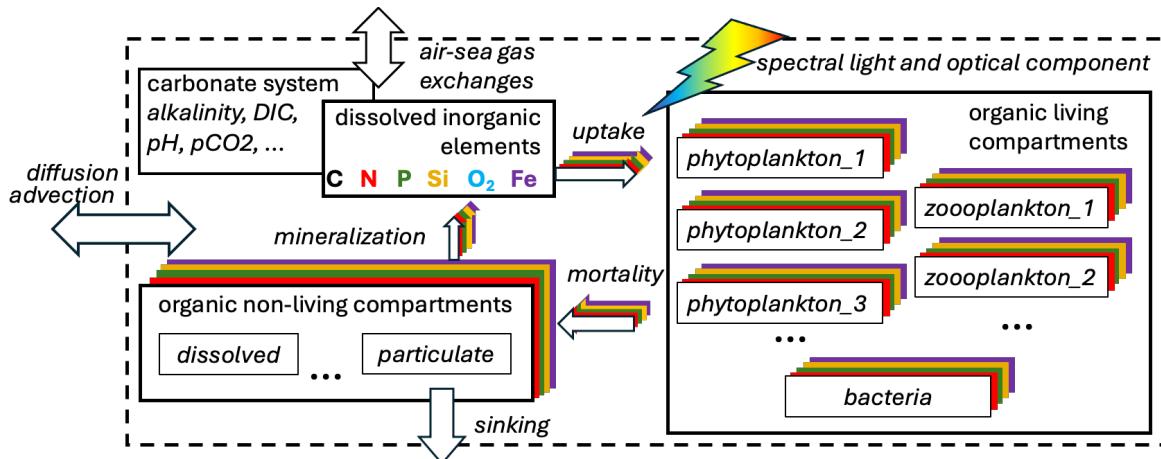
50 The last term, R_{bio} , represents the local source-minus-sink terms for the biogeochemical tracers and is typically based on the principle of conservation of mass to simulate the cycling of chemical elements through various marine compartments. Biogeochemical models (Eq.1) are generally discretized 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 advective-diffusion component of ocean dynamic models (i.e., on-line coupling). Alternatively, the 55 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 include also 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 60 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 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

65 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 parameters tuning (Wang et al., 2021, 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).

70 Unlike physical models based on Navier-Stokes equations (Bell et al., 2024), there are no fundamental laws and principles for the biogeochemical term (R_{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.

75 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 nutrient and living (phytoplankton and zooplankton) and nonliving (detritus) organic compartments. 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, 80 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 Figure 1.



85 Figure 1: simplified scheme of compartments (boxes) and processes (arrows) representing the cycles of multiple chemical elements typically included in a biogeochemical model. The symbol ... indicates the increase of the number of compartments and variables (e.g., multiple plankton functional types, multiple size compartment of non-living organic matter or additional variables resolved by the carbonate system.

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 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, 95 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, eutrophication, deoxygenation), supporting resource management, and studying pollutant impacts.

The number of chemical elements is often increased, to include typically 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 100 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; Gregoire 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 105 values of fixed nutrient ratios are 138[O₂] : 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 110 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 growth rate and variable chlorophyll-carbon ratio as a function of light, nutrient limitation, and temperature (Geider et al., 1997).

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., 115 silicifiers, calcifiers, nitrogen fixers, and dimethylsulfide -DMS- producers), cell size (e.g., pico-, nano-, and micro-phytoplankton), 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-, 120 or macro-) 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 125 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 modeling 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 130 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 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 135 timescales ranging from days to years (Anderson et al., 2015; Glibert and Mitra, 2022). In coastal and shallow water applications, a benthic model allows to represent the mutual interaction and nutrients, 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, 2024). This requires parameterization or explicit representation of the link of phytoplankton productivity and zooplankton mortality with higher 140 trophic level (HTL) compartments such as nekton and fishes, and possibly the feedbacks from HTL 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 145 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 level of complexity in response to specific regions and topics of interest for which were developed. As part of the UN Decade of Ocean 150 Science for Sustainable Development program, the Ocean Prediction Decade Collaborative Center (Alvarez-Fanjul et al., 2024) is promoting the Atlas of Operational Systems, which also describes their biogeochemical component (oceanprediction.org). 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 155 zooplankton, 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 nutrients 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 160 N dynamics with two phytoplankton and two zooplankton, that has been coupled with 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 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 et al., 2019; Irby et al., 2018).

165 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, O₂ and C dynamics with a single phytoplankton and single zooplankton group, a sediment-water fluxes parameterization, and the carbonate system (Fennel et al., 2011; Laurent et al., 2017).

PISCES: is a model of intermediate complexity (24 state variables) with five nutrients, fixed-stoichiometry, two phytoplankton and two zooplankton size classes and includes carbonate system and dissolved oxygen dynamics--(Aumont et al., 2015). It is 170 currently used in regional (north-eastern 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 Northern Atlantic and Artic Ocean (Yumruktepe et al., 2022) has two phytoplankton, two zooplankton, multiple nutrients (N, P an Si) and fixed molar Redfield ratio but a variable 175 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 includes processes related to hypoxia and anoxia, carbonate system and a radiative model with dynamics for coloured dissolved organic matter (Neumann, 2000; Neumann et al., 2015).

180 BAMHBI: developed for the Black Sea which is characterized by an anoxic deep layer, the model includes 33 pelagic state variables, with multinutrients, 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 marine ecosystem, it is a complex model resolving 185 N, P, C, O₂ 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; Baird et al., 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; Cossarini et al., 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).

190 ERSEM: developed for regional (north-eastern Atlantic and North Sea) and global studies, it is a complex model (more than 50 state variables) including multi nutrients, multi-plankton, 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).

195 **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; Séférion et al., 2020). Indeed, despite recent significant technological advances in observing systems, the lack of biogeochemical observations, both in terms of 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 resolution of the numerical solution and 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 optimising 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.

220

References

Alvarez-Fanjul, E., Ciliberti, S., and Bahurel, P.: Implementing Operational Ocean Monitoring and Forecasting Systems. IOC-UNESCO, GOOS-275. <https://doi.org/10.48670/ETOOFs>, 2022.

Alvarez-Fanjul, E., Ciliberti, S., Pearlman, J., Wilmer-Becker, K., Bahurel, P., Ardhuin, F., Arnaud, A., Azizzadenesheli, K.,
225 Aznar, R., Bell, M., Bertino, L., Behera, S., Brassington, G., Calewaert, J. B., Capet, A., Chassignet, E., Ciavatta, S., Cirano, M., Clementi, E., Cornacchia, L., Cossarini, G., Coro, G., Corney, S., Davidson, F., Drevillon, M., Drillet, Y., Dussurget, R., El Serafy, G., Fearon, G., Fennel, K., Ford, D., Le Galloudec, O., Huang, X., Lellouche, J. M., Heimbach, P., Hernandez, F., Hogan, P., Hoteit, I., Joseph, S., Josey, S., Le Traon, P. -Y., Libralato, S., Mancini, M., Martin, M., Matte, P., McConnell, T., Melet, A., Miyazawa, Y., Moore, A. M., Novellino, A., O'Donncha, F., Porter, A., Qiao, F.,
230 Regan, H., Robert-Jones, J., Sanikommu, S., Schiller, A., Siddorn, J., Sotillo, M. G., Staneva, J., Thomas-Courcoux, C., Thupaki, P., Tonani, M., Garcia Valdecasas, J. M., Veitch, J., von Schuckmann, K., Wan, L., Wilkin, J., Zhong, A., and Zufic, R.: Promoting best practices in ocean forecasting through an Operational Readiness Level. *Frontiers in Marine Science*, 11, 1443284, 2024

Álvarez, E., Lazzari, P., and Cossarini, G.: Phytoplankton diversity emerging from chromatic adaptation and competition for
235 light. *Progress in Oceanography*, 204, 102789. <https://doi.org/10.1016/j.pocean.2022.102789>, 2022.

Amadio, C., Teruzzi, A., Pietropolli, G., Manzoni, L., Coidessa, G., and Cossarini, G.: Combining neural networks and data assimilation to enhance the spatial impact of Argo floats in the Copernicus Mediterranean biogeochemical model. *Ocean Science*, 20(3), 689-710, 2024.

Anderson, T.R., Christian, J.R., and Flynn, K.J.: Chapter 15 - Modeling DOM Biogeochemistry, Editor(s): Dennis A. Hansell,
240 Craig A. Carlson, *Biogeochemistry of Marine Dissolved Organic Matter* (Second Edition), Academic Press, 635-667. doi.org/10.1016/B978-0-12-405940-5.00015-7, 2015.

Artioli, Y., Blackford, J.C., Butenschön, M., Holt, J.T., Wakelin, S.L., Thomas, H., Borges, A.V. and Allen, J.I.: The carbonate system in the North Sea: Sensitivity and model validation. *Journal of Marine Systems*, 102, pp.1-13. <https://doi.org/10.1016/j.jmarsys.2012.04.006>, 2012.

245 Aumont, O., Ethé, C., Tagliabue, A., Bopp, L., and Gehlen, M.: PISCES-v2: an ocean biogeochemical model for carbon and ecosystem studies. *Geosci. Model Dev.*, 8, 2465-2513, doi.org/10.5194/gmd-8-2465-2015, 2015.

Baird, D., Christian, R. R., Peterson, C. H., and Johnson, G. A.: Consequences of hypoxia on estuarine ecosystem function: energy diversion from consumers to microbes. *Ecological Applications*, 14(3), 805-822. <https://doi.org/10.1890/02-5094>, 2004.

250 Baird, M. E., Cherukuru, N., Jones, E., Margvelashvili, N., Mongin, M., Oubelkheir, K. and Wild-Allen, K. A.: Remote-sensing reflectance and true colour produced by a coupled hydrodynamic, optical, sediment, biogeochemical model of the Great Barrier Reef, Australia: comparison with satellite data. *Environmental Modelling & Software*, 78, 79-96. <https://doi.org/10.1016/j.envsoft.2015.11.025>, 2016.

255 Baird, M. E., Wild-Allen, K. A., Parslow, J., Mongin, M., Robson, B., Skerratt, J. and Steven, A. D.: CSIRO Environmental Modelling Suite (EMS): scientific description of the optical and biogeochemical models (vB3p0). *Geoscientific Model Development*, 13(9), 4503-4553. <https://doi.org/10.5194/gmd-13-4503-2020>, 2020.

Baretta, JW., Ebenhöh, W., and Ruardij, P.: The European regional seas ecosystem model, a complex marine ecosystem model. *Netherlands Journal of Sea Research*, 33, 233-246. [https://doi.org/10.1016/0077-7579\(95\)90047-0](https://doi.org/10.1016/0077-7579(95)90047-0), 1995.

260 Bell, M.J., Drillet, Y., Martin, M., Schiller, A., Ciliberti, S.: Numerical Models for Simulating Ocean Physics. *State Planet Discuss.* [pre-print], <https://doi.org/10.5194/sp-2024-41>, 2024.

Bieser, J., Amptmeijer, D. J., Daewel, U., Kuss, J., Soerensen, A. L., and Schrum, C.: The 3D biogeochemical marine mercury cycling model MERCY v2.0 – linking atmospheric Hg to methylmercury in fish, *Geosci. Model Dev.*, 16, 2649–2688, <https://doi.org/10.5194/gmd-16-2649-2023>, 2023.

265 Bopp, L., Resplandy, L., Orr, J. C., Doney, S. C., Dunne, J. P., Gehlen, M., Halloran, P., Heinze, C., Ilyina, T., Séférian, R., Tjiputra, J., and Vichi, M.: Multiple stressors of ocean ecosystems in the 21st century: projections with CMIP5 models. *Biogeosciences*, 10, 6225-6245. <https://doi.org/10.5194/bg-10-6225-2013>, 2013.

270 Brasseur, P., Gruber, N., Barciela, R., Brander, K., Doron, M., El Moussaoui, A., Hobday, A.J., Huret, M., Kremeur, A.-S., Lehodey, P., Matear, R., Moulin, C., Murtugudde, R., Senina, I., and Svendsen, E.: Integrating biogeochemistry and ecology into ocean data assimilation systems. *Oceanography*, 22(3), 206-215. <https://doi.org/10.5670/oceanog.2009.80>, 2009.

Bruggeman, J. and Bolding, K.: A general framework for aquatic biogeochemical models. *Environmental Modelling & Software*, 61, 249-265. <https://doi.org/10.1016/j.envsoft.2014.04.002>, 2014.

275 Butenschön, M., Clark, J., Aldridge, J. N., Allen, J. I., Artioli, Y., Blackford, J., and Torres, R.: ERSEM 15.06: a generic model for marine biogeochemistry and the ecosystem dynamics of the lower trophic levels. *Geoscientific Model Development*, 9(4), 1293-1339. <https://doi.org/10.5194/gmd-9-1293-2016>, 2016.

Capet, A., Meysman, F.J.R., Akoumianaki, I., Soetaert, K., and Grégoire, M.: Integrating sediment biogeochemistry into 3D oceanic models: A study of benthic-pelagic coupling in the Black Sea. *Ocean Modelling*, 101, 83-100. <https://doi.org/10.1016/j.ocemod.2016.03.006>, 2016.

280 Ciavatta, S., Kay, S., Saux-Picard, S., Butenschön, M., and Allen, J.I.: Decadal reanalysis of biogeochemical indicators and fluxes in the North West European shelf-sea ecosystem. *Journal of Geophysical Research: Oceans*, 121(3), 1824-1845. <https://doi.org/10.1002/2015JC011496>, 2016.

Ciavatta, S., Torres, R., Saux-Picart, S., and Allen, J. I.: Can ocean color assimilation improve biogeochemical hindcasts in shelf seas? *Journal of Geophysical Research: Oceans*, 116(C12). <https://doi.org/10.1029/2011JC007219>, 2011.

285 Ciavatta, S., Torres, R., Martinez-Vicente, V., Smyth, T., Dall'Olmo, G., Polimene, L., and Allen, J. I.: Assimilation of remotely-sensed optical properties to improve marine biogeochemistry modelling. *Progress in Oceanography*, 127, 74-95, 2014.

Ciavatta, S., Brewin, R. J. W., Skákala, J., Polimene, L., de Mora, L., Artioli, Y., and Allen, J. I.: Assimilation of ocean-color plankton functional types to improve marine ecosystem simulations. *Journal of Geophysical Research: Oceans*, 123(2), 834-854, 2018.

290 Ciliberti, S.A.. Grégoire, M.. Staneva, J.. Palazov, A.. Coppini, G.. Lecci, R.. Peneva, E.. Matreata, M., Marinova, V., Masina, S. and Pinardi, N.: Monitoring and Forecasting the Ocean State and Biogeochemical Processes in the Black Sea: Recent Developments in the Copernicus Marine Service. *J. Mar. Sci. Eng.*, 9, 1146. <https://doi.org/10.3390/jmse9101146>, 2022.

Cossarini G., Feudale, L., Teruzzi, A., Bolzon, G., Coidessa, G., Solidoro, C., Di Biagio, V., Amadio, C., Lazzari, P., Brosich, A., and Salon, S.: High-Resolution Reanalysis of the Mediterranean Sea Biogeochemistry (1999–2019). *Frontiers in Marine Science*, 8. <https://doi.org/10.3389/fmars.2021.741486>, 2021.

295 Cossarini, G., Mariotti, L., Feudale, L., Mignot, A., Salon, S., Taillandier, V., Teruzzi, A., and D'Ortenzio, F.: Towards operational 3D-Var assimilation of chlorophyll Biogeochemical-Argo float data into a biogeochemical model of the Mediterranean Sea. *Ocean Modelling*, 133, 112-128. <https://doi.org/10.1016/j.ocemod.2018.11.005>, 2019.

Cossarini, G., Querin, S., and Solidoro, C.: The continental shelf carbon pump in the northern Adriatic Sea (Mediterranean Sea): Influence of wintertime variability. *Ecological Modelling*, 314, 118-134. <https://doi.org/10.1016/j.ecolmodel.2015.07.024>, 2015a.

Cossarini, G., Lazzari, P. and Solidoro, C.: Spatiotemporal variability of alkalinity in the Mediterranean Sea. *Biogeosciences*, 12(6), pp.1647-1658, 2015b.

300 Cossarini, G., Querin, S., Solidoro, C., Sannino, G., Lazzari, P., Di Biagio, V., and Bolzon, G.: Development of BFMCOUPLER (v1. 0), the coupling scheme that links the MITgcm and BFM models for ocean biogeochemistry simulations. *Geoscientific Model Development*, 10(4), 1423-1445. <https://doi.org/10.5194/gmd-10-1423-2017>, 2017.

Daewel, U. and Schrum, C.: Simulating long-term dynamics of the coupled North Sea and Baltic Sea ecosystem with ECOSMO II: Model description and validation. *Journal of Marine Systems*, 119-120, 30-49. <https://doi.org/10.1016/j.jmarsys.2013.03.008>, 2013.

310 Dutkiewicz, S., Follows, M. J., and Bragg, J. G.: Modeling the coupling of ocean ecology and biogeochemistry. *Global Biogeochemical Cycles*, 23(4), 2009.

Eilola, K., Meier, H. E. M., and Almroth, E.: On the dynamics of oxygen, phosphorus and cyanobacteria in the Baltic Sea: a model study. *Journal of Marine Systems*, 75, 163-184. <https://doi.org/10.1016/j.jmarsys.2008.08.009>, 2009.

Falls, M., Bernardello, R., Castrillo, M., Acosta, M., Llort, J., and Galí, M.: Use of genetic algorithms for ocean model 315 parameter optimisation: a case study using PISCES-v2_RC for North Atlantic particulate organic carbon, *Geosci. Model Dev.*, 15, 5713–5737, <https://doi.org/10.5194/gmd-15-5713-2022>, 2022.

Fasham, M.J.R., Ducklow, H.W., and McKelvie, S.M.: A nitrogen-based model of plankton dynamics in the oceanic mixed layer. *Journal of Marine Research*, 48,(3). https://elischolar.library.yale.edu/journal_of_marine_research/1981, 1990.

Feng, Y., Friedrichs, M.A.M., Wilkin, J., Tian, H., Yang, Q., Hofmann, E.E., Wiggert, J.D. and Hood, R.R.: Chesapeake Bay
320 nitrogen fluxes derived from a land-estuarine-ocean biogeochemical modeling system: model description, evaluation and
nitrogen budgets. *J. Geophys. Res. Biogeosci.*, 120, 1666-1695. <https://doi.org/10.1002/2015JG002931>, 2015.

Fennel, K., Gehlen, M., Brasseur, P., Brown, C. W., Ciavatta, S., Cossarini, G., Crise, A., Edwards, C.A., Ford, D., Friedrichs,
M.A. and Gregoire, M.: Advancing marine biogeochemical and ecosystem reanalyses and forecasts as tools for monitoring
and managing ecosystem health. *Frontiers in Marine Science*, 6, 89. <https://doi.org/10.3389/fmars.2019.00089>, 2019.

325 Fennel, K., Hetland, R., Feng, Y., and DiMarco, S.: A coupled physical biological model of the Northern Gulf of Mexico shelf:
model description, validation and analysis of phytoplankton variability. *Biogeosciences*, 8, 1881-1899.
<https://doi.org/10.5194/bg-8-1881-2011>, 2011.

Fennel, K., Mattern, J. P., Doney, S. C., Bopp, L., Moore, A. M., Wang, B., and Yu, L.: Ocean biogeochemical modelling.
Nature Reviews Methods Primers, 2(1), 76. <https://doi.org/10.1038/s43586-022-00154-2>, 2022.

330 Fennel, K., Long, M. C., Algar, C., Carter, B., Keller, D., Laurent, A., Mattern, J. P., Musgrave, R., Oschlies, A., Ostiguy, J.,
Palter, J. B., and Whitt, D. B.: Modelling considerations for research on ocean alkalinity enhancement (OAE), in: Guide to
Best Practices in Ocean Alkalinity Enhancement Research, edited by: Oschlies, A., Stevenson, A., Bach, L. T., Fennel, K.,
Rickaby, R. E. M., Satterfield, T., Webb, R., and Gattuso, J.-P., Copernicus Publications, State Planet, 2-oae2023, 9,
<https://doi.org/10.5194/sp-2-oae2023-9-2023>, 2023.

335 Flynn, K. J., Stoecker, D. K., Mitra, A., Raven, J. A., Glibert, P.M., Hansen, P.J., Granéli, E. and Burkholder, J.M.: Misuse of
the phytoplankton–zooplankton dichotomy: the need to assign organisms as mixotrophs within plankton functional types.
Journal of Plankton Research, 35(1), 3-11. <https://doi.org/10.1093/plankt/fbs062>, 2013.

Follows, M. J., Dutkiewicz, S. Grant, S., and Chisholm, S.W.: Emergent biogeography of microbial communities in a model
ocean. *Science*, 315, 1843-1846, <https://doi.org/10.1126/science.1138544>, 2007.

340 Fontana, C., Brasseur, P., and Brankart, J. M.: Toward a multivariate reanalysis of the North Atlantic Ocean biogeochemistry
during 1998–2006 based on the assimilation of SeaWiFS chlorophyll data. *Ocean Science*, 9(1), 37-56.
<https://doi.org/10.5194/os-9-37-2013>, 2013

Ford, D., and Barciela, R.: Global marine biogeochemical reanalyses assimilating two different sets of merged ocean colour
products. *Remote Sensing of Environment*, 203, 40-54. doi.org/10.1016/j.rse.2017.03.040, 2017.

345 Ford, D., Key, S., McEwan, R., Totterdell, I. and Gehlen, M.: Marine biogeochemical modelling and data assimilation for
operational forecasting, reanalysis, and climate research. *New Frontiers in Operational Oceanography*, 625-652.
<https://doi.org/10.17125/gov2018.ch22>, 2018.

Ford, D. A., Grossberg, S., Rinaldi, G., Menon, P. P., Palmer, M. R., Skakala, J., Smyth, T., Williams, C.A.J., Lopez, A.L. and
Ciavatta, S.: A solution for autonomous, adaptive monitoring of coastal ocean ecosystems: Integrating ocean robots and
350 operational forecasts. *Frontiers in Marine Science*, 9, 1067174, 2022.

Gehlen, M., Barciela, R., Bertino, L., Brasseur, P., Butenschön, M., Chai, F. and Simon, E.: Building the capacity for forecasting marine biogeochemistry and ecosystems: recent advances and future developments. *Journal of Operational Oceanography*, 8(sup1), s168-s187. <https://doi.org/10.1080/1755876X.2015.1022350>, 2015.

355 Geider, R. J., MacIntyre, H. L., and Kana, T. M.: Dynamic model of phytoplankton growth and acclimation: responses of the balanced growth rate and the chlorophyll a: carbon ratio to light, nutrient-limitation and temperature. *Marine Ecology Progress Series*, 148, 187-200. <http://www.jstor.org/stable/24857483>, 1997.

Glibert, P. M. and Mitra, A.: From webs, loops, shunts, and pumps to microbial multitasking: Evolving concepts of marine microbial ecology, the mixoplankton paradigm, and implications for a future ocean. *Limnology and Oceanography*, 67(3), 585-597. <https://doi.org/10.1002/limo.12018>, 2022.

360 Grégoire, M. and Soetaert, K.: Carbon, nitrogen, oxygen and sulfide budgets in the Black Sea: A biogeochemical model of the whole water column coupling the oxic and anoxic parts. *Ecological Modelling*, 221, 2287-2301. <https://doi.org/10.1016/j.ecolmodel.2010.06.007>, 2010.

Grégoire, M., Garçon, V., Garcia, H., Breitburg, D., Isensee, K., Oschlies, A., Telszewski, M., Barth, A., Bittig, H.C., Carstensen, J. and Carval, T.: A global ocean oxygen database and atlas for assessing and predicting deoxygenation and 365 ocean health in the open and coastal ocean. *Frontiers in Marine Science*, 8, 724913. <https://doi.org/10.3389/fmars.2021.724913>, 2021.

Grégoire, M., Raick, C., and Soetaert, K.: Numerical modeling of the deep Black Sea ecosystem functioning during the late 80's (eutrophication phase). *Progress in Oceanography*, 76(3), 286-333. <https://doi.org/10.1016/j.pocean.2008.01.002>, 2008.

370 Gutknecht, E., Bertino, L., Brasseur, P., Ciavatta, S., Cossarini, G., Fennel, K., Ford, D., Grégoire M., Lavoie D. and Lehodey, P.: Biogeochemical Modelling. In "Implementing Operational Ocean Monitoring and Forecasting Systems", Eds: Alvarez-Franjul, E., Ciliberti, S., Bahurel, P.. IOC-UNESCO, GOOS-275. <https://doi.org/10.48670/ETOOFs>, 2022.

Gutknecht, E., Reffray, G., Mignot, A., Dabrowski, T., and Sotillo, M. G.: Modelling the marine ecosystem of Iberia–Biscay–Ireland (IBI) European waters for CMEMS operational applications. *Ocean Science*, 15(6), 1489-1516. 375 <https://doi.org/10.5194/os-15-1489-2019>, 2019.

Heinze, C. and Gehlen, M.: Chapter 26: Modelling ocean biogeochemical processes and resulting tracer distributions. *International Geophysics*, 103, 667-694. <https://doi.org/10.1016/B978-0-12-391851-2.00026-X>, 2013.

Hernandez, F., Smith, G., Baetens, K., Cossarini, G., Garcia-Hermosa, I., Drévillon, M., Maksymczuk, J., Melet, A., Régnier, C. and Schuckmann, K.V.: Measuring performances, skill and accuracy in operational oceanography: new challenges and 380 approaches. In "New Frontiers in Operational Oceanography", E. Chassignet, A. Pascual, J. Tintoré, and J. Verron, Eds., GODAE OceanView, 759-796. DOI: 10.17125/gov2018.ch29, 2018.

Hood, R. R., Laws, E. A., Armstrong, R. A., Bates, N. R., Brown, C. W., Carlson, C.A., Chai, F., Doney, S.C., Falkowski, P.G., Feely, R.A. and Friedrichs, M.A.: Pelagic functional group modeling: Progress, challenges and prospects. *Deep Sea Research Part II: Topical Studies in Oceanography*, 53(5-7), 459-512. <https://doi.org/10.1016/j.dsr2.2006.01.025>, 2006.

385 Irby, I.D. and Friedrichs, M.A.M.: Evaluating confidence in the impact of regulatory nutrient reduction on Chesapeake Bay water quality. *Estuar. Coasts*, 42, 16-32. <https://www.jstor.org/stable/48703007>, 2019.

Irby, I.D., Friedrichs, M.A.M., Da, F., and Hinson, K.E.: The competing impacts of climate change and nutrient reductions on dissolved oxygen in Chesapeake Bay. *Biogeosciences* 15, 2649-2668. <https://doi.org/10.5194/bg-15-2649-2018>, 2018.

390 Jones, E. M., Baird, M. E., Mongin, M., Parslow, J., Skerratt, J., Lovell, J., Margvelashvili, N., Matear, R. J., Wild-Allen, K., Robson, B., Rizwi, F., Oke, P., King, E., Schroeder, T., Steven, A., and Taylor, J.: Use of remote-sensing reflectance to constrain a data assimilating marine biogeochemical model of the Great Barrier Reef, *Biogeosciences*, 13, 6441–6469, <https://doi.org/10.5194/bg-13-6441-2016>, 2016.

Kishi, M.J., Ito, S.I., Megrey, B.A., Rose, K.A. and Werner, F.E.: A review of the NEMURO and NEMURO.FISH models and their application to marine ecosystem investigations. *J. Oceanogr.*, 67, 3-16. <https://doi.org/10.1007/s10872-011-0009-4>, 2011.

395 Kishi, M.J., Kashiwai, M., Ware, D.M., Megrey, B.A., Eslinger, D.L., and Werner, F.E.: NEMURO A lower trophic level model for the north pacific marine ecosystem. *Ecological Modelling*, 202, 12-25. <https://doi.org/10.1016/j.ecolmodel.2006.08.021>, 2007.

Klausmeier, C. A., Litchman, E., and Levin, S. A.: Phytoplankton growth and stoichiometry under multiple nutrient limitation. *Limnology and Oceanography*, 49(4part2), 1463-1470. https://doi.org/10.4319/lo.2004.49.4_part_2.1463, 2004.

400 Kwiatkowski, L., Yool, A., Allen, J. I., Anderson, T. R., Barciela, R., Buitenhuis, E. T., Butenschön, M., Enright, C., Halloran, P. R., Le Quéré, C., de Mora, L., Racault, M.-F., Sinha, B., Totterdell, I. J., and Cox, P. M.: iMarNet: an ocean biogeochemistry model intercomparison project within a common physical ocean modelling framework. *Biogeosciences*, 11, 7291-7304. <https://doi.org/10.5194/bg-11-7291-2014>, 2014.

405 Kwiatkowski, L., Aumont, O., Bopp, L., and Caias, P.: The impact of variable phytoplankton stoichiometry on projections of primary production, food quality, and carbon uptake in the global ocean. *Global Biogeochemical Cycles*, 32(4), 516-528., 2018.

Laurent, A., Fennel, K., Cai, W.-J. Huang, W.-J. Barbero, L., and Wanninkhof, R.: Eutrophication induced acidification of coastal waters in the northern Gulf of Mexico: Insights into origin and processes from a coupled physical-biogeochemical model. *Geophys. Res. Lett.*, 44, 946-956, <https://doi.org/10.1002/2016GL071881>, 2017.

410 Lazzari, P., Salon, S., Terzić, E., Gregg, W. W., D'Ortenzio, F., Vellucci, V., Organelli, E., and Antoine, D.: Assessment of the spectral downward irradiance at the surface of the Mediterranean Sea using the radiative Ocean-Atmosphere Spectral Irradiance Model (OASIM), *Ocean Sci.*, 17, 675-697. <https://doi.org/10.5194/os-17-675-2021>, 2021.

Le Traon, P.-Y., Reppucci, A., Alvarez Fanjul, E., Aouf, L., Behrens, A., Belmonte, M., Bentamy, A., Bertino, L., Brando, V.E., Kreiner, M.B., Benkiran, M., Carval, T., Ciliberti, S.A., Claustre, H., Clementi, E., Coppini, G., Cossarini, G., De Alfonso Alonso-Muñoyerro, M., Delamarche, A., Dibarboure, G., Dinessen, F., Drevillon, M., Drillet, Y., Faugere, Y., Fernández, V., Fleming, A., Garcia-Hermosa, M.I., Sotillo, M.G., Garric, G., Gasparin, F., Giordan, C., Gehlen, M., Gregoire, M.L., Guinehut, S., Hamon, M., Harris, C., Hernandez, F., Hinkler, J.B., Hoyer, J., Karvonen, J., Kay, S., King,

420 R., Lavergne, T., Lemieux-Dudon, B., Lima, L., Mao, C., Martin, M.J., Masina, S., Melet, A., Buongiorno Nardelli, B.,
Nolan, G., Pascual, A., Pistoia, J., Palazov, A., Piolle, J.F., Pujol, M.I., Pequignet, A.C., Peneva, E., Pérez Gómez, B., Petit
de la Villeon, L., Pinardi, N., Pisano, A., Pouliquen, S., Reid, R., Remy, E., Santolieri, R., Siddorn, J., She, J., Staneva, J.,
Stoffelen, A., Tonani, M., Vandenbulcke, L., von Schuckmann, K., Volpe, G., Wettre, C., and Zacharioudaki, A.: From
Observation to Information and Users: The Copernicus Marine Service Perspective. *Front. Mar. Sci.*, 6.
<https://doi.org/10.3389/fmars.2019.00234>, 2019.

425 Legendre, L. and Rassoulzadegan, F.: Plankton and nutrient dynamics in marine water. *Ophelia*, 41, 153-172.
<https://doi.org/10.1080/00785236.1995.10422042>, 1995.

Lenton, T. M., and Watson, A. J.: Redfield revisited: 1. Regulation of nitrate, phosphate, and oxygen in the ocean. *Global
biogeochemical cycles*, 14(1), 225-248. <https://doi.org/10.1029/1999GB900065>, 2000.

430 Libralato, S.: Numerical Models for Monitoring and Forecasting Ocean Ecosystems: a short description of present status. *State
Planet Discuss. [pre-print]*, <https://doi.org/10.5194/sp-2024-42>, 2024.

Litchman, E. and Klausmeier, C. A.: Trait-based community ecology of phytoplankton. *Annual Review of Ecology, Evolution,
and Systematics*, 39, 615-639. <https://doi.org/10.1146/annurev.ecolsys.39.110707.173549>, 2008.

Liu, Y., Meier, H. E. M., and Eilola, K.: Nutrient transports in the Baltic Sea -- results from a 30-year physical-biogeochemical
reanalysis. *Biogeosciences*, 14, 8, 2113-231. doi.org/10.5194/bg-14-2113-2017, 2017.

435 Melaku Canu, D., Rosati, G., Solidoro, C., Heimbürger, L.-E., and Acquavita, A.: A comprehensive assessment of the mercury
budget in the Marano–Grado Lagoon (Adriatic Sea) using a combined observational modeling approach. *Marine
Chemistry*, 177, 742-752. <https://doi.org/10.1016/j.marchem.2015.10.013>, 2015.

Mignot, A., Claustre, H., Cossarini, G., D'Ortenzio, F., Gutknecht, E., Lamouroux, J., Lazzari, P., Perruche, C., Salon, S.,
Zauzède, R., Taillandier, V. and Teruzzi, A.: Using machine learning and Biogeochemical-Argo (BGC-Argo) floats to
440 assess biogeochemical models and optimize observing system design. *Biogeosciences*, 20(7), 1405-1422.
<https://doi.org/10.5194/bg-20-1405-2023>, 2023.

Mitra, A., Castellani, C., Gentleman, W. C., Jónasdóttir, S. H., Flynn, K. J., Bode, A., Halsband, C., Kuhn, P., Licandro, P.,
Agersted, M.D. and Calbet, A.: Bridging the gap between marine biogeochemical and fisheries sciences; configuring the
zooplankton link. *Progress in Oceanography*, 129, 176-199. <https://doi.org/10.1016/j.pocean.2014.04.025>, 2014.

445 Mongin, M., Baird, M. E., Tilbrook, B., Matear, R. J., Lenton, A., Herzfeld, M., Wild-Allen, K., Skerratt, J., Margvelashvili,
N., Robson, B.J. and Duarte, C.M.: The exposure of the Great Barrier Reef to ocean acidification. *Nature communications*,
7(1), 10732. <https://doi.org/10.1038/ncomms10732>, 2016.

Nerger, L. and Gregg, W. W.: Improving assimilation of SeaWiFS data by the application of bias correction with a local SEIK
filter. *Journal of Marine Systems*, 73(1-2), 87-102. <https://doi.org/10.1016/j.jmarsys.2007.09.007>, 2008.

450 Neumann, T.: Towards a 3D-ecosystem model of the Baltic Sea. *Journal of Marine Systems*, 25(3-4), 405-419.
[https://doi.org/10.1016/S0924-7963\(00\)00030-0](https://doi.org/10.1016/S0924-7963(00)00030-0), 2000.

Neumann, T., Siegel, H., and Gerth, M.: A new radiation model for Baltic Sea ecosystem modelling. *Journal of Marine Systems*, 152, 83-91. <https://doi.org/10.1016/j.jmarsys.2015.08.001>, 2015.

Palmer, J. R. and Totterdell, I. J.: Production and export in a global ocean ecosystem model. *Deep Sea Research Part I: Oceanographic Research Papers*, 48, 1169-1198. doi.org/10.1016/S0967-0637(00)00080-7, 2001.

455 Pradhan, H. K., Völker, C., Losa, S. N., Bracher, A., and Neger, L.: Global assimilation of ocean-color data of phytoplankton functional types: Impact of different data sets. *Journal of Geophysical Research: Oceans*, 125(2), e2019JC015586, 2020

Redfield, A. C.: On the proportions of organic derivatives in sea water and their relation to the composition of plankton (Vol. 1). University Press of Liverpool, 1934.

460 Rosati, G., Canu, D., Lazzari, P., and Solidoro, C.: Assessing the spatial and temporal variability of methylmercury biogeochemistry and bioaccumulation in the Mediterranean Sea with a coupled 3D model. *Biogeosciences*, 19(15), 3663-3682. <https://doi.org/10.5194/bg-19-3663-2022>, 2022.

Salon, S., Cossarini, G., Bolzon, G., Feudale, L., Lazzari, P., Teruzzi, A., Solidoro, C., and Crise, A.: Novel metrics based on 465 Biogeochemical Argo data to improve the model uncertainty evaluation of the CMEMS Mediterranean marine ecosystem forecasts. *Ocean Sci.*, 15, 997-1022. <https://doi.org/10.5194/os-15-997-2019>, 2019.

Schmidtko, S., Stramma, L., and Visbeck, M.: Decline in global oceanic oxygen content during the past five decades. *Nature*, 542, 335-339. <https://doi.org/10.1038/nature21399>, 2017.

Séférian, R., Berthet, S., Yool, A., Palmiéri, J., Bopp, L., Tagliabue, A., Kwiatkowski, L., Aumont, O., Christian, J., Dunne, J. and Gehlen, M.: Tracking improvement in simulated marine biogeochemistry between CMIP5 and CMIP6. *Current 470 Climate Change Reports*, 6(3), 95-119. <https://doi.org/10.1007/s40641-020-00160-0>, 2020.

Skákala, J., Ford, D., Brewin, R. J., McEwan, R., Kay, S., Taylor, B., De Mora, L. and Ciavatta, S.: The assimilation of phytoplankton functional types for operational forecasting in the northwest European shelf. *Journal of Geophysical Research: Oceans*, 123(8), 5230-5247, 2018

Skákala, J., Bruggeman, J., Brewin, R.J., Ford, D.A. and Ciavatta, S.: Improved representation of underwater light field and 475 its impact on ecosystem dynamics: A study in the North Sea. *Journal of Geophysical Research: Oceans*, 125(7), p.e2020JC016122. <https://doi.org/10.1029/2020JC016122>, 2020.

Skákala, J., Ford, D., Bruggeman, J., Hull, T., Kaiser, J., King, R. R., Loveday, B., Palmer, M.R., Smyth, T., Williams, C.A. and Ciavatta, S.: Towards a multi-platform assimilative system for North Sea biogeochemistry. *Journal of Geophysical Research: Oceans*, 126(4), e2020JC016649. <https://doi.org/10.1029/2020JC016649>, 2021.

480 Soetaert, K., Middelburg, J. J., Herman, P. M., and Buis, K.: On the coupling of benthic and pelagic biogeochemical models. *Earth-Science Reviews*, 51(1-4), 173-201. [https://doi.org/10.1016/S0012-8252\(00\)00004-0](https://doi.org/10.1016/S0012-8252(00)00004-0), 2000.

Tagliabue, A., Bopp, L., and Gehlen, M.: The response of marine carbon and nutrient cycles to ocean acidification: large uncertainties related to phytoplankton physiological assumptions. *Global Biogeochem. Cycles* 25(3), GB3017. <https://doi.org/10.1029/2010GB003929>, 2011.

485 Teruzzi, A., Bolzon, G., Feudale, L., and Cossarini, G.: Deep chlorophyll maximum and nutricline in the Mediterranean Sea: emerging properties from a multi-platform assimilated biogeochemical model experiment. *Biogeosciences*, 18, 6147-6166. <https://doi.org/10.5194/bg-18-6147-2021>, 2021.

Teruzzi, A., Dobricic, S., Solidoro, C., and Cossarini, G.: A 3-D variational assimilation scheme in coupled transport-biogeochemical models: Forecast of Mediterranean biogeochemical properties. *Journal of Geophysical Research: Oceans*, 490 119(1), 200-217. <https://doi.org/10.1002/2013JC009277>, 2014.

Travers, M., Shin, Y.J., Jennings, S., Machu, E., Huggett, J.A., Field, J.G. and Cury, P.M.: Two-way coupling versus one-way forcing of plankton and fish models to predict ecosystem changes in the Benguela. *Ecological Modelling*, 220(21), 3089-3099. <https://doi.org/10.1016/j.ecolmodel.2009.08.016>, 2009.

Verdy, A. and Mazloff, M. R.: A data assimilating model for estimating Southern Ocean biogeochemistry. *Journal of Geophysical Research: Oceans*, 122(9), 6968-6988, 2017.

Vichi, M., Pinardi, N., and Masina, S.: A generalized model of pelagic biogeochemistry for the global ocean ecosystem. Part I: Theory. *Journal of Marine Systems*, 64(1-4), 89-109. <https://doi.org/10.1016/j.jmarsys.2006.03.006>, 2017.

Wagner, C. C., Amos, H. M., Thackray, C. P., Zhang, Y., Lundgren, E. W., Forget, G., and Sunderland, E. M.: A global 3-D ocean model for PCBs: Benchmark compounds for understanding the impacts of global change on neutral persistent organic pollutants. *Global Biogeochemical Cycles*, 33(3), 469-481. <https://doi.org/10.1029/2018GB006018>, 2019.

500 Wang, B., Fennel, K., Yu, L., and Gordon, C.: Assessing the value of biogeochemical Argo profiles versus ocean color observations for biogeochemical model optimization in the Gulf of Mexico. *Biogeosciences*, 17(15), 4059-4074, 2021.

Xiao, Y. and Friedrichs, A.M.: Using biogeochemical data assimilation to assess the relative skill of multiple ecosystem models in the Mid-Atlantic Bight: effects of increasing the complexity of the planktonic food web. *Biogeosciences*, 11, 3015-3030. <https://doi.org/10.5194/bg-11-3015-2014>, 2014.

505 Yumruktepe, V. Ç., Samuelsen, A., and Daewel, U.: ECOSMO II(CHL): a marine biogeochemical model for the North Atlantic and the Arctic. *Geoscientific Model Development*, 15, 3901-3921, <https://doi.org/10.5194/gmd-15-3901-2022>, 2022.

Yumruktepe, V. Ç., Mousing, E. A., Tjiputra, J., and Samuelsen, A.: An along-track Biogeochemical Argo modelling framework: a case study of model improvements for the Nordic seas. *Geoscientific Model Development*, 16(22), 6875-6897, 2023.

510 Zeebe, R. E., and Wolf-Gladrow, D.: CO₂ in seawater: equilibrium, kinetics, isotopes. Elsevier Science, 2001.

Zhang, Y., Soerensen, A. L., Schartup, A. T., and Sunderland, E. M.: A global model for methylmercury formation and uptake at the base of marine food webs. *Global Biogeochemical Cycle*, 34, 1-21. <https://doi.org/10.1029/2019GB006348>, 2020.

Competing interests

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

Data and/or code availability

Not applicable.

Authors contribution

CG prepared the first draft, all co-authors participated to review and finalization.

520