12.
Challenges and future perspectives in ocean prediction

CHAPTER COORDINATOR

Fraser Davidson

ChAPTER AUTHORS *(in alphabetical order)*

Enrique Alvarez Fanjul, Alain Arnaud, Stefania Ciliberti, Marie Drevillon, Ronan Fablet, Yosuke Fujii, Isabel Garcia-Hermosa, Stéphanie Guinehut, Emma Heslop, Villy Kourafalou, Julien Le Sommer, Matt Martin, Andrew M. Moore, Nadia Pinardi, Elizabeth Remy, Paul Sandery, Jun She, Marcos G. Sotillo, and Joaquin Tintorè.

12. Challenges and future perspectives in ocean prediction

12.1. Introduction

The growth of ocean prediction research, capability, applicability, availability, maturity, and user uptake from an initial idea 25 years ago, while gradual, has been unrelenting. Today's capacity and maturity in ocean prediction goes beyond what was initially conceived and provides a strong basis for advancement of societal benefits. Over the next 10 years, ocean prediction systems will continue to gradually rival weather prediction systems in the sense of ubiquitous use, protecting lives, economic impact, and supporting custodianship of the environment. Building a framework with standards and best practices for the full operational oceanography value chain will enable further harnessing of prediction systems in supporting a healthy ocean at the same time of a blue economic growth for all countries. This will further awareness and accessibility of the marine environment through digital platforms underpinning increases in ocean prediction literacy, capacity building, applications, and services (Figure 4.1).

Herein we outline the expected advances of ocean prediction and other supporting components of operational oceanography over the next decade. An underlying theme is the integration of ocean prediction systems within the larger context of operational oceanography, seamless environmental prediction, and the blue economy. This requires a transparent framework approach of standards and best practices, enabling all countries, particularly those with the least resources, to engage and benefit.

This chapter introduces the key drivers for the next generation of OOFS, spanning from global to coastal scale observing systems (Section 12.2) to numerical models evolution (Section 12.3), data assimilation (Section 12.4) and ensemble systems for prediction (Section 12.5), from the growing AI techniques for understanding physical processes (Section 12.6) to seamless approach (Section 12.7) and DTO (Section 12.8), including as well the evolution in quality assessment (Section 12.9). The last sections focus on planned evolution for state-of-the-art services like the Copernicus Marine Service (Section 12.10) and international initiatives promoted by the UN Decade of the Ocean (Section 12.11).

12.2. Observing system evolution with ocean prediction engagement

The quality of the ocean analysis and forecasts highly relies on observations assimilated for constraining the ocean circulation in ocean forecasting systems. The evolution of the forecasting systems towards increased realism to represent a larger spectrum of ocean processes and scales will be underpinned by the 'adapted' in situ and satellite observations that efficiently constrain the different scales of the ocean variability. Close collaboration between ocean forecasting centres and the observation providers is crucial to promote such evolution. Communication ensures the best use of information from the present to the future observation systems. It allows forecasting centres to inform on the observation use and to report on their impacts on analysis and forecasts. In the longer term, it also increases opportunities for the ocean forecasting centres to contribute to evolve ocean observing system designs to optimally meet requirements and enable capabilities of future operational systems. Inclusion of forecasting centres in designing and evaluating the future impact of the GOOS [1] component has started to be recognized as a best practice in the observation and prediction community.

In such a context, OOFS strictly depends on the availability of near-real time observations for assimilation and validation purposes. Accuracy of forecast products is largely impacted by the quality of assimilated observations, so that the effort of the community is to support the forecasters with high quality data in space and time sampling. Le Traon et al. (2019) provides the Copernicus Marine Service strategy for observational network evolutions and the requirements for OOFS to support maritime safety, marine resources, marine and coastal environments, weather, seasonal forecasting, and climate. According to this document, the main priorities are:

1. https://www.goosocean.org/

- For satellite data:

  - Guaranteeing continuity of the present operational missions' capacity of Sentinel for downstream coastal applications, and of Cryosat mission for monitoring of sea ice thickness and sea level in polar regions;
  - Developing new capacity for wide swath altimetry for the future OOFS and services;
  - Developing microwave mission for the improvement of spatial coverage of sea surface temperature, sea ice drift, sea ice thickness, and sea surface salinity;
  - Enforcing R&D for observing sea surface salinity and ocean currents from space.

- For in-situ data:

  - At global scale, the main future challenges are: a) to improve the coverage of biogeochemical measurement, b) the measurement of deep temperature and salinity, and c) measurement of in-situ velocity observations, sea ice observations, and open-ocean wave measurements;
  - At a regional scale, the main priority is to fill gaps for a wide range of variables in the shelf-coastal observational networking, in order to improve monitoring and forecasting capacities.

Copernicus Marine Service provides specific strategic documents [2] for both satellite and in-situ observations to support monitoring and forecasting activities. The GOOS defines the following strategic objectives for observing systems at global level towards 2030:

- to deepen engagement and impact by enforcing the connection with forecasting centres;
- to deliver an integrated fit-for-purposes observing system able to support and expand the implementation of observing systems and ensuring data management according to the FAIR principles;
- to build future observational networks by supporting innovation in observing technologies and extending systematic observations to understand impacts on the ocean.

12.2.1. Challenges for the current ocean observing systems

Major challenges for the current ocean observing systems include: i) most of the ocean observations made by non-operational oceanography communities (e.g. environment, fishery, research, and industrial sectors) have not been used for operational forecasting; the ocean observations are made by various sectors with different monitoring and data collection standards, and little efforts have been made to harmonise observations from the different sectors; and ii) technologic bottlenecks and significant data gaps in sub-surface, sea bottom, geological and biological observations.

For developing an integrated and unified ocean observing system to support the seamless information service, three pillars are recommended, , as shown in Fig. 12.1. The first pillar is to maximise the value of existing observations by breaking the institutional and sectorial barrier (She et al., 2019) and fit for the purposes of multi-sectors. This can be implemented by performing multidimensional integration of operational and non-operational ocean observing communities, including operational monitoring, environment monitoring, fishery monitoring, research monitoring, crowd (citizens and NGOs) monitoring and other sectoral monitoring (industrial and socioeconomic). The observations should be "collected once and used for many times" (Martín Míguez et al., 2019). Due to the existing mandate of monitoring entities, either public or private, current ocean observing practices are designed separately to fit for the purpose of individual sectorial service, and observations are hardly shared from different monitoring communities. When designing multidimensional integration on a national and regional scale, unified standards should be applied. The operational and autonomous platform is an efficient framework for the integrated and unified ocean observing, which is highly recommended.

The second pillar is to develop, deploy, and utilise large networks of autonomous, cost-effective, innovative sensors to fill the observation gaps in subsurface and emerging observations, e.g. marine litter, biological variables, and underwater noise. A combination of breakthroughs in underwater communication technology, underwater robotics, and ML/AI may significantly improve the capacity of underwater monitoring, especially for pollutants, biogeochemical and biological variables. Adaptable observations are also needed for characterising key processes underpinning predictability in the marine earth system.

The third pillar is to design and optimise existing ocean observing to fill gaps in the characterizations of processes and sensitive regions that are crucial to the predictability and fit for the purposes in multi-sectors. It is essential that the monitoring capacity is based on an integrated system of in-situ, remote sensing, models, assimilation, and ML/AI tools. Sampling schemes of such a system can then be designed to optimise the integrated monitoring capacity, so that observations would most effectively be used to reduce the earth system prediction uncertainties. It should be noted that dedicated observations should be identified and included to address specific predictability in the UOM (She et al., 2016).

2. https://marine.copernicus.eu/about/observation-requirements

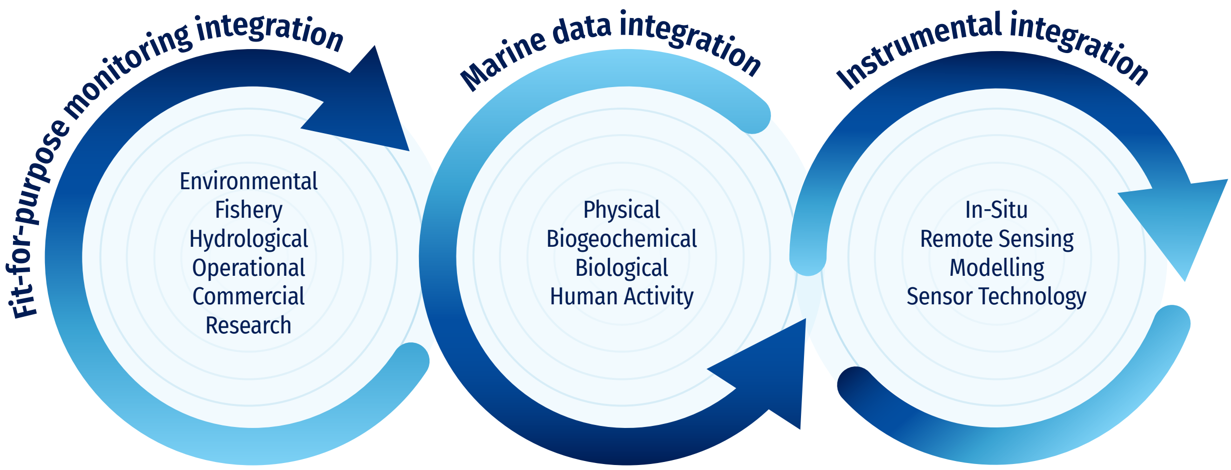

Figure 12.1. Integrated observing. Unlocking the value of ocean observing by integrating observations in three dimensions: fit for purpose, parameter, and instrumental (source: She et al., 2019).

12.2.2. Observing System Evaluation

At present, OS-Eval, based on ocean forecasting systems, are not often conducted in a coordinated manner. The most used techniques of OS-Eval are data denial experiments with real or simulated observations (e.g., OSE and OSSE). Although only observation platforms which are already existing with real observations can be evaluated, simulated observations allow us to evaluate the impact of future platforms or evolution of the observation network. Impact assessment methods will evolve in the future with more sophisticated techniques based on ensemble and adjoint methods, and potentially also AI. Considering that BGC applications and the earth system predictions, including the ocean component, are progressively becoming more important, the development of suitable evaluation methods for those applications is also indispensable. Improving analysis/forecast accuracy and developing methods assimilating new types of observation data will increase the ability to make fair assessments for various platforms. Multi-system evaluation and regular re-assessment of the observation impact to follow the system evolutions are required to improve the robustness of the results by moderating system-dependency.

Enhanced communication and coordination between modelling/data assimilation experts and observation/network experts will be essential for a proper design and interpretation of OS-Eval, especially to extract compelling messages on the ability of the ocean observing system to control processes having different temporal and spatial scales. The provision of regular reports on ocean observation impacts in ocean prediction systems is expected to enhance such communication. It should also be noted that OS-Eval activities require dedicated infrastructures and resources. Cooperation with international partners (e.g. OceanPredict, GOOS/ROOS, WMO, IOC, etc.) is hence essential to establish a substantial value chain between ocean observation networks and ocean prediction systems.

OS-Eval activities require dedicated infrastructures and resources. It is essential to strengthen the capabilities of operational and climate centres to assess the impact of present and future observations to guide observing system agencies but also to improve the use of observations in models.

An observation network cannot be considered by its own but should be evaluated in complementarity with other in-situ and satellite networks. The synergy from a combination of observation platforms' data with the other existing and planned in-situ and satellite observations should be evaluated. This will be necessary since the model forecasts need to be constrained on a large spectrum of scales, as individual platforms cannot provide it. Optimally leveraging satellite and in-situ observations to improve the ocean predictability is an important research topic with strategic importance. Understanding and being able to showcase and demonstrate the impact of both present and future observing systems in improving ocean prediction (and environmental prediction in general) is important to justify and maintain long term investments for the observation system. Feedback from such efforts enables observation groups to know where to invest their efforts, both technologically and in terms of geographic coverage in density and scope.

To best showcase evaluations of the observing system, prediction impact metrics should be generated in terms of value for: (1) user and application needs; and (2) observing system needs. On the user and application side, elements like the WMO RRR can be used, in which the impact of an observation on the forecast system is framed in terms of impact on a user or application. This can entail further post processing of prediction output, to translate forecasting impact into information that the end user will use directly. For example, for Search and Rescue at sea it may be necessary to know the impact of an observing system on drift prediction, and quantifying how much it would decrease the search area at sea while still ensuring high probability of detection. There is also a need to show the impact of an observing system on a variety of applications, as well as to provide insight into the impact of decreasing or augmenting the number of observations. Additionally, when developing metrics to support observing system needs, the multi-purposeless of the observations (climate, ocean services and health) needs to be covered.

Real-time impact assessment methods should also be developed to monitor and report on the use and impact of the different assimilated observation networks by operational ocean forecasting centres. This will help to detect impacts of changes in the observation network, and take countermeasures against them.

In the next subsections are presented the evolution plans for the observatory component, i.e. ARGO and satellite observations, which will drive the next generation of OOFS.

12.2.3. Argo evolution plans

The international programme Argo ([3]) is currently the major global initiative for the collection of "information from inside the ocean using a fleet of robotic instruments that drift with the ocean currents and move up and down between the surface and a mid-water level". In Chapter 4 can be found an overview on the current ARGO operational capabilities for OOFS. Argo design after 2020 is available at [4], including the following major targets:

- Improved observational capacity in the polar sea-ice regions and marginal seas;
- Increased resolution in key areas like the Western Boundary Currents in which mesoscale noise is high, and the Equatorial region for which high temporal resolution is needed;
- Launch of new missions for biogeochemical and deep region variables.

Next generation Argo programme is also oriented towards validation and deployment of new sensors for measuring ocean turbulence and small-scale mixing, which is fundamental for improving OOFS, numerical models, data assimilation schemes, and validation of forecast products.

Expansion of the observing network requires maintenance and advancements of data management systems among providers and forecasting centers to ensure interoperability and open access to growing data inflow (Roemmich et al., 2019)

12.2.4. Next phase for satellite missions

Satellite observations, together with those in-situ, are the key element for the global ocean observing system. In Chapter 4, it has already been provided a general overview of the type of data used for building OOFS. Next generation of forecasting systems will also exploit the new technological advancements in the observational network, and satellite measurements will play an important role in monitoring the cryosphere, coastal zones, and inland waters to improve the quality of marine services. The International Altimetry Team has recently published a contribution about the future 25 years of progress in altimetry measurements (International Altimetry Team, 2021); according to this work, the main requirements by altimetry for scientific and operational advances of operational oceanography, and more in general for Earth system science, are:

- Increasing the coverage of satellite measurements to support ocean dynamics understanding, from smaller mesoscale to sub-mesoscale, by means of multi-platform in-situ measurements, multi-satellite and SAR, and SAR-interferometry altimetry;
- The design of ad-hoc experiments for in-situ data collection guided by remote data;
- The evaluation of vertical circulation by means for in-situ and high resolution sea surface height measurements;
- Guaranteeing the continuity of the current operational measurements;
- Estimating uncertainties on regional sea level trends by comparing tide gauges with GNSS positioning with altimetry;
- Improving sea level record at coastal scale by using high resolution SAR altimetry, tide gauges with GNSS positioning, and developing GNSS reflectometry (the last is very promising for providing sea level change measurements);
- Increasing the spatial resolution of altimetry products with advanced techniques like SARIn-based "swath mode" processing and fully focused SAR over polar oceans;
- Increasing not only spatial but also temporal resolution by means of higher resolving altimeter such as SWOT, accompanied by larger altimetry constellation that includes swath and conventional altimetry, doppler wave and current scatterometer, and integrated altimeter.

3. https://argo.ucsd.edu/
4. https://argo.ucsd.edu/argo-beyond-2020/

To support operational oceanography and marine applications, Copernicus Marine Service has drawn up a document [5] that describes the main requirements for the evolution of the Copernicus Satellite Components. It focuses on the need of a multi-sensor and multi-mission approach for collecting SST, SSS, ocean colour, currents, wind, and wave measurements. This would constrain future high resolution open ocean, coastal models, and coupled ocean/wave models. The document also recognizes the need of improving space/time resolution, to better monitor and forecast the physical and biogeochemical state of the ocean at fine scale, and to improve the monitoring of coastal zones and of rapidly changing polar regions.

12.3. Numerical models planned evolutions, including adaptation to new HPC systems

Ocean models are one of the pillars for OOFS. Chapter 4 provides information on current modelling capacities while Chapters from 5 to 10 deepen the theoretical aspects, but still remain a main question to be answered: *What is expected by ocean models for the future OOFS*? Fox-Kemper et al. (2019) provided an extensive review on challenges and perspectives in ocean models, touching many scientific open questions and issues to solve. In particular, evolving the core models to address adequate scales in space and time, accurately representing physical processes, and running fastly is the baseline for improving predictability, as well as past reconstruction of the blue, green and white ocean. These are the challenges that have to be tackled for the improvement of future OOFS.

Le Sommer et al. (2018) showed that the evolution in ocean modelling for operational oceanography is strictly connected to resolve physical processes down to the submesoscale (Chassignet and Xu, 2021) and to describe internal wave and internal tides at a global scale thanks to increase in computer power and improved physical parameterization (Shriver et al., 2012). Increasing resolution in space and time is not the only way to address high quality operational products: modularity of modern geoscientific models is key for addressing modelling complexity (Le Sommer et al., 2018).

Modelling complexity and modularity for the next generation of OOFS have a computational cost that needs to be accounted for once we consider evolutions in numerics. Evolutions in High Performance Computing is then another pillar on which establishing OOFS; scientific questions to be solved require also to face technological challenges. Le Sommer et al. (2018) highlighted how the main current limitations in the modelling framework capacity is not due to computational speed of the processors, but on access to memory and latency in input/output. Such limits require a deep revision on the way developments are carried on, but sustained collaboration between ocean modellers and computer scientists is also key.

The usage of graphics processing units (GPU) is progressively accelerating the Earth system modelling the atmosphere and the ocean. This transition to modern massive supercomputers requires re-design numerical codes and HPC optimization/parallelization strategies. In the oceanographic community, codes have been progressively ported on hybrid CPU/GPU architectures: for example, Xu et al. (2015) provided a first example of porting of the POM on GPU architecture, focusing on adopted strategy for memory access optimization, new design of communications, boundary optimization overlapping approach, and I/O optimization, achieving over 400x speedup against a single CPU core, reducing energy consumption by about seven times. Liu et al. (2019) provided a description of the first parallel implementation and optimization of the ROMS on a *many-processor* system, the Sunway sw26010: the result showed that the speedup of optimised hotspot program can be up to 3.69x with respect to original ROMS one. Such examples demonstrate how future complex computing architectures can be exploited for accelerating ocean models execution, benefiting operational systems, and opening new frontiers in numerical modelling.

Growing application requirements push from petascale to exascale: in the near future larger datasets, more parameters, much more computing, more need for parallelism, and large power consumption will be available. These improvements are strictly connected to evolutions in climate and ocean modelling that aim to represent real-world systems characterised by multi-physics and multi-scale interaction in space and time, opening to predictive science.

5. https://marine.copernicus.eu/sites/default/files/media/pdf/2020-10/CMEMS-requirements-satellites.pdf

Exascale computing is then the next frontier to build global climate systems at the optimal model resolution that requires a high level of performance capabilities but remaining within a specific power budget. Operational centres need to account for heterogeneous computing resources: heterogeneous computing aims to match the requirements of each application to the strengths of CPU/GPU architectures (Mittal and Vetter, 2015). The collaborative framework among different hardware components is an open research field that aims at:

- Port large-scale codes written in CPU or GPU-suited languages into heterogeneous computing systems minimising overhead and error-prone;
- Design new suitable data-access strategies to take full advantage of fused CPU-GPU systems;
- Reduce use of more classical programming languages like Fortran in favour of more modern computing languages such as Python;
- Increase data analytics capacities;
- Decrease energy consumption towards Green Computing.

12.4. Future evolutions in ocean data assimilation for operational ocean forecasting

Emerging observing technologies provide impetus to the development of DA systems. Operational ocean DA systems are constantly evolving their application of improved data assimilation methods, their use with increased resolution models and models with increased complexity, their use of new and upcoming observing technology, and their use of new community DA software and computer hardware infrastructures. Below is a summary of some of the areas in which DA is expected to evolve in operational forecasting systems over the next 10 years.

In terms of the DA methodology, the most immediate development is the merging of ensemble and variational methods. Drawing on the strengths of both approaches, the “hybrid” approach is being developed in a number of forecasting centres. The static or parametrized version of the background error covariances used in variational methods and the flow-dependent estimates from an ensemble are combined. Experience from NWP suggests that the hybrid approach performs better than an either pure variational or pure ensemble method (Lorenc and Jardak, 2018); efforts are underway to implement similar capability in global and regional ocean forecasting systems. These are likely to reach some maturity over the coming few years. More sophisticated DA methods, which do not rely on the assumption that forecast errors have an unbiased Gaussian distribution (such as particle filters, van Leeuwen et al., 2015), are being actively pursued to deal with, for instance, biogeochemical variables. Another growing area of methodological development is the application of machine learning to the data assimilation problem (Bonavita et al., 2021), particularly in regard to model error estimation, model parameter estimation, and the estimation of forecast error covariance statistics.

Ocean model resolution is constantly being increased as more computer resources become available. DA systems need to evolve to make sure they can deal with the larger range of scales in the models. The complexity of models is also increasing in both the ocean models themselves and the different types of coupled models being used. Applying DA methods to ocean/sea-ice models, physical-biogeochemical models, acoustic-physical models, and more complete earth system models that include many different earth system components, is an active area of research (Penny et al., 2019). Models used for operational ocean, sea-ice, and atmosphere forecasting on short timescales are increasingly becoming coupled together and the data assimilation methods needed to effectively initialise these systems are being developed. Most operational coupled weather forecasting systems do not currently use strongly coupled data assimilation methods, whereby ocean observations can directly influence the atmospheric analysis and vice versa, but they are expected to be developed and implemented over the next decade.

The software infrastructure needed to apply the data assimilation is also under development by several new community DA software systems, including the DART (Anderson et al., 2009), the OOPS, the JEDI, EnKF-C (Sakov, 2014), and the PDAF (Nerger et al., 2020). The computer hardware used to run forecasting systems is also evolving with different architectures such as GPUs, which will become a strong computational candidate for operational forecasting systems in a 10-year timeframe along with the evolution of numerical codes. The community software systems provide the opportunity for more collaboration between operational forecasting groups, and between operational and research groups.

12.5. Future of ensemble prediction systems

Numerical ocean, weather, seasonal and climate forecasting systems across the world are tending towards becoming coupled ensemble data assimilation prediction systems (Brassington et al., 2015; Barton, 2021; Buizza, 2021; Frolov, 2021; Fujii et al., 2021; Komaromi, 2021), including a better coverage of the inter-relationships among the geophysical domains of the ocean, atmosphere, sea ice, land, and biogeochemistry (Sandery et al., 2020; O'Kane et al., 2021). Forecasting systems are also increasingly applied to finer spatiotemporal scales.

The need to quantify the probability distribution of forecast error in coupled and downscaled models, as well as the reliability and accuracy of forecasts, will be served well by ensemble prediction systems, such as those using the EnKF (e.g., Sandery et al., 2020; O'Kane et al., 2021; Sun et al., 2020; Minamide and Posselt, 2022).

Ensemble prediction systems enable synthesis of models and observations leading to data that can be used to provide best estimates of geophysical variables and quantify the dynamics of their uncertainty (Sandery et al., 2019) (Figure 12.2). Uncertainty quantification will become as important in forecasts as the forecasts themselves, providing guidance on reliability and insight into fast growing disturbances in the geophysical environment. As described in other sections of this chapter, advances in ensemble prediction will also be coupled to improvements in models, observations, data assimilation, computer resources and technology.

There is an associated loss of predictability towards finer scales (Jacobs et al., 2021). Prediction systems using coupled data assimilation and finer spatial resolution will require larger ensembles, more frequent, representative and accurate observations, and improved data assimilation practices. Extending the range of predictability will be facilitated by advances to ensemble prediction systems. Operational ensemble systems will incorporate improved methods for data assimilation in the presence of model error and strong non-linearities, such as the iterative EnKF (Sakov et al., 2017), hybrid covariance methods (Kotsuki and Bishop, 2022), and assimilation of non-linear observations such as water vapour, cloud, precipitation, sea-ice, and phytoplankton concentration (Bishop, 2016; Posselt and Bishop, 2018).

Combining ensemble prediction with machine learning and artificial intelligence will also play an increasing role in forecasting (Brajard et al., 2021; Weyn et al., 2021). In some instances, forward models with reduced order low dimensional and data-driven differentiable emulators (Maulik et al., 2021) will be able to replace full non-linear models to reduce computational cost and assist in searches for initial conditions, patterns, parameterisations and ensemble perturbations appropriate for particular forecasts. Ensemble prediction systems will be used to identify initial states, forcing and dynamics that contribute to regime transitions (O'Kane et al 2019; Quinn et al., 2020) and in the forecasting of extreme events (Hawcroft et al., 2021).

Forecast model parameters will continue to be poorly known, subject to uncertainty, dependent on grid resolution, and a source of model bias requiring joint state and parameter estimation (Kitsios et al., 2021). With this approach, predictability of certain geophysical processes may be improved (Zhang et al., 2017). Future ensemble prediction systems will be optimised with model parameters that minimise bias in the ensemble mean but that adequately represent the parameter's error probability distribution in the ensemble (Gao et al., 2021). Coupled model forecasts will be able to be optimised in state and parameter space. Model error minimization will be multi-variate and simultaneous across the geophysical realms with respect to the global network of observations (Sandery et al., 2020).

Ensemble prediction systems will play an increasing role in the future design of observation systems (Sandery et al., 2019 and 2020). Coupled ensemble prediction provides insight into unobserved variables through cross domain covariances. Future applications of coupled ensemble prediction systems will provide improved reanalysis products with tighter constraints on carbon, sea-ice volume, air-sea fluxes, ocean heat storage and transport, using optimally designed observing systems.

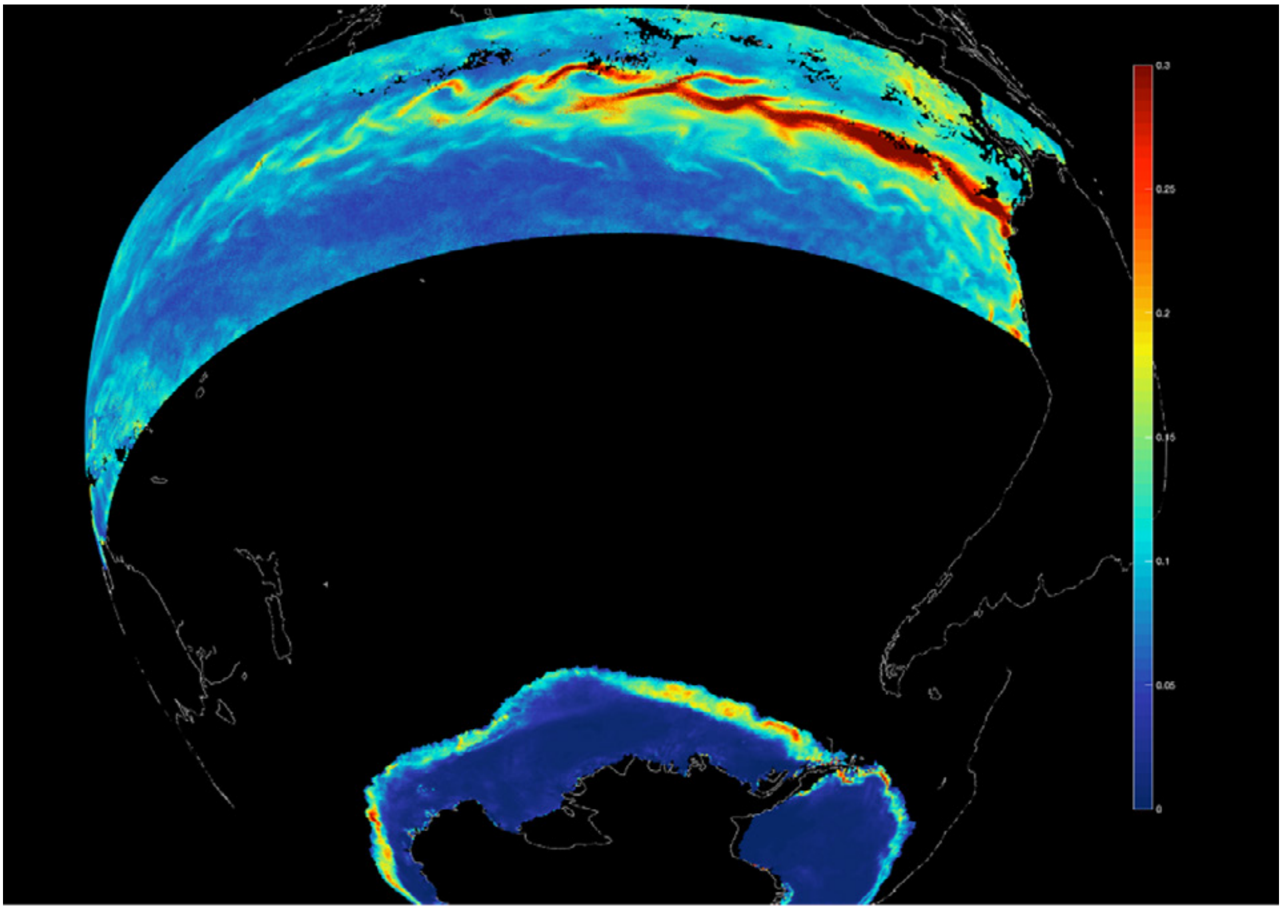

Figure 12.2. Quantifying the dynamics of system uncertainty. This image shows forecast ensemble spread in sea surface temperature (K) and sea ice concentration on 28th September 2017 (in observation space) from a 96 member, 0.1o horizontal resolution coupled ocean-sea-ice EnKF prediction system, known as ACCESS-OM2-EnKF-C (Sakov, 2014; Kiss et al., 2020). SST spread is related to uncertainty: the forecast dynamical state of Tropical Instability Waves and sea ice spread shows that forecast uncertainty at this time of year is greatest in certain areas.

Unstructured mesh models that enhance resolution towards the coastline for detailed hydrodynamic and biogeochemical forecasting of coastal and river, lake and estuarine circulation processes (Herzfeld et al., 2020) will be run as ensemble prediction systems. Meshes that adapt resolution according to areas of most rapidly growing geophysical instabilities, such as in tropical cyclone, tsunami, and flood forecasting (Beisiegel et al., 2021) will also be run as ensemble prediction systems.

As systems continue to be developed, improving the accuracy of forecast error covariance estimates will deliver coupled downscaled analyses and forecasts with greater skill. With advances to observation systems, relatively higher resolution monitoring and ensemble prediction of sea-ice, waves, currents, sea-levels, temperatures, biogeochemistry, and the tracing of river plumes containing sediments, contaminants, and pollutants may be made possible using ensemble prediction systems. Access to future higher resolution ocean in-situ and satellite data may enable prediction of the ocean sub-mesoscale circulation and near-field currents for search and rescue, ship-routing, safety, and recreation. As science, technology, networking, and connectivity improves, real-time assimilation of user-supplied observations into ensemble prediction systems to augment local predictability may become possible.

12.6. Opportunities of artificial intelligence for ocean forecasting systems

Recent developments in AI open many interesting opportunities in the context of operational oceanography and ocean forecasting systems. Operational forecasting systems are indeed not only based on observational data but also on algorithms. These algorithms gather and encode our understanding of physical systems and their dynamics, as well as of observation networks and associated uncertainties. They also reflect our collective knowledge on the relevant criteria for evaluating ocean data products. As in many activities relying on algorithms, the emergence of artificial intelligence, and especially of deep learning, opens a number of new possibilities, and is therefore the subject of growing interest in our community.

The ML generally refers to all the methods used to build algorithms whose components and parameters are not defined a priori but are trained according to a given objective. This field encompasses a large number of different methods, algorithms, and training strategies. It is a wide and fast-moving research field that includes, but is not restricted to, deep learning. ML is also intimately linked to a technological landscape and a software ecosystem in constant evolution. These technologies allow researchers and engineers to assemble complex algorithms from elementary building blocks in a very versatile and modular way, with interesting performances compared to state-of-the-art methods in many disciplines.

Applications of artificial intelligence are currently in vogue but, beyond the hype, artificial intelligence and machine learning can help us to overcome some of the current limitations of ocean forecasting systems. Ocean models and data assimilation methods, which are the scientific underpinning of current ocean forecasting systems, are indeed facing important challenges. Performing large ensemble simulations with full ocean models at increasingly fine spatial resolution is becoming more and more difficult computationally. We still do not know how to fully exploit hybrid computing architectures in our systems. We do not have a robust and plug-and-play framework to adapt their complexity to new custom applications. Although they are constantly being improved, our systems are also becoming increasingly difficult to modify and maintain. As developed in the following subsections, AI and ML may well help us to overcome these limitations and may even deeply impact on the structure of our operational systems.

12.6.1. Expected contributions of machine learning to ocean forecasting pipelines

Machine learning has long been used in ocean sciences and operational oceanography. However, these applications have so far mostly been limited to data retrieval algorithms upstream of forecasting systems (remote sensing, quality control), or to data processing and analysis in downstream applications (data mining, data fusion). In this context, ML algorithms have been essentially seen as black boxes without much physical basis. This perception is fundamentally renewed with the emergence of physics based machine learning and differentiable programming, which now allow to bridge physical sciences, scientific computing, uncertainty quantification, and machine learning (Carleo et al., 2019).

If we adopt a data-centric viewpoint, ocean forecasting systems can indeed be described as a succession of independent data processing steps in sequential pipelines (see Figure 4.1). These pipelines include the collection of past observational data, data-assimilation to reconstruct the current state of the ocean, forecasting with a physics-based model, and eventually the post-processing and dissemination to users. Data is being processed with algorithms at each step of the pipelines. It is now obvious that modern machine learning has the potential to impact each step of the data-processing pipelines of operational oceanography and ocean forecasting systems.

As mentioned above, many applications can be identified upstream or downstream of the core engines of ocean forecasting systems. Typical applications of ML upstream of core engines include, for instance, algorithms for alleviating observational noise, for retrieving parameters (Malmgren-Hansen, 2021), or for data quality control (Castelão, 2021). ML can thus be used for detecting outliers in Argo profiles (Maze et al., 2017). The range of possible downstream uses of core forecasting engines is even wider. ML is here expected to help design tailored services addressing key challenges (Persello et al., 2022), such as improving the prediction of Lagrangian drift or detecting anomalous extreme events.

However, what is probably more difficult to perceive is how machine learning may soon affect the core engine of ocean forecasting systems, and eventually all the services to users. Machine learning and differentiable programming are indeed opening many opportunities in computational fluid dynamics (Vinuesa and Brunton, 2021), while deeply renewing inverse methods in many areas (Cranmer et al., 2020). These recent advances could be leveraged for improving ocean models, e.g. for better accounting for unresolved processes (Brunton et al., 2020; Zanna and Bolton, 2021). They could also help improve data assimilation schemes (Bonavita and Laloyaux, 2020), or even possibly replace full inversion pipelines (Fablet et al., 2021).

These recent advances open the possibility to design and train our core forecasting engines in such a way that their complexity and performance could be optimised for specific applications, ultimately improving our ability to meet the diversity of user needs.

12.6.2. Designing fully trainable ocean forecasting systems core engines

The core engines of current ocean forecasting systems are based on two types of objects that are still quite independent, namely ocean circulation models and data assimilation methods. Ocean models, data assimilation methods, and their implementation in forecasting systems are being continuously improved. But our core forecasting engines are still rather static in their design and structure, due to technological, organisational and historical reasons. For instance, ocean models are generally developed without taking into account how they will be implemented with data assimilation. As such, there is no guarantee of the optimality of the overall design of our systems and its fit for purpose in specific contexts.

Recent developments at the interface of machine learning and scientific computing could open the possibility of optimising the design of our core prediction engines according to predefined objectives. Indeed, beyond the improvements of specific components of ocean models or data assimilation schemes, the real benefit to be expected from machine learning in forecasting systems is the ability to optimise entire pipelines with end-to-end strategies. The term end-to-end here refers to the ability to optimise components of processing pipelines based on metrics measuring the performance of the entire pipeline. End-to-end strategies may eventually allow the design of fit for purpose and user-centric processing chains and products.

There are obviously technological conditions to realise this potential. Integrating trainable components in core forecasting engines is indeed greatly facilitated if these engines are already composed of independent modules with robust and stable interfaces. It is therefore necessary a gradual evolution to make the system more modular and composable. Moreover, if we want to take advantage of end-to-end strategies, the core engines should be fully differentiable. This would allow to back-propagate a misfit in the prediction into an increment in the parameters of the engine. This is only possible if the core engine is written in a high-level differentiable language or programming framework.

Such prerequisites may at first appear daunting, but a gradual evolution towards modular, composable, and differentiable core engines would also have important side benefits. First, this effort to redesign our core engines, may actually provide a viable strategy for exploiting upcoming computing architectures, starting from GPUs (Kochkov et al., 2021). It may also simplify the maintenance of our engines, as for instance the development of adjoint models (Hatfield et al., 2021), therefore speeding up the transfer from research to operation (R2O). Another benefit is also the built-in treatment of uncertainties, thanks to recent advances in probabilistic programming (van de Meent et al., 2021) and Bayesian Machine Learning [6].

12.6.3. Towards user-centric, ocean digital twins leveraging lightweight emulators

Looking further ahead, it can be guessed what future digital twins of the ocean will eventually look like. The integration of AI components may indeed gradually change the underlying paradigm of ocean forecasting systems. While current systems essentially implement “single-core engines” with a predefined level of complexity, future systems may be based on collections of core engines, tailored to the specific needs of particular users. These tailored core engines would instantiate core methods and building blocks in a versatile and user-centric way, providing fit for purpose tools and products to users.

Whatever form digital twins will eventually take, a key methodology will be the ability to train emulators of existing systems at reduced costs and with controlled complexity. As described above, a gradual evolution of our core forecasting engines will be needed for leveraging the full potential of AI and ML. This transition may in particular leverage DDEs. They provide approximations of pre-existing algorithms (Kasim et al., 2021) and can be integrated in data assimilation schemes (Nonnenmacher and Greenberg, 2021). As such, DDEs offer a good solution for building upon existing expertise and tools, while benefiting from the pace of scientific and technological advances in AI.

6. https://jorisbaan.nl/2021/03/02/introduction-to-bayesian-deep-learning.html

In conclusion, it appears that we are at the beginning of an exciting phase in the evolution of ocean forecasting systems, which could deeply transform the entire service offered to users. The integration of AI in ocean forecasting systems will require a gradual but profound change of the algorithms that constitute their underpinnings. This transition will take advantage of the wealth of expertise on ocean physics, observing networks, and user needs available in ocean forecasting centres. It will also require developing and nurturing new collaborations with the broader AI technological and scientific community, and benefit from the adoption of open science practices.

12.7. Seamless prediction

Palmer et al. (2008) used “seamless” to refer to predictions across the range of weather and climate time scales, e.g. ranging from forecast in days to projections in decades. The WMO, in its document “Seamless prediction of the Earth system: from minutes to months” (WMO, 2015), further developed this concept, with a main focus on the weather component but also starting to consider its importance for the ocean. Then, within EuroGOOS this concept has been expanded to promote next generation of ocean services able to seamlessly span spatially from global ocean to coastal areas and estuaries as a continuum with high resolution information (She et al., 2021). To achieve the objectives of the seamless approach, numerical ocean models need to evolve (Chassignet and Xu, 2021; Fox-Kemper et al., 2019) towards:

- Use of nested and regional downscaling simulations, by means of high-resolution spatial grid spacing or using variable-resolution and multi-scale modelling;
- New parameterizations and improvement of the existing ones (e.g. air-sea parameterization, turbulence and mixing, internal tides, vertical convection, coastal estuaries interface with open ocean);
- More direct simulation of sea level changes and tides.

Seamless is also connected to coupling as global coupled ocean-atmosphere-land-ice modelling systems are used to perform climate change projections and studies, from decadal to seasonal timescales (Hewitt et al., 2017). The overall advancements of numerics in ocean dynamics, biogeochemistry, weather modelling, and hydrology open new opportunities for coupled systems to address predictions on short-range timescales from regional to coastal scales.

In order to establish a seamless marine information service, integrated and unified ocean observing systems and seamless unified modelling and forecasting systems should be developed. Integrated ocean observing implies that ocean observations made by multiple sectors for all subsystems with multiple means - remote sensing, robotics, and in-situ - are integrated, while monitoring schemes and data management are designed in an unified way, so that the observations, after being integrated with the seamless models, will be able to fit users' purposes. Furthermore, ocean observing should be cost effective and sustainable.

The seamless models can be based on mathematical equations or statistical and AI algorithms, which simulate or emulate marine physical-chemical-geological-biological systems. There are still significant gaps in current forecasting capacity to reach seamless predictability. The development of a seamless modelling capacity will be discussed in the next subsections from three aspects: space, time, and system of systems. The seamless ocean earth system prediction models should be based on UOMs and including atmospheric models. Development of UOMs has been identified as one of the four EuroGOOS research priorities (She et al., 2016).

12.7.1. Optimal use of modelling workforce and model consolidation

A seamless UOM modelling framework should be developed to leverage global efforts to enable joint code development. One notable feature of the ocean modelling community is the great diversity of the models but the very limited research workforce for each model. An incomplete survey of ocean circulation modelling by EuroGOOS ([7]) showed that EU countries use 32 ocean models for operational and/or ocean climate modelling, among which 24 were developed in the EU and 8 from the US. Twenty ocean circulation models have been used in Europe for operational forecasting (Capet et al., 2020). In the US, at least ten ocean models are currently used for operational forecasts. If this count would be extended to ocean circulation models developed and used in other countries (i.e. Australia, Canada, China, and Japan) the number of ocean models in use could be huge. It is well-known that a significant workforce is needed to keep an ocean model at the state-of-the-art.

7. https://eurogoos.eu/models/

However, each ocean modelling group has only a very limited workforce for ocean model development. Even though joint or community model development has improved the situation for a small number of models, the number of ocean model developers is still far from sufficient for most of the models. Therefore, it is necessary to optimise the use of ocean modelling workforces focusing only on a limited number of models. The future UOMs can be made so that one model would have options with multiple coordinates and parameterizations, hence emulating different model behaviours.

Optimal use of modelling workforce should be coordinated in national, regional (such as the GRAs), and global scales so that the UOMs in different scales can be well addressed and consolidated with a critical mass of model developers. However, it is not always possible to have a critical mass of model developers at the national level, as only countries with strong national investment in ocean science have such a capacity. It is easier to reach a critical mass at the regional or global levels. In fact, most of the effective modelling co-operation is carried out at regional level. The global co-development of models is probably less active due to both administrative and political barriers. It is highly recommended to strengthen global collaboration on UOM development.

12.7.2. Development of seamless UOM for multiple temporal scales

Predictability in an ocean earth system has a multi-scale feature, relating to the spatiotemporal scales of its subsystems as well as their interactions, which can be divided into forcing-based predictability, self-constrained subsystem predictability, and coupled system predictability. For atmospheric systems, according to the high-resolution global forecast model experiments, the upper limit of the self-constrained predictability for deterministic prediction is two weeks. Longer-scale predictability is related to blocking events with time scales ranging from weeks to years, e.g. MJO, PNA, NAO, AO, ENSO, QBO, which relies on interaction between atmosphere and ocean-ice systems and solar radiation. It is well-known that the surface ocean is mainly dominated by forcing-based predictability, i.e. variability of waves, ice and sea level in synoptic scale are largely determined by weather conditions. Subsurface ocean and sea ice can store forcing signals and release them to affect the atmosphere at a "slower" pace. This generates longer predictability in the coupled ocean-ice-atmospheric system. MJO, PNA, NAO, AO, and ENSO are all phenomena generated in such a coupled system. As stated by Brian Hoskins in the WMO Lecture 2011[8]: "The background provided by the longer time-scales and by external conditions, and the phenomena that occur on each range of time-scales in the seamless weather-climate prediction problem, give the promise of some predictive power on all time-scales".

8. https://public.wmo.int/en/bulletin/predictability-beyond-deterministic-limit

Most of these long-scale processes can still not be predicted successfully by current coupled-system models. UOM development is a key to improve the earth system predictability in the current stage as it will provide insight knowledge, as well as simulate the processes that the ocean-ice system filters, absorbs, and transfers the atmospheric signals into a slow-motion signal and then feeds back to the atmosphere.

To reach breakthroughs in longer-scale predictability, it is important to consider that: i) ocean earth system forecast is a probability prediction problem; ii) multi-model ensemble has shown expanded atmospheric forecasting skills than the deterministic prediction; iii) shorter-scale phenomena, although constrained by longer-scale ones, are also a statistical forcing to the longer-scale, thus should not be treated only as noise; and iv) solar radiation, volcano eruption, and changes of pollutants in both ocean and atmosphere can affect the intrinsic signals in the system and then should be included. UOM development should address these issues.

12.7.3. Geographic configurations and seamless UOM in space and in a marine system of systems

For a coordinated UOM development, proper geographic scales should be defined as well, so that both scientific requirements and collaboration needs are met. Three types of forecast UOMs can be expected: i) global-scale coupled UOMs aiming at longer-scale prediction of the earth system, which is not necessarily high resolution but should be able to use short-scale as a statistical forcing; ii) global and regional scale coupled models aiming at produce refined forecast within a "foreseeable" time, e.g. a month, for which high resolution will be important; and iii) for "touchable" spatiotemporal scale, i.e. inland water-estuary-coastal-regional sea in space and a few days in time. It should also be noted that the smaller-scale UOMs can be easily applied to long-term forecast applications when forecasts at boundaries are well defined.

The coupled UOMs will mainly be developed for global and regional scale to address longer scales from months to seasons. For the regional scale coupled UOMs, geographic coverage should be sufficiently large to reflect impacts of the atmosphere-ocean coupling. The resolution of the coupled UOMs can be a few kilometres (mesoscale resolving) for global scale and hundreds to thousands metres for regional scale to resolve sub-mesoscale eddies and narrow straits connecting sea basins. Therefore for regional scale coupled UOMs, flexible grid and high-performance computing are two basic requirements. For one regional scale there might be more than one coupled UOM.

High resolution is required to provide a seamless prediction in space. For example, narrow straits connecting two large water bodies and archipelago water areas may need a resolution of 100-1000 m; inland waters-estuary-coastal-open sea continuum, essential for pollutant transport modelling, nutrient cycle, and carbon cycle modelling, needs also a similar model resolution. An even higher resolution (10-100 m) may be required when dealing with river inputs to the sea, impact of flooding, hydropower, barriers to pollutant transport, coastal inundation, compound flooding-surge events, and port management. Hence, a spatial seamless UOM should have flexible grids, either unstructured grid or dynamic two-way nested grid.

12.7.4. Evolution in short-, mid- and long-term perspectives

In short- to mid-term (3-5 years) perspectives, the objective would be to develop a UOM framework and continuous improvement of prediction skills of the marine earth system models with a forecast range of 10 days to 1 month. The research should focus on: (i) establishing UOM global cooperation framework to harmonise, coordinate, and further evolve existing UOM development work; (ii) designing the UOM concept, framework, and multiple configurations for different scales, considering international cooperation and sharing of best practices, optimal use of workforce, critical mass for UOM development, code portability, relocatability, scalability, flexibility, resolvability, and reducing the redundancy of models; (iii) improving model process description, so that each UOM sub-model can effectively model major features in the subsystem; (iv) investigate possibility for establishing forecasting capacity in emerging modelling areas, such as SPM, marine litter, underwater noise, and fisheries, and also develop prototype pre-operational models in these areas; v) improving high-performance computing through code modernization; (vi) improving the UOM subsystem coupling; and (vii) develop high-resolution models with flexible grids and interfaces with basin and global scale models, as well as resolving coastal processes for downstream applications

In the long-term (10 years), the objective is to improve prediction skills in time scales from months to seasons for climate, physical, and biogeochemical systems, establish and improve forecasting capacity in emerging areas such as SPM, marine litter, underwater noise, and fisheries. For the ESP in seasonal and longer scales, coupled UOMs including atmosphere-ocean-wave-ice coupling and ocean-optics-SPM-biogeochemical coupling will be developed for ensemble prediction. UOM code will also be optimised for efficient hybrid parallel computing.

12.8. Operational forecasting and scenarios in a digital ocean

A Digital Twin of the Ocean (DTO) is a highly accurate model of the ocean to monitor and predict environmental change, human impact, and vulnerability, with the support of an openly accessible and interoperable dataspace that can function as a central hub for informed decision making (Figure 12.3) (see for example [9]). Such an information system consists of one or more digital replicas of the state and temporal evolution of the oceanic system constrained by the available observations and the laws of physics, making imperative to integrate a set of models or software that pairs the digital world with physical assets, and to feed this set with information from sensors.

A DTO aims to deliver a holistic and cost-effective solution for the integration of all information sources related to seas and oceans, like in situ-data and satellite information combined with IoT techniques, Citizen science, state-of-the-art ocean modelling together with AI and HPC resources into a digital, consistent, high-resolution, multi-dimensional, and near real-time representation of the ocean. This will result in a shared capacity to access, manipulate, analyse, and visualise marine information. The knowledge generated by the DTO platform will empower scientists, citizens, governments, and industries to collectively share the responsibility to monitor, preserve and enhance marine and coastal habitats, while promoting action and sustainable measures in the framework of the blue economy (tourism, fishing, aquaculture, transport, renewable energy, etc.), contributing to a healthy and productive ocean.

9. https://digitaltwinocean.mercator-ocean.eu/

Figure 12.3. Schematic representation of Digital Twin of the Ocean concept.

12.8.1. Construction of an open DTO service platform

To properly address the construction of a digital twin, breakthroughs are needed in various aspects of the digital twin information system, including information completeness and quality, information access and intervention, as well as the underlying supporting infrastructure, tools, and services. The operational pilot of DTO, under development at European level, will encompass the production of a new quality of information, incorporating human systems in the prediction problem and leveraging advances in information theory and digital technologies. Ensembles of simulations combining models from different disciplines, informed by spatial correlations determined from high-resolution observations and by data-driven learning of unknown processes and missing constraints, will enable the DTO to reduce uncertainty in estimation and forecasting of ocean states, changes, and impacts.

Enhancing information quality requires a step change in computational complexity. This means adequate infrastructure including support of very high computing throughputs, concurrency, and extreme-scale hardware. However, it is important to conceal this complexity so that users can run and configure involved workflows and access the information but without requiring expert intervention. In addition, the underlying models and data need to be scientifically sound.

This will require a multi-layered software framework where tasks like simulations, observational data ingestion, and post-processing are treated as objects that are executed on federated computing infrastructures, feed data into virtual data repositories with standardised metadata, and from which a heavily machine-learning-based toolkit extracts information that can be manipulated in any possible way. The result should be the provision of on-demand, conveniently accessible modelling and simulation products, data and processes or MSaaS.

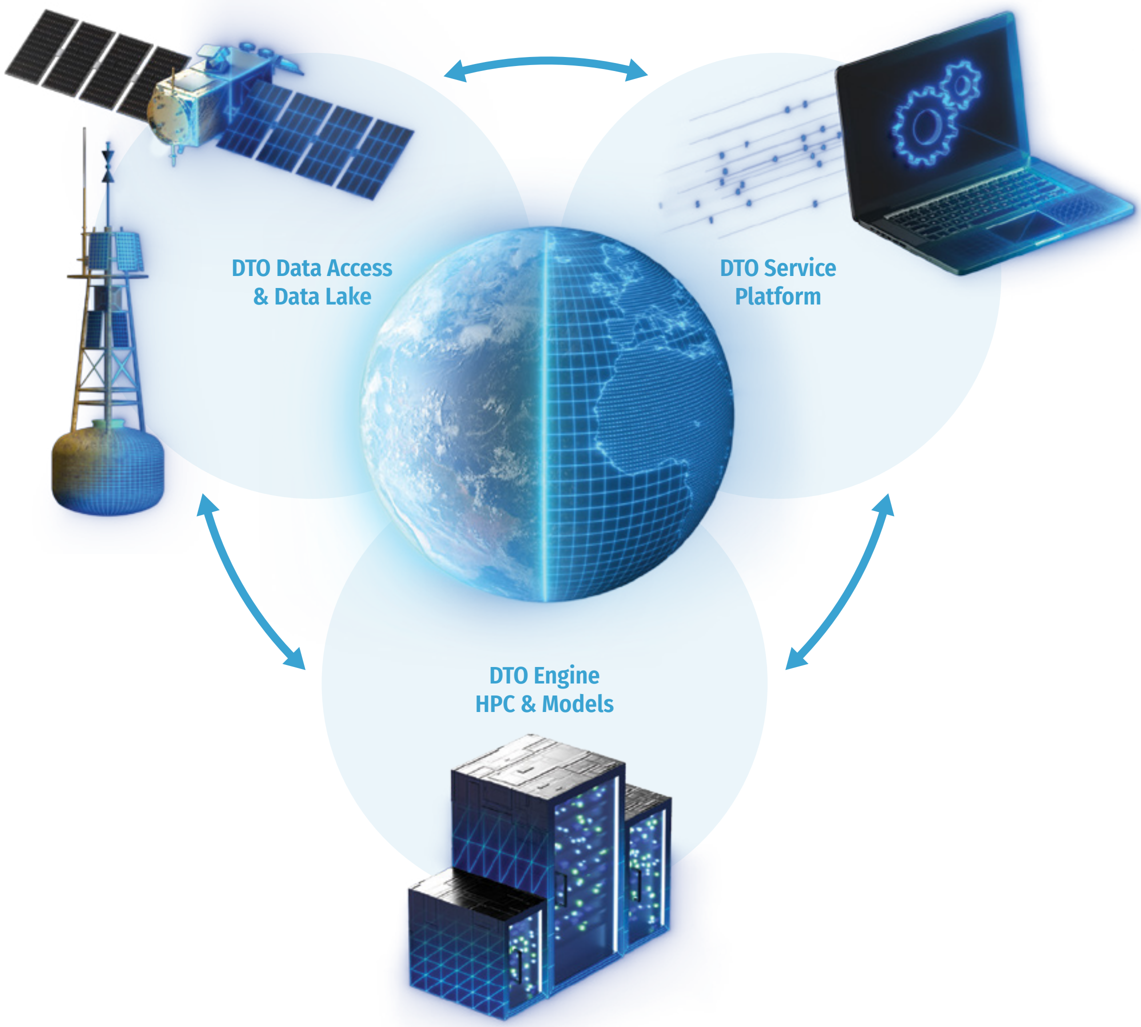

Figure 12.4. DTO Architecture.

12.8.2. Underlying architecture

The multi-layered framework enabling this digital twin ocean pilot operational service comprises 3 major interrelated structural elements (Figure 12.4):

- A DTO data access layer that mixes results and tools from ongoing projects and existing infrastructures with new developments targeting data ingestion, and data harmonising into a Data lake for subsequent use in the DTO engine;

- A DTO engine comprising a set of modelling capabilities, including on-demand modelling and what-if scenario modelling that fill the observational gaps in space and time in a physically consistent way, and observation-driven learning of unknown processes and missing constraints, which will enable to reduce uncertainty in estimation and forecasting;

- A DTO interactive service layer supplying tools, libraries, and interfaces to simplify running and configuration of workflows, as well as access to information, including its analysis and visualisation.

12.9. Quality assessment for intermediate and end users

As described in Chapter 4, PQ assessment is an essential service component for any operational oceanographic centre. In the case of climate and short-term forecasting services, validation of ocean models (physical and biogeochemical) is a crucial issue. Despite the continuous progress of the services towards providing regularly updated quality information, there are still gaps and deficiencies in the operational capacity to assess model solutions. It is still challenging to properly quantify the uncertainties in real time and in a way that is directly understandable and useful to the users. Capet et al. (2020), in their review of the operational modelling capacity in European Seas, pointed out that only 20% of operational coastal model services provide a dynamic uncertainty together with the forecast products. This deficit in terms of operational model validation processes may be mainly linked to the lack of real-time access to a local ocean observation network.

This limitation seems to be partially alleviated within core services that have a regional or global focus. In these services, the PQ processes seems to be favoured by: 1) a wider scope (services dealing not only with forecast models but also with the monitoring component and observational data products); 2) a more integrated data use (for instance through data assimilation in ocean analysis and reanalysis products); and 3) wider spatial coverages (allowing the use of a higher number of observational data sources to validate model predictions). The Copernicus Marine Service is one of these core comprehensive services and in recent years has built some standards for model assessments and delivery of PQ information to end-users. This service, and its evolution roadmap in terms of PQ processes, can illustrate the main expectations for the future evolution of validation and quality information on operational oceanography products.

As described in Sotillo et al. (2021), the Copernicus Marine Service ensures:

- Standardised processes to assess each product's scientific quality against appropriate metrics;
- Product quality information regularly updated and available from a central website, called the "PQ-Dashboard" (https://pqd.mercator-ocean.fr/);
- Specific PQ documentation delivered with each Copernicus Marine Service product, completed by regularly updated quality summaries, including fit for purpose information, and evolving towards peer reviewed technical reports.

From this baseline, the Copernicus Marine Service Product Quality Strategic Plan [10], identified a list of developments, challenges and opportunities foreseen for the next Copernicus-2 service phase period (2022-2028). The availability of an increasing number of ocean observations should enable and support new developments, and eventually improve the information quality associated with oceanographic products. The three main working lines along which the plan will unfold are discussed in the following subsections and shown in Figure 12.5: future observations, future developments in OO centres, and future quality information. These lines are the way forward for the future development of model validation and quality assessment techniques.

12.9.1. New observations for improved quality assessment

The use of new satellite products (e.g. from next Sentinel missions or wide swath altimetry) will enable a significant increase of data coverage towards higher resolution, allowing not only a quality increase but also more validation opportunities for a wide range of operational oceanography products. The continuation of the BGC-Argo and Deep Argo missions and networks are crucial for providing quality information in areas and on variables that are still highly undersampled. The potential extension of Argo coverage towards coastal areas may also be essential for its important socio-economic impact and the benefit for coastal model assessments. In that sense, there are some on-going initiatives in the framework of R&D Projects (such as the Euro-Argo RISE H2020 one) to test Argo on shelf extensions, targeting shallower waters in European marginal seas.

Additionally, operational oceanography centres should improve the effective use of existing observing products and networks through:

- Upgrade of PQ processes to properly assess high frequency datasets: PQ metrics are generally computed daily. However, currently, and to a greater extent in the future, some near real-time (NRT) model product datasets that are delivered with higher frequency (i.e. every 15 minutes) would need a dedicated assessment.

10. https://marine.copernicus.eu/about/service-evolution-strategy

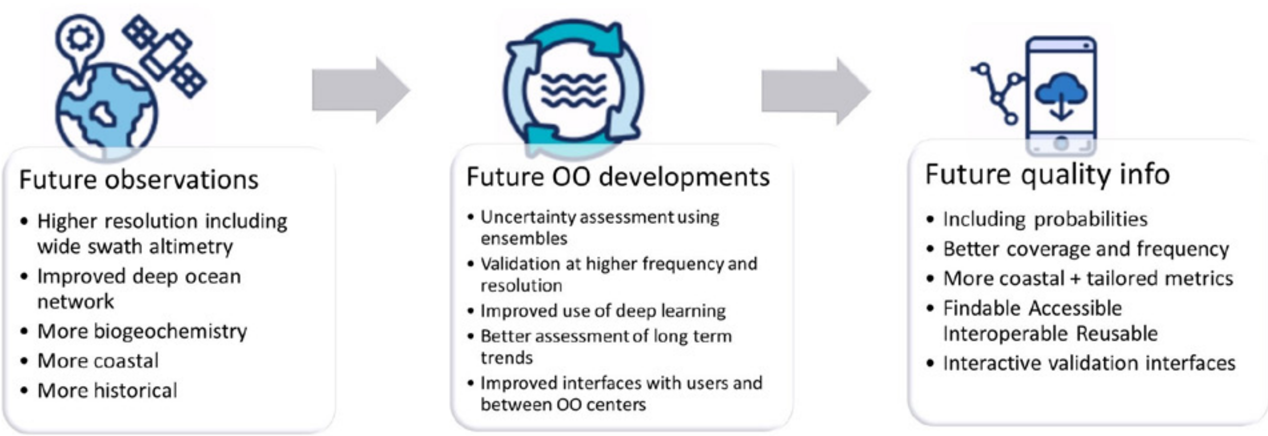

Figure 12.5. New observations enable new developments in operational oceanography centres, which will also benefit from growing computational resources and advanced AI and big data techniques. This will allow significant improvements of the quality information, improving its relevance and its frequency.

- Enhancement of water mass assessment at synoptic scales: at present, sampled only partially. To improve their characterisation in the upper ocean, it is necessary to extend the use of available observational platforms (i.e. more ship of opportunity measurements, thermosalinograph/ferry box data, new glider opportunities, sea mammals). Below 2000m, water mass distributions are still poorly understood, and historical data do not guarantee the reliability of existing climatologies. Deep floats and deep ocean observations also need to be considered to support global prediction assessment.

- Promote the use of data from specific multi-platform campaigns (specially in hot spots): regular and periodic campaigns in the same waters are necessary for climate monitoring and periodic model assessments (i.e. glider periodic missions along straits); current measurements are also much needed (both Lagrangian and Eulerian observations), not only for temperature and salinity.

- Ensure easy access to historic observations: there are large amounts of data from research surveys that are either not available or available only in operational catalogues. These independent data (in the sense of not assimilated) can be crucial for assessing model performance. A progressive integration of this kind of data will be advantageous for forecasters, and its “discovery” is foreseen to increase. Access to these sources should be automated, data loss reduced, and the investment on data collection will be recovered. In the context of Copernicus Marine Service, EMODNET, EuroGOOS alliances or other networks, it is crucial for OO centres and data providers to connect initiatives and efforts to better integrate the existing ocean observing systems, as well as the new expected instruments/observations.

12.9.2. Expected development of quality assessment techniques

The use of ensemble data assimilation methods and the expected increase in the use of prediction systems based on model ensembles should significantly improve the quantification of model product uncertainty using probabilistic scores, the evaluation of error propagation, and of model systematic errors and attractors. An increasing number of high-resolution observations will be used to characterise model skill at all observed scales, while advanced statistical techniques (such as deep learning) should contribute to improve cross-validation capabilities between different types of observations, and between observations and models.

Errors in the ocean circulation models, in particular on vertical transport and mixing, strongly impact the coupled biogeochemical model solutions. Thus, monitoring errors in key parameters of the physical forcing should characterise errors (their causes) and subsequent impacts in biogeochemical solutions. The mixed layer depth variable is a typical example of this due to its impact on biogeochemistry processes.

Quality assessment of model downscaling should be eased in the future by advances in integrated systems (following on the idea of monitoring uncertainties “propagating” along the value chain). The added value of downscaling (higher resolution with better representation of the ocean processes) needs to be assessed through a more systematic comparison of global vs. regional and coastal models. To this aim, alternative/innovative validation metrics are needed for model assessment that avoid double penalty when comparing different resolution models (Ebert, 2009). More relevant skill scores are needed for forecasting, implementing new approaches to validate and inter-compare new physical, and biogeochemical model products at very high-resolution.

Finally, there is a growing need to identify and understand long-term trends in ocean parameters and their impact at regional to coastal scale. The validation of such signals is challenging for physical and even more for biogeochemical parameters, such as carbon, oxygen, and ocean acidification, which are of great interest on both regional and global scales. It is crucial to improve the validation methodology and to increase the number of reference observations as much as possible.

12.9.3. Quality information communication improvements

There is an increasing demand for regional fit for purpose assessments, especially in coastal areas. The quality information content must evolve following users' needs. The current OceanPredict product quality metric monitoring has to be complemented with process- (and user-) oriented metrics, and better quantification of uncertainties. Probabilistic scores and robustness assessments with multi-product (model and observed) intercomparisons should help answer many user requirements. The use of application-oriented metrics, such as Lagrangian drift metrics or "event oriented" metrics (e.g. categorical scores based on thresholds) should also be generalised.

The collaboration among forecasting services to agree on international validation standards must continue. Collaboration between forecast services and users should result in the introduction of new user-oriented metrics to be considered as local case studies and validation "benchmarks".

Operational oceanography centres will have to develop both high-level summarised quality information and high-resolution uncertainty estimates to be delivered alongside the products following FAIR guidelines, as initiated by Peng et al. (2021a, 2021b).

High-level quality summaries, such as product "maturity matrices", will guide users to choose the most appropriate product for a given use, while the uncertainty information delivered alongside the product will enable the access to tailored product quality information, as a valuable addition to many oceanographic applications.

12.10. Expected future evolution of Copernicus Marine Service products and services

The first operational phase 2014-2021 of the Copernicus Marine Service has successfully implemented a service chain devoted to ocean information, involving committed producers throughout Europe, and serving expert users worldwide. The Copernicus Marine Service will develop an ambitious 7-year plan (Copernicus 2, 2021-2027) with staged implementation that answers to increasing user and policy (e.g. EU Green Deal) needs. The objective is to fully embrace the capabilities of new digital services and implement the next generation of ocean monitoring and forecasting for the Blue/White/Green ocean.

Copernicus Marine Service products and services are delivered by means of state-of-the-art, user-oriented, scientific and technical methodologies, which induces openness to newly developing ideas and associated capacities. Apart from guaranteeing service continuity, the Copernicus Marine Service is continuously evolving to ensure that its services and products remain state-of-the-art and meet a wide range of existing and emerging user and policy needs related to all marine and maritime sectors: maritime safety, coastal environment monitoring, trade and marine navigation, fishery, aquaculture, marine renewable energy, marine conservation and biodiversity, ocean health, climate and climate adaptation, recreation, education, science and innovation.

The following major improvements of current products, as well as new products benefiting from science and technology advances, are already planned to ensure an enhanced continuity of the service, keeping the service at the state-of-art and at internationally competitive and fit for purpose standards, considering the European policies' priorities (Green Deal, Common Fisheries Policy, Marine Strategy Framework Directive, and Convention on Biological Diversity):

- High resolution monitoring, modelling, and forecasting of the blue ocean with an increase of the horizontal resolutions of the current systems by a factor of at least 3 (e.g. global 1/36°, regional 1/108°). Coupling and interaction with waves, sea ice, atmosphere, biogeochemistry, and rivers will also be implemented for improved ocean forecasts. New high-resolution sea level observations from the SWOT wide swath altimeter mission, new ocean topography, sea surface temperature, salinity from the Sentinel, HPMC, CRISTAL, and CIMR missions will be included as observational products. These improvements will impact the different Copernicus Marine Service areas and their key applications: maritime security and safety, maritime transport, pollution monitoring and offshore operations, and coastal zone monitoring and forecasting.

- Probabilistic forecasting and extended (1-month) forecasts based on model ensembles, allowing a better characterization of model uncertainties in analyses and forecast. Data assimilation techniques will evolve toward more multivariate schemes to constrain in a more extended and coherent way the different inanimate components of the marine environment (physics, sea ice, and biogeochemistry). Coupled ocean/atmosphere data assimilation will also be implemented. Probabilistic forecasts will be instrumental for early warning systems, and to support decision-making based on operational products by better characterising the confidence level associated with the provided information.

- Reanalyses of the 20th century physical and biogeochemical data for the global ocean and the European regional seas, assimilating historical in-situ observations (e.g. sea surface temperature and tige gauges mainly for the first half of the century and temperature and salinity profiles from 1950 onwards). The purpose of these reanalyses is to better assess the past evolution of the ocean in response to climate change and to better monitor Essential Ocean Variables and Essential Climate Variables related to the ocean.

- Step changes in Arctic Ocean monitoring, modelling, and forecasting through upgrade in sea-ice models, improved coupling with the atmosphere and hydrology (river discharge and nutrient loads), higher-resolution, extended forecasting ranges from a week to a month, and ensemble forecasting for an improved characterization of forecasting uncertainties. Provision of icebergs' forecasts will complement the information produced for ice services. Improved satellite products on sea-ice detection and a pan-Arctic ice chart will complete the offer. These evolutions will address user needs regarding maritime transport (e.g. ship routine) and marine safety in sea-ice and iceberg infested regions, marine resources (fisheries and conservation) and climate change impact in the Arctic.

- Air/sea fluxes of CO_2 monitoring and modelling, including advanced modelling/data assimilation systems at global and regional scales as well as including error estimations. Foreseen developments also include processing and quality control of novel in-situ observations from the BGC Argo array and improvement of observation-based products derived from Neural Network methods. These evolutions are required by the Copernicus anthropogenic CO_2 service as well as for blue carbon monitoring.

- Coastal zone monitoring and forecasting with improved capacities to link and co-production between coastal systems with Copernicus Marine Service upstream systems. Consistency and river-ocean continuity will be ensured by using standardised methods to couple hydrological models (for river run-offs) with global, regional, and coastal ocean models. Time-series (past, present, forecasts) of standardised modelled river discharges of freshwater, nutrients, particulate, and dissolved matter will be provided. Coastal zone monitoring will also be enhanced through satellite observations – based on Sentinel (especially S1, S2, S3, and S6) and other missions - for nearshore bathymetry and shoreline position and their evolution, high-resolution winds, spectral wave information, detection of plastic debris, monitoring of marine litter, ecosystems, water quality, and sea surface temperature. Given the huge social, economic, and biological value of coastal zones, these improvements will contribute to a wide range of applications (coastal zone management, climate adaptation, coastal modelling, aquaculture and fisheries, navigation and shipping, marine renewable energy, oil spill management and search and rescue), supporting various policies and resilience to climate change.

- Marine biology monitoring and forecasting with major improvement in numerical models to represent processes (e.g. benthic/pelagic coupling, riverine inputs) increasing accuracy, advanced data assimilation techniques (e.g. combining state and parameter estimation), and new modules linking optical properties in the near-surface ocean to biomass to better couple ocean colour and subsurface data from in-situ such as BGC Argo. End-to-end ecosystem modelling will also be included to link along the food web low trophic levels (e.g. plankton) to mid-trophic levels (e.g. micronekton), and to high-trophic levels (e.g. predator fishes and marine mammals). Marine biology monitoring will also be enhanced through the improvement of gathering, processing, quality control, and characterization of biogeochemical and marine biology in-situ (e.g. optical and acoustic sensors) and satellite (e.g. S2, S3 and hyperspectral) observations in open and coastal oceans. These products will support international and European

Union objectives in terms of biodiversity, development of sustainable food resources, water quality, assessment of blue carbon in the overall carbon stake accounting.

- Long-term projections of the marine environment (both physics, biogeochemistry, and marine ecosystems) under climate change from global to regional scales (downscaling of climate scenarios), and associated consequences for main stocks of exploited fishes. These products will support climate assessments for decision-making on adaptation and mitigation of climate risks (e.g. coastal floods, surges, etc.).

- Enhanced digital services with online cloud processing capabilities for manipulating and processing data with advanced analytics and scientific computing software (e.g. artificial intelligence toolboxes), access to Sentinel Level 1&2 data, marine data (e.g. from EMODnet, SAF, etc.), and connection to HPC computing nodes. This will consolidate the Copernicus Marine Service as a one-stop shop for operational and digital ocean services.

A document [11] presenting the Copernicus Marine Service Evolution Strategy for R&D priorities has been prepared by its STAC [12] and reviewed by MOI. This document details the expected future products and services by Copernicus Marine Service and the required developments. It is a living document, as it is updated periodically according to feedback from users and policy needs, the status of scientific developments achieved within and outside the Copernicus Marine Service community, and to the high-level Copernicus Marine Service evolution strategy.

12.11. The United Nations Decade of Ocean Science for Sustainable Development

At the beginning of the third millennium, ocean science was largely competent for diagnosing problems. However, its ability to offer solutions of direct relevance to sustainable development requires a massive upgrade.

The world needed a large-scale and adequately resourced campaign to transform ocean science empowering and engaging stakeholders across disciplines, geographies, generations, and genders, and of sufficiently long duration to deliver the lasting change that is required. In 2016, the IOC of UNESCO ([13]) initiated a concept for this campaign. In December 2017, this work culminated in the proclamation by the 72nd Session of the UNGA of the UN Decade of Ocean Science for Sustainable Development 2021-2030 (referred to as 'the Ocean Decade'). UNGA called on the IOC to prepare an Implementation Plan for the Ocean Decade in consultation with Member States, United Nations partners, and diverse stakeholder groups.

In 2021, the United Nations launched the Ocean Decade (2021-2030) ([14]) whose aim is to '*support efforts to reverse the cycle of decline in ocean health and gather ocean stakeholders worldwide behind a common framework that will ensure ocean science can fully support countries in creating improved conditions for sustainable development of the Ocean*'. In this framework, the IOC plays an important role: it coordinates the Decade's design and preparation, identifies programmatic contributions, and implements the Decade.

The vision of the Ocean Decade is '*the science we need for the ocean we want*'. The mission is '*to catalyse transformative ocean science solutions for sustainable development, connecting people and our ocean*'.

Seven outcomes describe what should be the 'ocean we want' at the end of the Ocean Decade:

1. A clean ocean where sources of pollution are identified and reduced or removed.
2. A healthy and resilient ocean where marine ecosystems are understood, protected, restored and managed.
3. A productive ocean supporting sustainable food supply and a sustainable ocean economy.
4. A predicted ocean where society understands and can respond to changing ocean conditions.
5. A safe ocean where life and livelihoods are protected from ocean-related hazards.
6. An accessible ocean with open and equitable access to data, information and technology and innovation.

11. https://marine.copernicus.eu/sites/default/files/media/pdf/2021-09/CMEMS%20Service_evolution_strategy_RD_priorities_v5-June-2021.pdf
12. http://marine.copernicus.eu/science-learning/service-evolution/about-stac
13. https://ioc.unesco.org/
14. https://www.oceandecade.org

7. An inspiring and engaging ocean where society understands and values the ocean in relation to human wellbeing and sustainable development.

The decade will be implemented via "Actions", which are the tangible initiatives that will be carried out across the globe over the next ten years to fulfil the Ocean Decade vision. They will be implemented by a wide range of proponents, including research institutes and universities, governments, UN agencies, intergovernmental organisations, other international and regional organisations, business and industry, philanthropic and corporate foundations, NGOs, educators, community groups or individuals. Actions can be implemented by promoting Activities, Contributions, specific Programs or Projects.

The Ocean Decade will involve a large number of partners and actors around the world, and hence it cannot be rigidly governed. A simple, robust coordination structure will manage day-to-day implementation. The DCU, to be located at the IOC Secretariat, will be the central hub for the coordination of Ocean Decade activities. Governments or partners will host a number of Decade Coordination Offices and DCCs – referred to as decentralised coordination structures – that will be located in different regions around the world. These structures will help to coordinate efforts between national, regional, and global initiatives, share knowledge and tools developed through the Ocean Decade, create links between potential Decade partners, and monitor and report on the impact of the Decade. One DCC will be devoted to Ocean Prediction [15].

The following subsections describe some examples of Actions and Collaborative Centres that will be linked to OOFS.

12.11.1. The Decade Collaborative Centre for Ocean Prediction

DCCs serve as the main interface between Decade Actions and the DCU at the IOC-UNESCO Secretariat. MOI has been selected to host the DCC for Ocean Prediction. It will provide:

- A communication and collaboration hub bringing together Decade programmes with ocean prediction activities, institutes, and organisations outside of the Decade;
- A global technical and organisational structure to establish a pilot for a Global Ocean Data Processing, Modelling, and Forecasting System, building on the innovations generated by the Decade programmes and other national, regional, and international partners.

The DCC for Ocean Prediction will ensure that the efforts of multiple Decade programmes combine to meet Decade objectives and that innovations are integrated into operational ocean forecasting systems through a harmonised global network with shared information and services.

12.11.2. CoastPredict Program

The University of Bologna (Italy) was selected for another thematic DCC which will focus on coastal resilience in a changing climate. The same University is also leading the CoastPredict Programme that was endorsed as a Decade Programme of Ocean Science in June 2021.

CoastPredict is one of the 3 Programmes co-designed with GOOS, and it has the purpose of revolutionising the global coastal ocean observing and forecasting sector ([16]). The high-level objectives of CoastPredict are:

1. A predicted global coastal ocean;
2. The upgrade to a fit for purpose oceanographic information infrastructure;
3. Co-design and implementation of an integrated coastal ocean observing and forecasting system adhering to best practices and standards, designed as a global framework, and implemented locally.

The Global Coastal Ocean is a concept central to the transformative science pursued by CoastPredict. CoastPredict will re-define the concept of the Global Coastal Ocean that was firstly described as follows by Robinson and Brink (2006; concept developed in volumes 10 to 14 of "The Sea" series): '*the coastal ocean – that area, extending inshore from the estuarine mouths to river catchments affected by salt waters and offshore from the surf zone to the continental shelf and slope where waters of continental origins meet open ocean currents.*'

According to this concept, all coastal ocean regions are an interface area where atmosphere, land, ice, hydrology, coastal ecosystems, open ocean, and humans interact on a multiplicity of space and time scales that need to be resolved with a proper observing and downscaling methodology, including the consideration of uncertainties.

The legacy of CoastPredict will be new science for the observing systems, and new methods for the development of reliable predictions extending as far as possible into the future to solve problems co-defined with stakeholders. Additionally, it will enhance the capacity to formulate R2O practices, a new set of coastal observing and modelling standards for all. This will go hand-in-hand with the organisation and upgrade of the basic global ocean information infrastructure for open

15. https://www.oceandecade.org/news/decade-collaborative-centres-to-provide-focused-regional-and-thematic-support-for-decade-actions/

16. https://www.coastpredict.org/

and free access to coastal information using standards and best practices.

CoastPredict will capitalise on three previous major international initiatives:

1. GOOS Coastal observation panels (i.e. COOP and succeeding PICO). COOP started in 2000 to define a strategy for integrated observing and forecasting in the coastal areas. One of the main outcomes was the recommendation that a global network of observations, data communications, data management, and data analysis/forecasting should be secured providing economies of scale. Another important COOP/PICO outcome was the initial definition of common variables to be monitored and forecasted in the coastal areas. However, PICO's work did not continue because the international ocean observing network was not adequately organised and technology was not yet ready for data collection on biogeochemistry, biodiversity, and other marine environmental variables. Furthermore, the satellite observing system for coastal areas was still under development (except for coastal ocean colour).

2. OceanPredict and its COSS-TT. OceanPredict organised the global ocean observation uptake for the development of global and regional forecasting systems. In addition, OceanPredict/COSS-TT defined the international quality control standards for ocean analyses, reanalyses, and forecasts in the coastal ocean and shelf seas. COSS-TT promoted the use of OceanPredict large scale products for seamless integration of ocean to coastal forecasting, defined the state-of-the-art methodology for downscaling, data assimilation, array design in the coastal/shelf areas. COSS-TT focuses on advancing science in support of coastal forecasting and is one of the backbones of CoastPredict.

3. The JCOMM. From 2000 to 2019, JCOMM has coordinated ocean observing networks, in particular the GLOSS network for tide gauges and the HF radar network. Furthermore, it started to develop coastal services for wave and storm surges by meteorological offices in developing countries. Moreover, it has coordinated the development of marine environmental emergency services. However, such developments led by JCOMM were not fully integrated and connected with the growing oceanographic research communities of OceanPredict and COSS-TT. While the observing systems and the large-scale ocean forecasting systems are now coordinated in GOOS, the coastal downscaling and forecasting research developments are not currently connected to coastal services.

All these activities have been partly disconnected and have not produced a global international network bringing together the fragmented scientific communities for advancing the research on the global coastal ocean. New advances that make a science-focused programme such as CoastPredict urgent and achievable are: a) operational oceanography is now implemented from the global to the regional scales, making available open and free data for coastal downscaling; and b) major technology advancements have taken place in observing, from satellites to in-situ robotics to the use of Artificial Intelligence, which makes the monitoring of the coastal ocean practical and feasible. CoastPredict will capitalise on this game-changing operational oceanography framework and extend to coastal predictive capabilities, including the land-water cycle (rivers, underground and transitional waters) and, for the first time, integrating the coastal ocean, through estuaries and rivers, with the "urban ocean" (waters within and around coastal cities).

CoastPredict will be implemented through several projects focusing on 6 areas:

- **Focus Area 1** - Integrated Observing and Modelling for short term coastal forecasting and early warnings. This area will contribute to Ocean Decade Challenge 6 'Increase community resilience to ocean hazards': enhance multi-hazard early warning services for all geophysical, ecological, biological, weather, climate and anthropogenic related ocean and coastal hazards, and mainstream community preparedness and resilience ([17]).

- **Focus Area 2** - Future Coastal Ocean climates: Earth system observing and modelling. This area will contribute to Challenge 5 'Unlock ocean-based solutions to climate change': enhance understanding of the ocean-climate nexus and generate knowledge and solutions to mitigate, adapt and build resilience to the effects of climate change across all geographies and at all scales, and to improve services including predictions for the ocean, climate and weather.

- **Focus Area 3** - Solutions for Integrated Coastal Management. This area will contribute to Challenge 8 'Create a digital representation of the Ocean': through multi-stakeholder collaboration, develop a comprehensive digital representation of the ocean, including a dynamic ocean map, which provides free and open access for exploring, discovering, and visualising past, current, and future ocean conditions in a manner relevant to diverse stakeholders.

- **Focus area 4** - Coastal Ocean and Human Health. This area does not match with a specific Decade Challenge but it is cross-cutting to all the 10 Challenges.

17. https://www.oceandecade.org/challenges/

- **Focus Area 5** - Coastal Information integrated in the open and free exchange international infrastructure. This area will contribute to Challenge 7 'Expand the Global Ocean Observing System': ensure a sustainable ocean observing system across all ocean basins that delivers accessible, timely, and actionable data and information to all users.

- **Focus Area 6** - Equitable coastal ocean capacity. This area will contribute to Challenge 9 'Skills, knowledge and technology for all': ensure comprehensive capacity development and equitable access to data, information, knowledge and technology across all aspects of ocean science and for all stakeholders.

12.11.3. ForeSea Program

ForeSea is hosted by OceanPredict ([18]), a science programme for the coordination and improvement of global and regional ocean analysis and forecasting systems. ForeSea aims to build the next generation of ocean predictions pursuing a strong co-ordination of the scientific community and institutes at the international level ([19]). Its main goals are:

- To improve the science, efficiency, use, and impact of ocean prediction systems;

- To build a seamless ocean information value chain, from observations to end users, able to support the economy and society.

ForeSea [20] focuses on 2 main themes:

1. Catalysing transformative ocean prediction science solutions for sustainable development, connecting people and ocean prediction;
2. Increasing impact and relevance: improving science and science capacity for the ocean we want.

Such themes are developed through a number of items. In theme 1 they span from integrating forecasts of ocean hazards with socioeconomic forecasts for supporting policy and management to maximisation of the impact and value of observations, from capacity building and training to contribution to a digital ocean. In theme 2, they cover from usage of advanced ocean prediction technologies in weather and climate predictions to coupled systems (in partnership with CoastPredict), from usage of Earth system models (ESM) to development of limited ESM areas with coupled components to improve model predictability (in collaboration with CoastPredict).

Expected outcomes[21] are considerable as ForeSea should contribute to:

- An operational oceanography information value-chain where verified/certified information and knowledge are exchanged freely enabling all operational oceanographic components, integrated from the open ocean to the coastal areas, to effectively synergize;
- A continuously optimised ocean observing system integrated from the open ocean to the coastal areas that provides maximum information benefit with manageable cost;An ocean information delivery system that provides the right information at the right time for facilitating marine decisions in support of human safety and environmental safety, and an efficient and sustainable blue economy;
- Improved extended range forecasting capabilities for ocean prediction systems;
- Better assessment and prediction of the ocean state (including reliable uncertainty estimates) and ocean impact on forecasts of other earth system components (e.g. atmosphere, ice, waves, marine ecosystems, estuaries, etc.);
- An informed ocean literate society and global economy;
- Coordinated capacity building across all elements of the operational oceanography value chain to sustain production and delivery of ocean prediction;
- Demonstrated impact and value of predictions for coastal communities;
- Effective use of ocean prediction technologies for weather and climate predictions.

To facilitate realisation of the expected outcomes, ForeSea established through OceanPredict connections with GOOS, WMO, IOC, JCOMM, Argo, GHRSST, GEO, and GEO BluePlanet.

18. https://oceanpredict.org/
19. https://oceanpredict.org/foresea/
20. https://oceanpredict.org/foresea/foresea-planned-activities/
21. https://oceanpredict.org/foresea/foresea-expected-outcomes/

12.12. References

Anderson, J., Hoar, T. J., Raeder, K., Liu, H., Collins, N., Torn, R., et al. (2009). The data assimilation research test bed: a community facility. *Bulletin of the American Meteorological Society*, 90, 1283-1296, https://doi.org/10.1175/2009BAMS2618.1

Barton, N., Metzger, E.J., Reynolds, C.A., Ruston, B., Rowley, C., Smedstad, O.M., Ridout, J.A., Wallcraft, A., Frolov, S., Hogan, P. and Janiga, M.A. (2021). The Navy's Earth System Prediction Capability: A new global coupled atmosphere-ocean-sea ice prediction system designed for daily to subseasonal forecasting. *Earth and Space Science*, 8(4), e2020EA001199, https://doi.org/10.1029/2020EA001199

Beisiegel, N., Castro, C.E., and Behrens, J. (2021). Metrics for Performance Quantification of Adaptive Mesh Refinement. *Journal of Scientific Computing*, 87(1), 1-24, https://doi.org/10.1007/s10915-021-01423-0

Bishop, C.H. (2016). The GIGG-EnKF: ensemble Kalman filtering for highly skewed non-negative uncertainty distributions. *Quarterly Journal of the Royal Meteorological Society*, 142(696), 1395-1412, https://doi.org/10.1002/qj.2742

Bonavita, M., and Laloyaux, P. (2020). Machine learning for model error inference and correction. *Journal of Advances in Modeling Earth Systems*, 12(12), e2020MS002232, https://doi.org/10.1029/2020MS002232

Bonavita, M., Arcucci, R., Carrassi, A., Dueben, P., Geer, A. J., Le Saux, B., Longépé, N., Mathieu, P., and Raynaud, L. (2021). Machine Learning for Earth System Observation and Prediction. *Bulletin of the American Meteorological Society*, 102(4), E710-E716, https://doi.org/10.1175/BAMS-D-20-0307.1

Brajard, J., Carrassi, A., Bocquet, M. and Bertino, L. (2021). Combining data assimilation and machine learning to infer unresolved scale parametrization. *Philosophical Transactions of the Royal Society A*, 379(2194), https://doi.org/10.1098/rsta.2020.0086

Brassington, G.B., Martin, M.J., Tolman, H.L., Akella, S., Balmeseda, M., Chambers, C.R.S., Chassignet, E., Cummings, J.A., Drillet, Y., Jansen, P.A.E.M. and Laloyaux, P. (2015). Progress and challenges in short-to medium-range coupled prediction. *Journal of Operational Oceanography*, 8(sup2), s239-s258, https://doi.org/10.1080/1755876X.2015.1049875

Brunton, S. L., Noack, B. R., and Koumoutsakos, P. (2020). Machine learning for fluid mechanics. *Annual Review of Fluid Mechanics*, 52(1), 477-508 https://doi.org/10.1146/annurev-fluid-010719-060214

Buizza, R. (2021). Probabilistic view of numerical weather prediction and ensemble prediction. In "Uncertainties in Numerical Weather Prediction", Editors: H. Ólafsson and J.-W. Bao, Elsevier, https://doi.org/10.1016/C2017-0-03301-3

Carleo, G., Cirac, I., Cranmer, K., Daudet, L., Schuld, M., Tishby, N., Vogt-Maranto, L., and Zdeborová, L. (2019). Machine learning and the physical sciences. *Reviews of Modern Physics*, 91(4), 045002, https://doi.org/10.1103/RevModPhys.91.045002

Capet, A., Fernández, V., She, J., Dabrowski, T., Umgiesser, G., Staneva, J., Mészáros, L., Campuzano, F., Ursella, L., Nolan, G., El Serafy, G. (2020). Operational Modeling Capacity in European Seas - An EuroGOOS Perspective and Recommendations for Improvement. *Frontiers in Marine Science*, 7,129, https://doi.org/10.3389/fmars.2020.00129

Castelão, G. P. (2021). A machine learning approach to quality control oceanographic data. *Computers & Geosciences*, 155, 104803, https://doi.org/10.1016/j.cageo.2021.104803

Chassignet, E.P., and Xu, X. (2021). On the Importance of High-Resolution in Large-Scale Ocean Models. *Advances in Atmospheric Sciences*, 38, 1621-1634, https://doi.org/10.1007/s00376-021-0385-7

Cranmer, K., Brehmer, J., and Louppe, G. (2020). The frontier of simulation-based inference. *Proceedings of the National Academy of Sciences*, 117(48), 30055-30062 https://doi.org/10.1073/pnas.1912789117

Ebert, E.E. (2009). Neighborhood verification - a strategy for rewarding close forecasts. Weather and Forecasting 24(6), 1498-1510, https://doi.org/10.1175/2009WAF2222251.1

Fablet, R., Chapron, B., Drumetz, L., Mémin, E., Pannekoucke, O., and Rousseau, F. (2021). Learning variational data assimilation models and solvers. *Journal of Advances in Modeling Earth Systems*, 13(10), e2021MS002572, https://doi.org/10.1029/2021MS002572

Fox-Kemper, B., Adcroft, A., Böning, C.W., Chassignet, E.P., Curchitser, E., Danabasoglu, G., Eden, C., England, M.H., Gerdes, R., Greatbatch, R.J., Griffies, S.M., Hallberg, R.W., Hanert, E., Heimbach, P., Hewitt, E.T., Hill, C.N., Komuro, Y., Legg, S., Le Sommer, J., Masina, S., Marsland, S.J., Penny, S.G., Qiao, F., Ringler, T.D., Treguier, A.M., Tsujino, H., Uotila, P., Yeager, S.G. (2019). Challenges and Prospects in Ocean Circulation Models. *Frontiers in Marine Science*, 6, https://doi.org/10.3389/fmars.2019.00065

Frolov, S., Reynolds, C.A., Alexander, M., Flatau, M., Barton, N.P., Hogan, P. and Rowley, C. (2021). Coupled Ocean-Atmosphere Covariances in Global Ensemble Simulations: Impact of an Eddy-Resolving Ocean. *Monthly Weather Review*, 149(5), 1193-1209, https://doi.org/10.1175/MWR-D-20-0352.1

Fujii, Y., Ishibashi, T., Yasuda, T., Takaya, Y., Kobayashi, C. and Ishikawa, I. (2021). Improvements in tropical precipitation and sea surface air temperature fields in a coupled atmosphere–ocean data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 147(735), 1317-1343, https://doi.org/10.1002/qj.3973

Gao, Y., Tang, Y., Song, X. and Shen, Z. (2021). Parameter Estimation Based on a Local Ensemble Transform Kalman Filter Applied to El Niño-Southern Oscillation Ensemble Prediction. *Remote Sensing*, 13(19), 3923, https://doi.org/10.3390/rs13193923

Hatfield, S., Chantry, M., Dueben, P., Lopez, P., Geer, A., and Palmer, T. (2021). Building Tangent-Linear and Adjoint Models for Data Assimilation With Neural Networks. *Journal of Advances in Modeling Earth Systems*, 13(9), https://doi.org/10.1029/2021MS002521

Hawcroft, M., Lavender, S., Copsey, D., Milton, S., Rodríguez, J., Tennant, W., Webster, S. and Cowan, T. (2021). The benefits of ensemble prediction for forecasting an extreme event: The Queensland Floods of February 2019. *Monthly Weather Review*, 149(7), 2391-2408, https://doi.org/10.1175/MWR-D-20-0330.1

Herzfeld, M., Engwirda, D., and Rizwi, F. (2020). A coastal unstructured model using Voronoi meshes and C-grid staggering. *Ocean Modelling*, 148, 101599, https://doi.org/10.1016/j.ocemod.2020.101599

Hewitt, C. D., Garrett, N., Newton, P. (2017). Climateurope - Coordinating and supporting Europe's knowledge base to enable better management of climate-related risks. *Climate Services*, 6, 77-79, https://doi.org/10.1016/j.cliser.2017.07.004

International Altimetry Team (2021). Altimetry for the future: Building on 25 years of progress. *Advances in Space Research*, 68, 319-363, https://doi.org/10.1016/j.asr.2021.01.022

Jacobs, G., D'Addezio, J.M., Ngodock, H. and Souopgui, I. (2021). Observation and model resolution implications to ocean prediction. *Ocean Modelling*, 159, 101760, https://doi.org/10.1016/j.ocemod.2021.101760

Kasim, M. F., Watson-Parris, D., Deaconu, L., Oliver, S., Hatfield, P., Froula, D. H., Gregori, G., Jarvis, M., Khatiwala, S., Korenaga, J., Topp-Mugglestone, J., Viezzer, E., and Vinko, S. M. (2021). Building high accuracy emulators for scientific simulations with deep neural architecture search. *Machine Learning: Science and Technology*, 3(1), 015013, https://doi.org/10.1088/2632-2153/ac3ffa

Kiss, A.E., Hogg, A.M., Hannah, N., Boeira Dias, F., Brassington, G.B., Chamberlain, M.A., Chapman, C., Dobrohotoff, P., Domingues, C.M., Duran, E.R. and England, M.H. (2020). ACCESS-OM2 v1.0: A global ocean-sea ice model at three resolutions. Geosci. Model Dev., 13, 401–442, 2020, https://doi.org/10.5194/gmd-13-401-2020

Kitsios, V., Sandery, P., O'Kane, T.J. and Fiedler, R. (2021). Ensemble Kalman filter parameter estimation of ocean optical properties for reduced biases in a coupled general circulation model. *Journal of Advances in Modeling Earth Systems*, 13(2), https://doi.org/10.1029/2020MS002252

Kochkov, D., Smith, J. A., Alieva, A., Wang, Q., Brenner, M. P., and Hoyer, S. (2021). Machine learning–accelerated computational fluid dynamics. *Proceedings of the National Academy of Sciences*, 118(21), e2101784118, https://doi.org/10.1073/pnas.2101784118

Komaromi, W.A., Reinecke, P.A., Doyle, J.D., and Moskaitis, J.R. (2021). The Naval Research Laboratory's Coupled Ocean–Atmosphere Mesoscale Prediction System-Tropical Cyclone Ensemble (COAMPS-TC Ensemble). *Weather and Forecasting*, 36(2), 499-517, https://doi.org/10.1175/WAF-D-20-0038.1

Kotsuki, S., and Bishop, C.H. (2022). Implementing Hybrid Background Error Covariance into the LETKF with Attenuation-based Localization: Experiments with a Simplified AGCM. *Monthly Weather Review*, 150(1), 283-302, https://doi.org/10.1175/MWR-D-21-0174.1

Le Sommer, J., Chassignet, E.P. Wallcraft, A.J. (2018). Ocean circulation modeling for operational oceanography: Current status and future challenges. In "New Frontiers in Operational Oceanography", E. Chassignet, A. Pascual, J. Tintoré, and J. Verron, Eds., GODAE OceanView, 289-306, https://doi.org/10.17125/gov2018.ch12

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-Munoyerro, M., Delamarche, A., Dibarboure, G., Dinessen, F., Drevillon, M., Drillet, Y., Faugere, Y., Fernandez, V., Fleming, A., Garcia-Hermosa M.I., Sotillo, M.G., Garric, G., Gasparin, F., Giordan, C., Gehlen, M., Grégoire, M.L., Guinehut, S., Hamon, M., Harris, C., Hernandez, F., Hinkler, J.B., Hoyer, J., Karvonen, J., Kay, S., King, 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., Perez Gomez, B., Petit de la Villeon, L., Pinardi, N., Pisano, A., Pouliquen, S., Reid, R., Remy, E., Santoleri, R., Siddorn, J., She, J., Staneva, J., Stoffelen, A., Tonani, M., Vandenbulcke, L., von Schuckmann, K., Volpe, G., Wettre, C., Zacharioudaki, A. (2019) From Observation to Information and Users: The Copernicus Marine Service Perspective. *Frontiers in Marine Science*, 6, 234, https://doi.org/10.3389/fmars.2019.00234

Liu, T., Zhuang, Y., Tian, M., Pan, J., Zeng, T., Guo, Y., Yang, M. (2019). Parallel Implementation and Optimization of Regional Ocean Modeling System (ROMS) Based on Sunway SW26010 Many-core Processor. *IEEE Access*, 7, 146170-146182, doi:10.1109/ACCESS.2019.2944922

Lorenc, A., and Jardak, M. (2018). A comparison of hybrid variational data assimilation methods for global NWP. *Quarterly Journal of the Royal Meteorological Society*, 144(717), 2748-2760, https://doi.org/10.1002/qj.3401

Malmgren-Hansen, D. (2021). Deep learning for high-dimensional parameter retrieval. In: "Deep Learning for the Earth Sciences", G. Camps-Valls, D. Tuia, X. X. Zhu, and M. Reichstein Eds., Wiley, https://doi.org/10.1002/9781119646181.ch16

Martín Míguez, B., Novellino, A., Vinci, M., Claus, S., Calewaert, J.-B., Vallius, H. et al. (2019). The European Marine Observation and Data Network (EMODnet): Visions and Roles of the Gateway to Marine Data in Europe. Frontiers in Marine Science, 6, 313, https://doi.org/10.3389/fmars.2019.00313

Maulik, R., Rao, V., Wang, J., Mengaldo, G., Constantinescu, E., Lusch, B., Balaprakash, P., Foster, I. and Kotamarthi, R. (2021). Efficient high-dimensional variational data assimilation with machine-learned reduced-order models. Geoscientific Model Development, https://doi.org/10.5194/gmd-2021-415

Maze, G., Mercier, H., Fablet, R., Tandeo, P., Lopez Radcenco, M., Lenca, P., Feucher, C., and Le Goff, C. (2017). Coherent heat patterns revealed by unsupervised classification of Argo temperature profiles in the North Atlantic Ocean. *Progress in Oceanography*, 151, 275-292, https://doi.org/10.1016/j.pocean.2016.12.008

Minamide, M., and Posselt, D.J. (2022). Using Ensemble Data Assimilation to Explore the Environmental Controls on the Initiation and Predictability of Moist Convection. *Journal of the Atmospheric Sciences*, 79(4), 1151-1169, https://doi.org/10.1175/JAS-D-21-0140.1

Mittal, S., Vetter, J.S. (2015). A Survey of CPU-GPU Heterogeneous Computing Techniques. *ACM Computing Surveys*, 47(4), 1-35, https://doi.org/10.1145/2788396

Nerger, L., Tang, Q., and Mu, L. (2020). Efficient ensemble data assimilation for coupled models with the Parallel Data Assimilation Framework: example of AWI-CM (AWI-CM-PDAF 1.0). *Geoscientific Model Development*, 13, 4305-4321, https://doi.org/10.5194/gmd-13-4305-2020

Nonnenmacher, M., and Greenberg, D. S. (2021). Deep emulators for differentiation, forecasting, and parametrization in Earth science simulators. *Journal of Advances in Modeling Earth Systems*, 13, e2021MS002554, https://doi.org/10.1029/2021MS002554

O'Kane, T.J., Sandery, P.A., Kitsios, V., Sakov, P., Chamberlain, M.A., Squire, D.T., Collier, M.A., Chapman, C.C., Fiedler, R., Harries, D. and Moore, T.S. (2021). CAFE60v1: A 60-year large ensemble climate reanalysis. Part II: Evaluation. *Journal of Climate*, 34(13), 5171-5194, https://doi.org/10.1175/JCLI-D-20-0518.1

O'Kane, T.J., Sandery, P.A., Monselesan, D.P., Sakov, P., Chamberlain, M.A., Matear, R.J., Collier, M.A., Squire, D.T. and Stevens, L. (2019). Coupled data assimilation and ensemble initialisation with application to multi-year ENSO prediction. *Journal of Climate*, 32(4), 997-1024, https://doi.org/10.1175/JCLI-D-18-0189.1

Palmer, T. N., Doblas-Reyes, F. J., Weisheimer, A., Rodwell, M. J. (2008). Toward Seamless Prediction: Calibration of Climate Change Projections Using Seasonal Forecasts. *Bulletin of the American Meteorological Society,* 89(4), 459-470, https://doi.org/10.1175/BAMS-89-4-459

Peng, G., Downs, R.R., Lacagnina, C., Ramapriyan, H., Ivánová, I., Moroni, D., Wei, Y., Larnicol, G., Wyborn, L., Goldberg, M., Schulz, J., Bastrakova, I., Ganske, A., Bastin, L., Khalsa, S.J.S., Wu, M., Shie, C.-L., Ritchey, N., Jones, D., Habermann, T., Lief, C., Maggio, I., Albani, M., Stall, S., Zhou, L., Drévillon, M., Champion, S., Hou, C.S., Doblas-Reyes, F., Lehnert, K., Robinson, E. and Bugbee, K., (2021a). Call to Action for Global Access to and Harmonization of Quality Information of Individual Earth Science Datasets. *Data Science Journal*, 20(1), 19, http://doi.org/10.5334/dsj-2021-019

Peng, G., Lacagnina, C., Ivánová, I., Downs, R.R., Ramapriyan, H., Ganske, A., Jones, D. et al. (2021b). International Community Guidelines for Sharing and Reusing Quality Information of Individual Earth Science Datasets. AGU Fall Meeting, 1-17 December 2020, https://doi.org/10.1002/essoar.10508481.1

Persello, C., Wegner, J. D., Hänsch, R., Tuia, D., Ghamisi, P., Koeva, M., and Camps-Valls, G. (2022). Deep learning and earth observation to support the sustainable development goals. *IEEE Geoscience and Remote Sensing Magazine*, 2-30, https://doi.org/10.48550/arXiv.2112.11367

Posselt, D.J., Bishop, C.H. (2018). Nonlinear Data Assimilation for Clouds and Precipitation using a Gamma-Inverse Gamma Ensemble Filter. *Quarterly Journal of the Royal Meteorological Society*, 144(716), 2331-2349, https://doi.org/10.1002/qj.3374

Quinn, C., O'Kane, T.J., Kitsios, V. (2020). Application of a local attractor dimension to reduced space strongly coupled data assimilation for chaotic multiscale systems. *Nonlinear Processes in Geophysics*, 27 (1), 51-74, https://doi.org/10.5194/npg-27-51-2020

Robinson A. R., and K. Brink (Eds.). 2006. The Sea. Vols. 10 to 14. Harvard University Press.

Roemmich, D., Alford, M.J., Hervé, C., Johnson, K., King, B., Moum, J., Oke, P., Owens, W.B., Pouliquen, S., Purkey, S., Scanderbeg, M., Suga, T., Wijffels, S., Zilberman, N., Bakker, D., Baringer, M., Belbeoch, M., Bittig, H.C., Boss, E., Calil, P., Carse, F., Carval, T., Chai, F., Conchubhair, D.Ó., d'Ortenzio, F., Dall'Olmo, G., Desbruyeres, D., Fennel, K., Fer, I., Ferrari, R., Forget, G., Freeland, H., Fujiki, T., Gehlen, M., Greenan, B., Hallberg, R., Hibiya, T., Hosoda, S., Jayne, S., Jochum, M., Johnson, G.C., Kang, K., Kolodziejczyk, N., Körtzinger, A., Le Traon, P.-Y., Lenn, Y.-D., Maze, G., Mork, K.A., Morris, T., Nagai T., Nash, J., Garabato, A.N., Olsen, A., Pattabhi, R.R., Prakash, S., Riser, S., Schmechtig, C., Schmid, C., Shroyer, E., Sterl, A., Sutton, P., Talley, L., Tanhua, T., Thierry, V., Thomalla, S., Toole, J., Troisi, A., Trull, T.W., Turton, J., Velez-Belchi, P. J., Walczowski, W., Wang, H., Wanninkhof, R., Waterhouse, A.F., Waterman, S., Watson, A., Wilson, C., Wong, A.P.S., Xu, J., Yasuda, I.(2019). On the Future of Argo: A Global, Full-Depth, Multi-Disciplinary Array. *Frontiers in Marine Science*, 6, https://doi.org/10.3389/fmars.2019.00439

Sakov, P. (2014). EnKF-C User Guide, https://doi.org/10.48550/arXiv.1410.1233

Sakov, P., Haussaire, J.-M., Bocquet, M. (2017). An iterative ensemble Kalman filter in presence of additive model error. *Quarterly Journal of the Royal Meteorological Society*, 144(713), https://doi.org/10.48550/arXiv.1711.06110

Sandery, P., Brassington, G., Colberg, F., Sakov, P., Herzfeld, M., Maes, C., Tuteja, N. (2019). An ocean reanalysis of the western Coral Sea and Great Barrier Reef. *Ocean Modelling*, 144, 101495, http://dx.doi.org/10.1016/j.ocemod.2019.101495

Sandery, P., O'Kane, T., Kitsios, V., and Sakov, P. (2020). Climate model state estimation using variants of EnKF coupled data assimilation. *Monthly Weather Review*, 148(6), 2411-2431, https://doi.org/10.1175/MWR-D-18-0443.1

She, J, Muñiz Piniella, Á, Benedetti-Cecchi, L, Boehme, L, Boero, F, Christensen, A, et al. (2019). An integrated approach to coastal and biological observations. *Frontiers in Marine Science*, 6, 314, https://doi.org/10.3389/fmars.2019.00314

She, J., Allen, I., Buch, E., Crise, A., Johannessen, J.A., Le Traon P.-Y. et al. (2016). Developing European operational oceanography for Blue Growth, climate change adaptation and mitigation, and ecosystem-based management. Ocean Science, 12, 953-976, https://doi.org/10.5194/os-12-953-2016

She, J., Bethers, U., Cardin, V., Christensen, K.H., Dabrowski, T., et al. (2021). Develop EuroGOOS marine climate service with a seamless earth system approach. 9th EuroGOOS International conference, Shom; Ifremer; EuroGOOS AISBL, May 2021, Brest (Virtual), France, 554-561.

Shriver, J. F., Arbic, B. K., Richman, J. G., Ray, R. D., Metzger, E. J., Wallcraft, A. J., Timko, P. G. (2012), An evaluation of the barotropic and internal tides in a high-resolution global ocean circulation model. Journal of Geophysical Research: Oceans, 117(C10), https://doi.org/10.1029/2012JC008170

Sotillo, M.G., Garcia-Hermosa, I., Drévillon, M., Régnier, C., Szczypta, C., Hernandez, F., Melet, A., Le Traon, P-Y. (2021). Communicating CMEMS Product Quality: evolution & achievements along Copernicus-1 (2015-2021). Included in "Special Issue: The Copernicus Marine Service from 2015 to 2021: six years of achievements", by LeTraon et al., *Mercator Océan Journal #57*, https://doi.org/10.48670/moi-cafr-n813

Sun, Y., Bao, W., Valk, K., Brauer, C. C., Sumihar, J., and Weerts, A. H. (2020). Improving forecast skill of lowland hydrological models using ensemble Kalman filter and unscented Kalman filter. *Water Resources Research*, 56, e2020WR027468, https://doi.org/10.1029/2020WR027468

van de Meent, J.-W., Paige, B., Yang, H., AND Wood, F. (2021). An introduction to probabilistic programming, https://doi.org/10.48550/arXiv.1809.10756

van Leeuwen, S., Tett, P., Mills, D., van der Molen, J. (2015). Stratified and non stratified areas in the North Sea: Long-term variability and biological and policy implications. *Journal of Geophysical Research: Oceans*, 120(7), 4670-4686, https://doi.org/10.1002/2014JC010485

Vinuesa, R., and Brunton, S. L. (2021). The potential of machine learning to enhance computational fluid dynamics, https://doi.org/10.48550/arXiv.2110.02085

Weyn, J.A., Durran, D.R., Caruana, R., Cresswell-Clay, N. (2021). Sub-Seasonal Forecasting With a Large Ensemble of Deep-Learning Weather Prediction Models. J*ournal of Advances in Modeling Earth Systems,* 13(7), e2021MS002502, https://doi.org/10.1029/2021MS002502

WMO (2015). Seamless prediction of the Earth system: from minutes to months. WMO-No. 1156, ISBN 978-92-63-11156-2.

Xu, S., Huang, X., Oey, L.-Y., Xu, F., Fu, H., Zhang, Y., Yang, G. (2015). POM.gpu-v1.0: a GPU-based Princeton Ocean Model. *Geoscientific Model Development*, 8, 2815-2827, https://doi.org/10.5194/gmd-8-2815-2015

Zanna, L., and Bolton, T. (2021). Deep learning of unresolved turbulent ocean processes in climate models. In: "Deep Learning for the Earth Sciences", G. Camps-Valls, D. Tuia, X. X. Zhu, and M. Reichstein (Eds.), Wiley https://doi.org/10.1002/9781119646181.ch20

Zhang, L., Delworth, T.L., Jia, L. (2017). Diagnosis of Decadal Predictability of Southern Ocean Sea Surface Temperature in the GFDL CM2.1 Model. *Journal of Climate*, 30(16), 6309-6328, https://doi.org/10.1175/JCLI-D-16-0537.1

Editors and Authors

Editors: Enrique Alvarez Fanjul[1], Stefania Ciliberti[2], Pierre Bahurel[3]

Editorial support: Romane Zufic[3]

Chapter 1	Author: Enrique Alvarez Fanjul[1]
Chapter 2	Authors: Pierre Bahurel[3] and Enrique Alvarez Fanjul[1]
Chapter 3	Coordinator: Enrique Alvarez Fanjul[1] Authors: Marcos Garcia Sotillo[4] and John Wilkin[5]
Chapter 4	Coordinator: Avichal Mehra[6] Authors: Roland Aznar[7], Stefania Ciliberti[2], Laurence Crosnier[3], Marie Drevillon[3], Yann Drillet[3], Begoña Pérez Gómez[8], Antonio Reppucci[3], Joseph Sudheer[9], Marcos Garcia Sotillo[4], Marina Tonani[1], P. N. Vinaychandranand[10], and Aihong Zhong[11]
Chapter 5	Coordinator: Stefania Ciliberti[2] Authors: Nadia Ayoub[12], Jérôme Chanut[3], Mauro Cirano[13], Anne Delamarche[3], Pierre De Mey-Frémaux[12], Marie Drevillon[3], Yann Drillet[3], Helene Hewitt[14], Simona Masina[15], Clemente Tanajura[13], Vassilios Vervatis[16], and Liying Wan[17]
Chapter 6	Coordinator: Laurent Bertino[18] Authors: Ed Blockley[14], Johnny A. Johannessen[18], and Einar Örn Ólason[18]
Chapter 7	Coordinator: Fujiang Yu[17] Authors: David Byrne[19], Jianxi Dong[17], Shichao Liu[17], and Begoña Pérez Gómez[8]
Chapter 8	Coordinators: Gabriel Diaz-Hernandez[20], Lotfi Aouf[21] Authors: Alexander Babanin[22], Jean Bidlot[23], Andy Saulter[14], and Joanna Staneva[24]
Chapter 9	Coordinator: Elodie Gutknecht[3] Authors: Laurent Bertino[18], Pierre Brasseur[25], Stefano Ciavatta[26], Gianpiero Cossarini[27], Katja Fennel[28], David Ford[14], Marilaure Gregoire[29], Diane Lavoie[30], and Patrick Lehodey[31]
Chapter 10	Coordinator: John Siddorn[19] Authors: Øyvind Breivik[32,33], Natacha B. Bernier[34], Kai H. Christensen[32,35], Stephen G. Penny[36,37], and Keguang Wang[32]
Chapter 11	Coordinator: Giovanni Coppini[2] Authors: Enrique Alvarez Fanjul[1], José Chambel Leitão[38], Laurence Crosnier[3], Pierre Daniel[21], Tomasz Dabrowski[39], Svitlana Liubartseva[2], Gianandrea Mannarini[2], and Glen Nolan[39]
Chapter 12	Coordinator: Fraser Davidson[40] Authors: Enrique Alvarez Fanjul[1], Alain Arnaud[3], Stefania Ciliberti[2], Marie Drevillon[3], Ronan Fablet[41], Yosuke Fujii[42], Isabel Garcia-Hermosa[3], Marcos Garcia Sotillo[4], Stéphanie Guinehut[3], Emma Heslop[43], Villy Kourafalou[44], Julien Le Sommer[45], Matt Martin[14], Andrew M. Moore[46], Nadia Pinardi[47], Elizabeth Remy[3], Paul Sandery[48], Jun She[49], and Joaquin Tintorè[50]

1) Mercator Ocean International, France - previously at Puertos del Estado, Spain
2) Ocean Predictions and Applications Division, Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici, Lecce, Italy
3) Mercator Ocean International, France
4) Nologin Ocean Weather Systems, Spain - previously at Puertos del Estado, Spain
5) Rutgers University, USA
6) NWS/NOAA, USA
7) Nologin Ocean Weather Systems, Spain
8) Puertos del Estado, Spain
9) Indian National Centre for Ocean Information Services, India
10) Indian Institute of Science, India
11) Bureau of Meteorology, Canada
12) LEGOS, Université de Toulouse, CNRS, CNES, and IRD, France
13) Federal University of Rio de Janeiro, Brazil
14) Met Office, UK
15) Ocean modelling and Data Assimilation Division, Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici, Bologna, Italy
16) University of Athens, Department of Physics, Greece
17) National Marine Environmental Forecasting Center, China
18) Nansen Environmental and Remote Sensing Center, Norway
19) National Oceanography Centre, UK
20) IHCantabria - Instituto de Hidráulica Ambiental de la Universidad de Cantabria, Spain
21) MeteoFrance, France
22) University of Melbourne, Australia
23) ECMWF, UK
24) HEREON, Germany
25) Institute for Geosciences and Environmental research, France
26) Plymouth Marine Laboratory, UK
27) National Institute of Oceanography and Applied Geophysics, Italy
28) Dalhousie University, Canada
29) Liege University, Belgium
30) Fisheries and Oceans Canada, Canada
31) Collecte Localisation Satellites - CLS, France
32) Norwegian Meteorological Institute, Norway
33) University of Bergen, Norway
34) Environment and Climate Change, Canada
35) University of Oslo, Norway
36) NOAA Physical Sciences Laboratory (PSL), USA
37) Cooperative Institute for Research in Environmental Sciences (CIRES), University of Colorado, Boulder
38) Hidromod, Portugal
39) Marine Institute, Ireland
40) Dynamic Hydrographic Products with Fisheries and Oceans, Canada
41) IMT Atlantique, France
42) MRI/JMA, Japan
43) IOC/UNESCO, France
44) University of Miami, USA
45) CNRS, France
46) Ocean Sciences Department, Institute of Marine Sciences, USA
47) University of Bologna, Italy
48) CSIRO Australia's National Science Agency, Australia
49) Danish Meteorological Institute, Denmark
50) SOCIB, Spain

GOOS / ETOOFS Secretariat: Denis Chang Seng
Corresponding author: Enrique Alvarez Fanjul (ealvarez@mercator-ocean.fr)

ACNFS	Arctic Cap Nowcast/Forecast System
ADCIRC	ADvanced CIRCulation Model For Oceanic, Coastal And Estuarine Waters
ADCP	Acoustic doppler current profilers
AGRIF	Adaptive Grid Refinement in Fortran
AHI	Advanced Himawari Infrared
AI	Artificial Intelligence
AMR	Adaptive Mesh Refinement
AMSR-E	Advanced Microwave Scanning Radiometer for EOS
AMSR2	Advanced Microwave Scanning Radiometer 2
AO	Arctic Oscillation
AOGCM	Atmosphere-Ocean General Circulation Model
AUV	Autonomous Underwater Vehicle
AVHRR	Advanced Very High Resolution Radiometer
AWO	Atmosphere-Waves-Ocean
BAM	Bayesian Model Average
BAMHBI	Biogeochemical Model for Hypoxic and Benthic Influenced areas
BATS	Bermuda Atlantic Time-series Study
BBM	Brittle Bingham-Maxwell
BE	Boussinesq Equations
BFM	Biogeochemical Flux Model
BGC	Biogeochemistry
BSFS	Black Sea Forecasting System
BUFR	Binary Universal Form for the Representation
CCS	California Current System
CCSM	Community Climate System Model
CDOM	Coloured Dissolved Organic Matter
CERA	Coupled ECMWF ReAnalysis
CF	Climate and Forecast
CFD	Computational Fluid Dynamics
CFL	Courant-Friedrichs-Lewy
CFOSAT	Chinese-French Oceanography Satellite
CFSR	Climate Forecast System Reanalysis
CHL	Chlorophyll
CIMR	Copernicus Imaging Microwave Radiometer
CMA	Cuadro de Mando Ambiental
CMCC	Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici
CMIP	Coupled Model Intercomparison Project
CO-OPS	Center for Operational Oceanographic Products and Services

COARDS	Cooperative Ocean/Atmosphere Research Data Service
COAWST	Coupled Ocean-Atmosphere-Wave-Sediment Transport system
COE	Coefficient of Efficiency
COOP	Coastal Ocean Observing Panel
CORA	Coriolis Ocean Dataset for Reanalysis
COSMoS	Canadian Oil Spill Modelling Suite
COSS-TT	Coastal and Shelf Seas Task Team
CPU	Central processing unit
CROCO	Coastal and Regional Ocean Community Model
CRPS	Continuous Rank Probability Score
CRPS	Continuous Rank Probability Score
CTD	Conductivity-Temperature Depth
DA	Data assimilation
DART	Data Assimilation Research Testbed
DAS	Data assimilation scheme
DBCP	Data Buoy Cooperation Panel
DCCs	Decade Collaborative Centres
DCM	Deep Chlorophyll Maximum
DCSM	Dutch Continental Shelf Model
DCU	Decade Coordination Unit
DDE	Deep Differentiable Emulator
DEM	Digital Elevation Model
DEnKF	Deterministic EnKF
DEOS	Delft Institute for Earth-Oriented Space Research
DIAS	Data and Information Access Service
DIC	Dissolved inorganic carbon
DM	Delayed mode
DMS	Data Management System
DMSP	Defense Meteorological Satellite Program
DNS	Direct Numerical Simulation
DTO	Digital Twins for the Ocean
DUACS	Data Unification and Altimeter Combination System
EAP	Elastic-Anisotropic-Plastic
ECMWF	European Centre for Medium-Range Weather Forecasts
ECOSMO	ECOSystem MOdel
ECV	Essential Climate Variable
EFAS	European Flood Awareness System
EFI	Extreme Forecast Index
EKF	Extended Kalman Filter

EMODnet	European Marine Observation and Data Network
EnKF	Ensemble Kalman Filter
EnOI	Ensemble Optimal Interpolation
ENSO	El Niño-Southern Oscillation
ENSURF	ENsemble SURge Forecast
EORC	Earth Observation Research Centre
EOV	Essential Ocean Variable
EPS	Ensemble prediction systems
ERSEM	European Regional Seas Ecosystem Model
ESA	European Space Agency
ESM	Earth system model
ESMF	Earth System Modelling Framework
ESP	Earth System Prediction
ESTKF	Error-Subspace Transform Kalman Filter
ETOOFS	Expert Team on Operational Ocean Forecasting Systems
EU	European Union
EUMETSAT	European Operational Satellite Agency
EuroGOOS	European component of the Global Ocean Observing System
EVP	Elastic-Viscous-Plastic
FABM	Framework for Aquatic Biogeochemical Models
FAIR	Findability, accessibility, interoperability, and reusability
FAO	Food and Agriculture Organisation
FDM	Finite Difference Method
FEM	Finite Element Method
FESOM	Finite-Element/volumE Sea ice-Ocean Model
FESOM	Finite Element Solution
FNMOC	Fleet Numerical Meteorology and Oceanography Centre
FRAC	Full Resolution Area Coverage
FSS	Fraction of Skill Score
FVCOM	Finite Volume Community Ocean Model
FVCOM	Finite-Volume Coastal Ocean Model
FVM	Finite Volume Method
FYI	First-year Ice
GAC	Global Area Coverage
GBN	Global Buoy Network
GCOS	Global Climate Observing System
GDAC	Global Data Assembly Centre
GDP	Global Drifter Program
GDP	Gross Domestic Product

GEO	Group on Earth Observations
GFDL	Geophysical Fluid Dynamics Laboratory
GFLOPS	giga FLOPS
GFS	Global Forecasting System
GHFRN	Global High Frequency Radar Network
GHG	Greenhouse Gas
GHRSST	Group for High Resolution Sea Surface Temperature
GIS	Geographic Information System
GLO-PHY	Global Ocean Forecasting System
GLODAP	Global Ocean Data Analysis Project
GLOFAS	Global Flood Awareness System
GLOSS	Global Sea Level Observing System
GNOME	General NOAA Operational Modelling Environment
GNSS	Global Navigation Satellite System
GODAE	Global Ocean Data Assimilation Experiment
GOOS	Global Ocean Observing System
GPU	Graphics Processing Unit
GRDC	Global Runoff Data Centre
GSHHG	Global Self-consistent, Hierarchical, High-resolution Geography Database
GTS	Global Telecommunication System
HAB	Harmful Algal Bloom
HadOCC	Hadley Centre Ocean Carbon Cycle Model
HF	High Frequency
HPC	High Performance Computing
HTL	Higher Trophic Level
HYCOM	Hybrid Coordinate Ocean Model
I/O	Input/Output
IABP	International Arctic Buoy Program
IBI	Iberian-Biscay-Irish
IBM	Individual-Based Model
ICCAT	International Commission for the Conservation of Atlantic Tunas
ICESat	Ice, Cloud, and land Elevation Satellite
ICZM	Integrated Coastal Zone Management
IEO	Instituto Español de Oceanografía
IFS	Integrated Forecasting System
IHO	International Hydrographic Organization
IIEE	Integrated Ice Edge Error
IMO	International Maritime Organization
INCOIS	Indian National Centre for Ocean Information Services
INS	In-Situ

IOCCG	International Ocean Colour Coordinating Group
IOCCP	International Ocean Carbon Coordination Project
IOC	Intergovernmental Oceanographic Commission
IOOS	Integrated Ocean Observing System
IOP	Inherent Optical Property
IoT	Internet of Things
IPCC	Intergovernmental Panel on Climate Change
ITD	Ice Thickness Distribution
ITIC	International Tsunami Information Center
ITU	International Telecommunications Union
JAXA	Japan Aerospace Exploration Agency
JCOMM	Joint Technical Commission for Oceanography and Marine Meteorology
JEDI	Joint Effort for Data assimilation Integration
JMA	Japan Meteorological Agency
JPL	Jet Propulsion Laboratory
JPSS	Joint Polar Satellite System
KPI	Key performance indicators
LEO	Low Earth Orbit
LiDAR	Laser Imaging Detection and Ranging
LKF	Linear Kinematic Features
LOCEAN	Laboratoire d'Océanographie et du Climat: Expérimentation et Approches Numériques
MEAP-TT	Marine Ecosystem Analysis and Prediction Task Team
MedFS	Mediterranean Forecast System
MEDUSA	Model of Ecosystem Dynamics, nutrient Utilisation, Sequestration and Acidification
MEOP	Marine Mammals Exploring the Oceans Pole to Pole
MFC	Monitoring and Forecasting Centre
MFWAM	Météo-France WAve Model
MISST	Multi-sensor Improved Sea Surface Temperature
MITgcm	MIT general circulation model
MIZ	Marginal Ice Zone
MJO	Madden-Julian Oscillation
ML	Machine Learning
MLD	Mixed Layer Depth
MODIS	Moderate Resolution Imaging Spectroradiometer
MOI	Mercator Ocean International
MOM	Modular Ocean Model
MOTHY	Modèle Océanique de Transport d'HYdrocarbures
MPA	Marine Protected Area
MPAS	Model for Prediction Across Scales
MPQ	Model product quality
MSaaS	Modelling and Simulation as a Service
MSE	Mild-slope equation
MSP	Maritime Spatial Planning
MTCSWA	Multi-platform Tropical Cyclone Surface Winds Analysis
MY	Multi Year
MYI	Multiyear Ice
NAO	North Atlantic Oscillation
NAVOCEANO	US Naval Oceanographic Office
NcML	NetCDF Markup Language
NDBC	National Data Buoy Center
NEMO	Nucleus for European Modelling of the Ocean
NGO	Non-governmental organization
NIVA	Norwegian Institute for Water Research
NOAA	National Oceanic and Atmospheric Administration
NODC	National Oceanographic Data Centres
NORWECOM	Norwegian Ecological Model
NPP	Net Primary Production
NRT	Near-Real-Time
NSIDC DAAC	National Snow and Ice Data Center Distributed Active Archive Center
NSR	Northern Sea Route
NSWE	Non-linear Shallow Water Equations
NWP	Numerical weather prediction
NWS	North West Shelf
OBC	Open Boundary Condition
OC	Ocean Colour
OC	Ocean Colour
ODV	Ocean Data View
OGCM	Ocean general circulation model
OI	Optimal Interpolation
OMI	Ocean Monitoring Indicator
ONR	Office of Naval Research
OO	Operational Oceanography
OOFS	Operational Ocean Monitoring and Forecasting Systems
OOPC	Ocean Observations Physics and Climate
OOPS	Object-Oriented Prediction System
OpenFOAM	Open source Field Operation and Manipulation

OS-Eval	Observing System Evaluation
OSCAR	Oil Spill Contingency and Response
OSE	Observing System Experiment
OSI SAF	Ocean and Sea Ice Satellite Applications Facility
OSPO	Office of Satellite and Product Operations
OSR	Ocean State Report
OSSE	Observing System Simulation Experiment
PAR	Photosynthetically Available Radiation
PDAF	Parallel Data Assimilation Framework
PDF	Probability density function
PFT	Phytoplankton Functional Type
PICO	Panel for Integrated Coastal Observations
PISCES	Pelagic Interactions Scheme for Carbon and Ecosystem Studies
PMOST	Parallel Model Of Surge from Typhoon
PNA	Pacific-North American Pattern
PO.DAAC	Physical Oceanography Distributed Active Archive Centre
POC	Particulate Organic Carbon
POM	Princeton Ocean Model
PQ	Product Quality
PSMSL	Permanent Service for Mean Sea Level
PSS	Practical Salinity Scale
QBO	Quasi-Biennial Oscillation
QC	Quality Control
QUID	Quality Information Document
R/COFS	Regional/Coastal Ocean Forecasting Systems
R2O	Research to Operations
RADS	Radar Altimeter Database System
RANS	Reynolds-Averaged Navier–Stokes
RCP	Representative Concentration Pathways
RFMOs	Regional Fisheries Management Organisations
RHS	Right Hand Side
RIOPS	Regional Ice Ocean Prediction System
RMSD	Root Mean Square Difference
ROC	Receiver Operator Characteristic
ROMS	Regional Ocean Modeling System
ROSE-L	Copernicus Radar Observation System for Europe in L-band
RRR	Rolling Review of Requirements
Rrs	Remote Sensing Reflectance
SAMOA	System of Meteorological and Oceanographic Support for Port Authorities

SANGOMA	Stochastic Assimilation for the Next Generation Ocean Model Applications
SANIFS	Southern Adriatic - Northern Ionian Forecasting System
SARAL	Satellite with ARgos and ALtika
SAR	Synthetic Aperture Radar
SCDA	Strongly Coupled Data Assimilation
SCHISM	Semi-implicit Cross-scale Hydroscience Integrated System Model
SCOBI	Swedish Coastal and Ocean Biogeochemical Model
SCVTs	Spherical Centroidal Voronoi Tessellations
SD	Standard Deviation
SDGs	Sustainable Development Goals
SEEK	Singular Evolutive Extended Kalman filter
SHYFEM	Shallow water HYdrodynamic Finite Element Model
SI	Scatter Index
SI	International System of Units
SIDFEx	Sea Ice Drift Forecast Experiment
SIS	Sea Ice Simulator
SIT	System Information Table
SKEB	Stochastic Kinetic Energy Backscatter
SLA	Sea Level Anomaly
SLOSH	Sea, Lake, and Overland Surges from Hurricanes
SMAP	Soil Moisture Active Passive
SMMR	Scanning Multi-channel Microwave Radiometer
SMOS	Soil Moisture and Ocean Salinity mission
SOCAT	Surface Ocean CO_2 Atlas
SOCIB	Balearic Islands Coastal Observing and Forecasting System
SONEL	Système d'Observation du Niveau des Eaux Littorales
SOOP	Ship-of-opportunity
SPM	Suspended Particulate Matter
SPOT	Satellite pour l'Observation de la Terre
SPP	Stochastic Perturbed Parameters
SPPT	Stochastic Perturbed Parametrized Tendencies
SPUF	Stochastic Parameterization of Unresolved Fluctuations
SSES	Sensor Specific Error Statistics
SSH	Sea Surface Height
SSM/I	Special Sensor Microwave Imager
SSS	Sea surface salinity
SST	Sea surface temperature

STAC	Science and Technological Advisory Committee
SURF	Structured and Unstructured Relocatable Ocean Model for Forecasting
SWAN	Simulating WAves Nearshore
SWASH	Simulating WAves till SHore model
SWE	Shallow Water Equations
SWH, or Hs	Significant Wave Height
SWOT	Surface Water and Ocean Topography
TAC	Thematic Assembly Center
TGTT	Tide Gauge Task Team
TSG	Thermosalinographs
TVD	Total Variation Diminishing
UHSLC	University of Hawaii Sea Level Centre
UKMO	UK Met Office
UN	United Nations
UNCTAD	United Nations Conference on Trade and Development
UNDP	United Nations Development Programme
UNFCCC	United Nations Framework Convention on Climate Change
UNGA	United Nations General Assembly
UOM	Unified Ocean system Model
US	United States
USA	United States of America
USSR	Union of Soviet Socialist Republics
VARANS	Volume-Averaged Reynolds Averaged Navier–Stokes
VIIRS	Visible Infrared Imaging Radiometer Suite
VISIR	DiscoVerIng Safe and effIcient Routes
VOF	Volume-O-Fluid
VP	Viscous-plastic
WAM	Wave prediction Model
WAVERYS	Global Ocean Waves Reanalysis
WCDA	weakly coupled data assimilation
WCOFS	West Coast Operational Forecasting System
WMO	World Meteorological Organization
WMO/LC-WFV	World Meteorological Organisation Lead Centre for Wave Forecast Verification
WOA	World Ocean Atlas
WOD	World Ocean Database
WRF	Weather Research and Forecasting Model
XBT	Expendable bathythermograph

This guide hopes to be a guideline and inspiration to professionals all around the globe, stimulating the reader to research deeper knowledge on this vast field. If this objective is achieved, this publication is expected to foster the generation of valuable information that will be used in decision making processes and, therefore, to advocate a wiser and more sustainable relation with our always generous ocean.

unesco
Intergovernmental
Oceanographic
Commission

The Global Ocean
Observing System
GOOS

MERCATOR
OCEAN
INTERNATIONAL