Learning-Based Methods and the Future of Numerical Ocean and Sea Ice Modeling

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Abstract

The field of operational oceanography is undergoing a significant evolution with the increasing integration of artificial intelligence (AI) methods, which are complementing and, in some cases, redefining traditional numerical modeling approaches. This review explores how AI methods—particularly model-based autoregressive emulators, hybrid modeling, and end-to-end model-free approaches—are reshaping the representation of ocean and sea-ice dynamics in operational systems. We focus on three key objects: sea-ice parameters, near-surface ocean properties, and the 3D ocean state, each characterized by distinct observational and dynamical challenges. While AI-driven innovations offer new opportunities for improved monitoring, forecasting, and uncertainty quantification, their long-term impact on operational systems remains uncertain, especially given the sparsity of subsurface observations and the complexity of ocean dynamics. By synthesizing recent advances and identifying open questions, this paper aims to guide the ocean modeling community toward a future where AI and physics-based approaches coexist synergistically.

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1. INTRODUCTION

Reliable information about the state of the ocean is a prerequisite for safe operations at sea and environmental monitoring. Ocean states directly influence human societies by impacting marine resources, coastal hazards, and maritime activities, making accurate information critical for decision-making. This need is further amplified by the ongoing triple planetary crises—extreme events, pollution, and ecosystem degradation (von Schuckmann et al. 2025). Beyond operational safety, there is a therefore a growing demand for precise and spatially coherent ocean information that spans from global to local scales (GOOS 2025).

Monitoring: reconstructing past and near-real-time ocean states into dense, gridded data products from observations

Forecasting: using physics-based models or emulators to predict future ocean states based on current and past observations.

Observations alone, however, are insufficient to meet this demand, because of their sparsity, especially below the surface and in remote high latitude areas. Jointly leveraging observations and knowledge about ocean and sea-ice processes is therefore key for optimally integrating heterogeneous data, extrapolating information across space and time, and maintaining physical consistency. This approach forms the foundation of operational oceanography, a well structured field with established practices, and community frameworks (Drevillon et al. 2025). These frameworks provide the necessary guidelines and standards to ensure the effective use of observational data in ocean forecasting (Alvarez Fanjul et al. 2022).

Operational oceanography (OO) centers address this task of developing a variety of ocean data products, by integrating observations with prior knowledge of ocean physics. These products serve multiple purposes, including state estimation, short-term forecasting, as well as reanalyses that reconstruct past ocean states over multiple decades, which are essential for climate monitoring. These data products encompasse a large range of physical and biogeochemical parameters and span from regional to global scales. For a detailed overview of the current state of operational oceanography, see Alvarez Fanjul et al. (2025).

At the core of all these operational systems lies the concept of numerical model, which provide the dynamical backbone for forecasting, state estimation, and reanalysis. Numerical models are used in combination with data assimilation techniques to estimate ocean states and predict their future evolution (Drillet et al. 2025). By essence, numerical models encode our best understanding of the dynamical relationships between ocean variables. Their development is a collective, long-term undertaking, involving community effort in theory, numerics, parameterizations, and evaluation against observations.

The field of operational oceanography (OO) is undergoing a significant transformation driven by the integration of artificial intelligence (AI), with ongoing research and emerging data products (Heimbach et al. 2025). This evolution mirrors developments in numerical weather prediction (De Burgh-Day & Leeuwenburg 2023) and aligns with current trends in climate modeling (Lai et al. 2025). The new field of *Scientific Machine Learning* (Dietrich & Schilders 2025), which aims at optimally blending data-driven approaches and domain specific scientific knowledge, is central to these advancements. This includes in particular *Physics-based Deep Learning*, which aims at integrating physical laws into deep neural networks (Thuerey et al. 2021). These innovations are reshaping both the modeling components of existing systems (Zanna et al. 2025) and data assimilation techniques (Cheng et al. 2023).

But the long-term impact of AI on operational oceanography, especially its potential to transform existing numerical models, remains uncertain. The approaches leveraged in numerical weather prediction (as for instance AI models trained from reanalyses) may not immediately translate seamlessly to the ocean context. The density of subsurface ocean observations is indeed insufficient to directly resolve energy-containing scales resulting in greater uncertainty in ocean reanalyses (Yang et al. 2025a). It is therefore timely to review how AI is specifically affecting the field of operational oceanography, taking into account its distinct observational and dynamical constraints.

This paper aims to explore how the ongoing integration of AI methods into ocean monitoring and prediction is fundamentally challenging the traditional concept of the numerical ocean and sea-ice model. Rather than considering AI merely as an incremental tool for enhancing existing systems, we will here examine how it questions long-standing assumptions about the representation of ocean dynamics in core operational systems. This discussion complements a recent review on AI's impact on ocean data assimilation (Grande et al. 2026). Together, these two articles will assess how both core pillars of operational oceanography—models and data assimilation—are being reshaped by AI.

This review is structured around the three primary approaches emerging from the current research landscape in operational oceanography: autoregressive emulators, model-free methods, and hybrid modeling. These approaches define three distinct trajectories for evolving the representation of ocean and sea-ice dynamics within operational systems. Section 2 outlines the various tasks and focal areas addressed in the review, while Section 3 introduces fundamental concepts of learning-based methods and their application in operational oceanography. The subsequent sections delve into recent works on auto-regressive emulators (Section 4), hybrid modeling (Section 5), and model-free approaches (Section 6). Section 7 examines possible future trends and perspectives, and the review concludes with Section 8, which highlights the upcoming challenges for the operational oceanography community.

2. OCEAN, SEA ICE AND THEIR OPERATIONAL MODELING

The core services of operational oceanography systems are designed to fulfill two different and complementary tasks, namely monitoring the ocean's past and present states, and forecasting its future evolution, both of which have been recently challenged by AI (Heimbach et al. 2025). In this review, the term *monitoring* refers to the dense, grid-based reconstruction of past ocean states, encompassing high-level data products (e.g., L4 products like DUACS) and ocean reanalyses. The second task, *forecasting*, focuses on predicting future ocean states. A critical concept here is the fixed deterministic predictability horizon for a given grid or scale, beyond which pointwise forecasts lose reliability (Leroux et al. 2022, Fiol et al. 2026). Monitoring and forecasting serve distinct downstream applications: the former supports documentation and analysis of past states for model validation, resource management, and climate trend studies, while the latter enables anticipation of future conditions, crucial for navigation, coastal risk management, and early warning systems. Together, they provide a complementary framework for understanding and managing ocean systems.

This review article focuses on three distinct physical objects, sea ice state, near-surface ocean properties, and the 3D ocean state, as illustrated in Fig. 1. These objects were selected because they represent areas where AI methods have had varying impacts in monitoring and prediction. While biogeochemical parameters are also important, this review prioritizes physical parameters, as models for these are generally more trusted. Each of these objects exhibits specific spatial and temporal scales, governing physical processes, and observational availability, which will be detailed in the following.

- **Sea ice state in polar regions** : Machine learning methods are increasingly applied to improve the monitoring and prediction of sea-ice physical parameters in polar regions. Both the Arctic and Antarctic are critical areas of focus, given their rapid environmental changes, particularly in the Arctic, which is warming four times faster than the global average. The key parameters of interest include sea ice thickness, concentration, and velocities, driven by pressing applications such as ship routing and environmental monitoring. Observations primarily rely on satellite data, including radiometer, altimetry and radar and with typical resolutions of around dozens of kilometers for full-Arctic products. Current predictability is limited to a few days at most (Fiol et al. 2026).
- **Near-surface ocean state** : This review also examines the physical properties of the near-surface ocean—typically the upper 30 meters[1], as a second focal point. This area has garnered significant attention due to both the opportunities and challenges presented by the wealth of satellite remote sensing data. The key parameters of interest include sea surface height (SSH), sea surface temperature (SST), sea surface salinity (SSS), and sea surface currents (SSC) (Röhrs et al. 2023). These parameters are critical for applications such as ship routing, air-sea interactions, and ecosystem monitoring. Observations primarily rely on satellite remote sensing (radar altimetry, passive optical sensors, infrared radiometers, microwave radiometers and scatterometers) supplemented by surface drifters, and gliders, enabling monitoring at scales down to 1 km. Predictability remains uncertain, as it heavily depends on the interior ocean state.
- **Full-depth ocean state** : As a third focal area, this review addresses the full three-dimensional (3D) state of the ocean—from the surface to the seafloor, as typically represented in current-generation numerical ocean models. The key parameters of interest include ocean currents, temperature, and salinity at various depths, driven by critical applications such as marine heatwave prediction, climate variability studies, and energy sector needs. Observations rely on surface monitoring tools (e.g., satellites, drifters) plus deep-ocean platforms like Argo floats. However, unlike the well-observed surface ocean, in-depth observations of the full 3D state remain sparse. Predictability horizons are discussed by Leroux et al. (2022).

Predictability: the ability to forecast a dynamical system, measured by the forecast horizon, which depends on the spatial scale and the level of uncertainty

In operational systems, the dynamics of the above objects is generally accounted for through physics-based numerical models. Numerical models are computational tools that

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[1] Note that depth definitions may vary depending on the variable; see Röhrs et al. (2023)

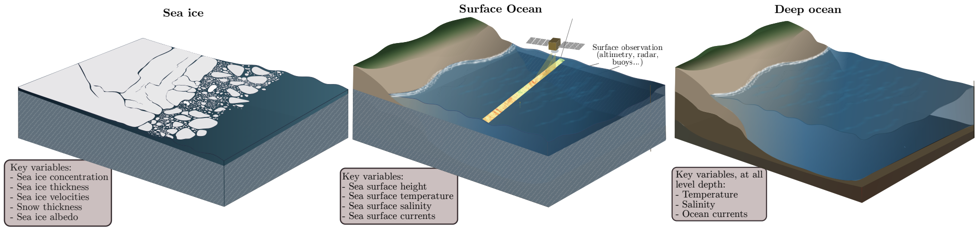

Figure 1

Schematic representation of the three focal areas in ocean monitoring and prediction: (left) Sea ice state in polar regions, highlighting key variables such as sea ice concentration, thickness, velocities, snow thickness, and albedo, primarily observed via satellite and radar altimetry. (center) Near-surface ocean, focusing on variables like sea surface height, temperature, and salinity, monitored through satellite remote sensing, buoys, and drifters. (right) Full 3D ocean state, from surface to seafloor, emphasizing temperature, salinity, and ocean currents at all depths, with observations supported by Argo floats and other in-situ platforms.

simulate the dynamics of oceans and sea ice by discretizing fundamental physical laws (and parameterizations for unresolved processes) onto numerical grids. These models integrate the governing equations for both dynamics and thermodynamics to represent the evolution of oceanic and sea ice systems (Chassignet et al. 2019, Fox-Kemper et al. 2019). In practice, these models consist of extensive codebases (see Bertino et al. (2025) for sea-ice models and Bell et al. (2025) for ocean models), predominantly written in low-level programming languages like Fortran or C, although some recent developments have begun to utilize more modern languages based on diverse codebases.

Numerical models are one of the cornerstones of operational monitoring and forecasting systems (Drillet et al. 2025). These models operate as Markovian state-space models, predicting the evolution of state space variables $\mathbf{X}_t$ under prescribed external forcing $\mathbf{F}_t$. This formulation enables to use data assimilation techniques to estimate the state of the system over a given time window $\{\mathbf{X}_t\}$ from observations $\{\mathbf{Y}_t\}$ (Martin et al. 2025a). The physical content and resolution of numerical ocean and sea-ice models evolve alongside both advances in computing resources and the expansion of observational networks (Haine et al. 2021). Numerical models used in operational oceanography are also often used as components of Earth System Models (Hurrell et al. 2009). In essence, the current generation of models acts as ”placeholders” for our evolving understanding of ocean and sea-ice dynamics.

3. LEARNING-BASED METHODS FOR OPERATIONAL MODELING

Machine Learning (ML) and Deep Learning (DL) can be understood as programs whose behavior is determined by learnable parameters, typically optimized using data. Unlike traditional modeling, where fixed equations ($\{\varphi\}$) manually define input-output mappings, ML/DL systems learn these relationships directly from data. Training neural networks f_θ, with θ the trainable weights of the neural network, involves iteratively optimizing a loss function $\mathcal{L}(\theta)$ to minimize prediction errors. The process begins with forward propagation, where input data is passed through the network to generate predictions. The discrepancy between predicted and true outputs is quantified using the loss function $\mathcal{L}(\theta)$. Next, backpropagation computes the gradient of the loss with respect to each parameter $\nabla_\theta \mathcal{L}(\theta_t)$ using the chain rule, efficiently propagating errors backward through the network. Parameters

Backpropagation: efficient algorithm that computes gradients for neural networks by applying the chain rule in reverse, enabling optimization of model parameters

Autoregressive: using past predictions as inputs to extend forecasts iteratively.

Lead time: fixed time interval for which emulators are trained to predict the future state of a system, starting from a given initial condition

Optimization: process of minimizing a loss function to find the best parameters or solution within a defined space.

are then updated via gradient descent. This cycle - forward propagation, loss computation, backpropagation, and parameter updates - repeats over the training dataset until the model converges, achieving optimal predictive performance. We can define two main objectives when using neural networks. First, they can be employed to predict a unique output given a specific input, a paradigm known as deterministic neural networks. Second, neural networks can be used to sample new examples from an unknown distribution—whether learned or inherent in the input data—falling under the category of stochastic neural networks or, more recently, Generative AI (GenAI).

We identify three distinct approaches for integrating neural networks into operational ocean modeling, as schematized in Fig. 2. It is important to note that this categorization is not rigid, as some studies may span or blur the boundaries between these approaches.

- **Autoregressive emulators** : neural networks are trained based on the fully gridded system state $\mathbf{X}_t$, which comes from a simulation model or reanalysis, and forcings $\mathbf{F}_t$ to predict the ulterior system state $\mathbf{X}_{t+1}$ for a given lead time : $\mathbf{X}_{t+1} = f_\theta(\mathbf{X}_t, \mathbf{F}_t)$. Once the neural networks are trained, they are used in inference by applying them iteratively over the predicted state. In this case the neural network **emulates** the physical model, by fully replacing it in inference. This method will be discussed in Sec. 4.
- **Hybrid modeling** : neural networks in this case are trained to improve the physical model. The neural network, trained on the state input $\mathbf{X}_t$ and additional forcings $\mathbf{F}_t$ is combined with the physical model to predict the ulterior state $\mathbf{X}_{t+1}$. The use of those methods are various and will be discussed in Sec. 5. There are two main frameworks in hybrid modeling, offline, where the neural network is trained separately and then applied after the physical model, or online, where the neural network is trained with the physical model. This require a differentiable physical model to compute the gradient of the loss function through the physical model during the neural network optimization.
- **Model-free methods** : In contrast to model-based approaches, model-free methods train neural networks directly on observational products $\{\mathbf{Y}_t\}$ and forcings $\{\mathbf{F}_t\}$ to recover the state $\{\mathbf{X}_t\}$. Given the potential sparsity and limited availability of observational data, model inputs $\{\mathbf{X}_t\}$, typically derived from simulations or reanalyses, may also be incorporated during training to augment the dataset. Unlike model-based emulators, where the temporal transition between successive states $\mathbf{X}_t$ is explicitly learned, model-free methods do not rely on a predefined dynamical model. These approaches, which can adopt diverse architectures, are further discussed in Sec. 6.

4. MODEL-BASED AUTOREGRESSIVE EMULATORS

Forecast horizon: the total duration of prediction achieved by iteratively applying the emulator to extend forecasts beyond the initial lead time

This section discusses the modeling of oceanic and sea-ice physical states using fully data-driven neural network emulators. These emulators are trained on large-scale datasets (e.g., GLORYS12, Lellouche et al. (2021)) to capture the underlying dynamics of the system at specified lead times, predicting future states (e.g., 12-hour forecasts) based on simulation data and external forcings (e.g., topography, auxiliary fields). During inference, the emulator autonomously generates long-term trajectories through recursive, auto-regressive prediction, iteratively extending the forecast horizon. This approach stems from atmospheric modeling, where datasets such as ERA5 and benchmarks like WeatherBench (Rasp

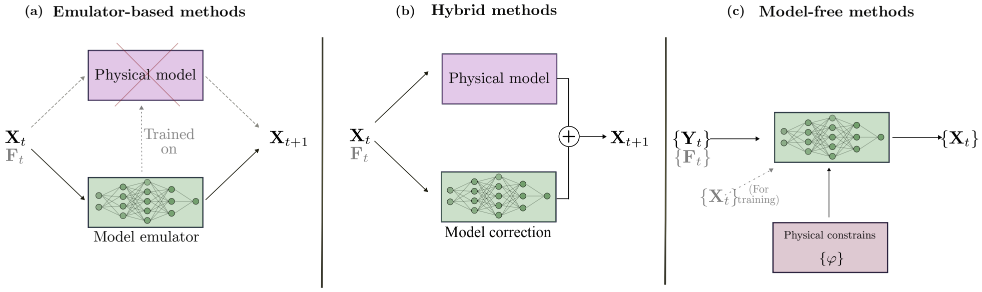

Figure 2

Schematic representation of three neural network paradigms in operational ocean modeling. (a) Model-based autoregressive emulators: Neural networks are trained on fully gridded system states $\mathbf{X}_t$ (derived from simulations or reanalyses) and external forcings $\mathbf{F}_t$ to predict the subsequent state $\mathbf{X}_{t+1}$. During inference, the network iteratively replaces the physical model. (b) Hybrid modeling: Neural networks augment the physical model by correcting or complementing its predictions, with training frameworks including offline (post-hoc correction) and online (joint optimization with a differentiable physical model) approaches. (c) Model-free methods: Neural networks learn directly from observational data $\{\mathbf{Y}_t\}$ and forcings $\{\mathbf{F}_t\}$, with optional integration of $\{\mathbf{X}_t\}$ to mitigate data scarcity.

et al. 2020, 2024) originally served as foundational tools, with early applications focusing on emulating key atmospheric variables from ERA5 (Lam et al. 2023, Bi et al. 2023). Given the rapid growth in ocean and sea-ice emulator research over recent years, we have initiated a living review to catalog all relevant publications (Durand & Le Sommer 2026). This review is designed to be continuously updated with new contributions, ensuring it remains a current and comprehensive resource for the community.

The training of ocean and sea ice emulators primarily relies on high-resolution model outputs or reanalysis datasets, with atmospheric forcings serving as essential inputs. The literature suggests that spatial resolution determines the maximum forecast horizon: fine resolutions allow for short-term, high-detail predictions, whereas coarse resolutions enable longer-term forecasts, sometimes spanning decades. This difference arises because emulators struggle to maintain stability when repeatedly simulating small-scale, rapidly changing features. For instance, global short-term forecasting emulators—such as those trained on high-resolution reanalyses like Glorys12—can predict detailed outputs at resolutions as fine as 1/24° in regional applications (e.g., the Mediterranean Sea (Holmberg et al. 2025)) or 1/12° in dynamic regions like the Kuroshio Current (Qian et al. 2026). Conversely, by coarse-graining high-resolution data, some emulators provide outputs at coarser resolutions (e.g., 1° (Dheeshjith et al. 2025), 1/2° Gao et al. (2025b), or 1/4° (El Aouni et al. 2025b, Wu et al. 2025a, Xiong et al. 2023)), thereby extending the forecast horizon and enabling longer-term predictions. Certain emulators are trained exclusively on model data, focusing either on sea ice (Durand et al. 2024) or ocean dynamics (Kim et al. 2025, Guo et al. 2025).

Encoder: uses operations like convolution to compress high-dimensional inputs into a compact latent representation, preserving key features.

Decoder: applies upsampling to expand latent data back into high-dimensional outputs, reconstructing predictions or original formats.

Most ocean and sea ice emulators adopt a three-stage architecture: an encoder compresses high-dimensional inputs, a latent-space processor models dynamics, and a decoder reconstructs predictions. The processor employs diverse paradigms to capture complex system behavior efficiently. Spatial convolutions (Dheeshjith et al. 2025, Huang et al. 2025) exploit local correlations via learned kernels, ideal for multi-scale geophysical interactions. Vision Transformers (Cui et al. 2025, Wang et al. 2024c) treat data as patch sequences, us-

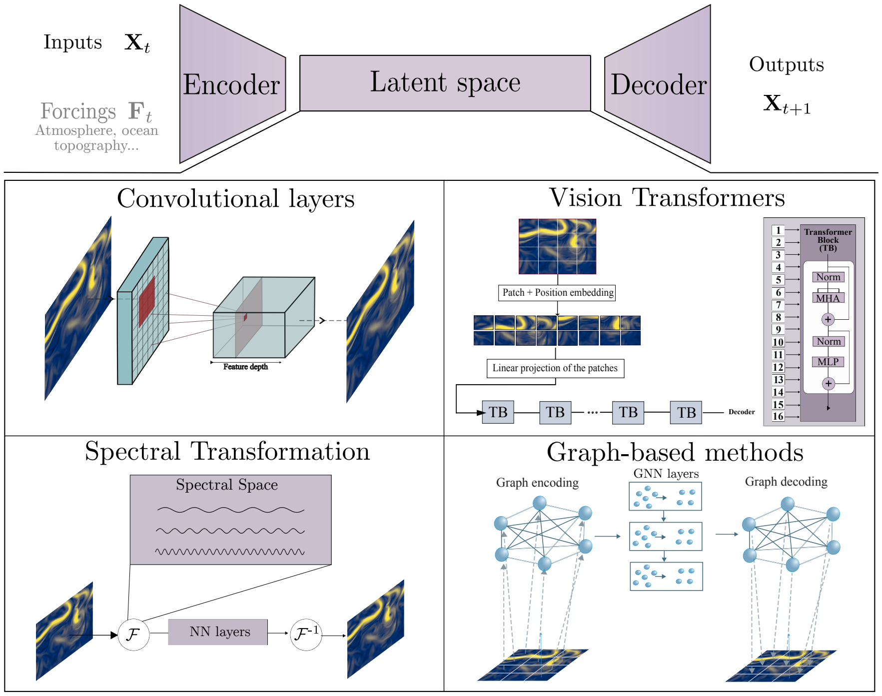

Figure 3

Schematic of neural network architectures for ocean and sea ice emulators, illustrating the encoder-latent-decoder paradigm. **Convolutional architectures** use an encoder composed of stacked convolutional layers to extract hierarchical features from gridded inputs ($\mathbf{X}_t$) and forcings ($\mathbf{F}_t$), compressing them into a low-dimensional latent space. The decoder reconstructs high-resolution outputs by progressively upsampling the latent representation. **Vision Transformers** encode inputs by partitioning them into patches, augmenting each with positional embeddings, and processing them through self-attention mechanisms in Transformer Blocks (TB). The latent space captures global dependencies, while the decoder linearly projects patch embeddings back to the original input space. **Spectral methods** employ an encoder that transforms inputs into spectral space via a Fourier transform ($\mathcal{F}$), where neural network layers model dynamics in frequency domain. The decoder applies an inverse Fourier transform ($\mathcal{F}^{-1}$) to return predictions to physical space. **Graph-based methods** encode inputs as graph structures, where nodes represent discrete spatial locations and edges encode interactions. Graph Neural Network (GNN) layers process node features in latent space, and the decoder maps the updated graph back to physical fields. All architectures support auto-regressive inference for long-term trajectory prediction.

ing self-attention to model long-range dependencies in large-scale systems. Fourier Neural Operators (El Aouni et al. 2025b, Wang et al. 2024a) operate in the spectral domain, efficiently capturing global patterns and periodic dynamics. Graph-based networks (Gao et al. 2025b, Holmberg et al. 2025) represent the system as nodes and edges, naturally handling irregular geometries and anisotropic flows. An illustrative schematic of this three-stage architecture is provided in Fig. 3.

Data-driven emulators, characterized by their low computational cost and automatic adjoint capabilities, offer significant advantages for operational forecasting. Their efficiency enables large-scale ensemble generation for uncertainty quantification (Brettin et al. 2025) and seamless integration into data assimilation frameworks (Xiang et al. 2025a, Xiao et al. 2023, Durand et al. 2025, Li et al. 2024b). However, their operational deployment raises critical challenges: long-term stability during extended autoregressive roll-outs remains uncertain, as error accumulation over time necessitates a delicate balance between lead time and forecast horizon. Furthermore, deterministic emulators, often trained via L2-based loss minimization, tend to smooth fine-scale features, potentially degrading the representation of small-scale physical processes. Looking ahead, the coupling of emulators with other model components presents both opportunities and complexities. While such integration could enhance predictive capabilities, it also demands careful attention to maintaining physical consistency and coherence across coupled systems. Addressing these challenges is essential to fully harness the potential of emulators in operational forecasting and research applications (Duncan et al. 2025, Wu et al. 2025a, Wang et al. 2024a).

5. MACHINE-LEARNING-AUGMENTED HYBRID MODELS

Instead of replacing the entire prediction pipeline by an emulator, an alternative strategy consists in augmenting the dynamical core of physics-based models with trained components, adopting what is now referred to the *hybrid* modeling paradigm. In this framework, the trained components are formulated with the aim of improving the representation of key physical processes affecting model predictions. In practice, these trained components are formulated as ML/DL models, which are directly integrated as model components and calibrated using a combination of physical hypotheses and data. Hybrid modeling strategies have been leveraged for developing parameterizations of individual physical process, or providing state-dependent representation of model errors for improving model predictions.

Dynamical core: component of a physics-based numerical model that explicitly solves the partial differential equations describing large scale dynamics.

The performance of hybrid models is not only determined by the architecture of the trained neural networks and availability of training data, but also by the chosen target and training strategy used to optimize the model parameters. As described above in section 2, there are two main approaches for developing hybrid models components. With the *offline training* approach, neural networks are trained independently of the dynamical core, by solving a regression task formulated from a reference dataset (high-resolution model, historical reanalysis). With the *online training* (over multiple roll-out) approach, neural networks are trained by minimizing a loss which involves integrating the physics-based dynamical core over a control window (Kochkov et al. 2021). Several pieces of work have shown that online training can improve notably the performance, stability and ability to generalize of hybrid geoscientific models (Frezat et al. 2022). One practical difficulty of online training over multiple roll-outs is that it requires to compute the gradient of dynamical core with respect to the model state (Gelbrecht et al. 2023, Shen et al. 2023, Sapienza et al. 2025).

Subgrid-scale: physical processes that occur at spatial scales smaller than the model's grid resolution and therefore must be represented through parameterization rather than explicitly resolved.

In ocean modeling, hybrid approaches have been proposed to improve the representation of various physical processes, and in particular unresolved subgrid-scale turbulence. Neural networks have for instance been used for the parameterization of ocean vertical physics and ”microscale” (1-100m) turbulent mixing. Artificial neural networks have been developed for improving existing vertical physics schemes, which predict turbulent eddy diffusivity (Sane et al. 2023). They have also been leveraged for directly replacing existing parameterizations for heat (Zhu et al. 2022) and momentum fluxes (Falga et al. 2025), enabling the representation of non-local and upgradient fluxes. Hybrid approaches for ocean

LES (Large Eddy Simulation): numerical modeling approach that explicitly resolves the largest turbulent motions while parameterizing only the smallest subgrid-scale turbulence.

vertical physics are often leveraging Large Eddy Simulation (LES), in particular for the parameterization of ocean surface boundary layer physics (Ramadhan et al. 2020, Lee et al. 2025). Hybrid approaches have also been used to design parameterizations of ocean macroturbulence, as for instance for mesoscale thickness (Balwada et al. 2025) and momentum forcings (Bolton & Zanna 2019, Zanna & Bolton 2020) sometimes with stochastic models (Guillaumin & Zanna 2021) with implementations in large-scale ocean models (Zhang et al. 2023). Their effect has been analyzed (Gultekin et al. 2024) and indicates in particular some degree of generalization in the horizontal extent but not depth-wise, although some progress has been made by incorporating local scaling based on the grid scale (Perezhogin et al. 2025), reducing the need of model tuning across configurations. Hybrid approaches have also been tested for parameterizing the impact of submesoscale processes, as for instance vertical buoyancy fluxes in the ocean mixed layer (Zhou et al. 2024, Bodner et al. 2025).

For sea-ice, hybrid modeling has been leveraged for improving the representation of both sea ice dynamics and thermodynamics. Hybrid approaches have for instance been developed for improving the representation of sea ice rheology, with explorations focusing on Maxwell elasto-brittle rheology (Finn et al. 2023) and viscous–plastic sea-ice models (Margenberg & Mehlmann 2025). Some works also proposed to directly target specific subgrid-scale processes, as for instance wave-induced sea ice floe fracture (Horvat & Roach 2022), and melt ponds (Driscoll et al. 2024), aiming to better capture small-scale heterogeneity that strongly influences albedo and surface energy fluxes. Beyond subgrid-scale parameterizations, hybrid methods have also been developed for improving the representation of external forcing, including air-sea fluxes (Wu et al. 2025b, Storto et al. 2025) and to learn corrections for the model bias with respect to reanalyses or observations. Exploration have so far targeted idealized contexts (Liu et al. 2023, He et al. 2025), with realistic application for both ocean (Storto et al. 2025) and sea-ice dynamics (Gregory et al. 2024, Palerme et al. 2024, Gooya & Sospedra-Alfonso 2025).

The use of hybrid modeling in the context of operational monitoring and forecasting is still relatively limited, as hybrid approaches have primarily been developed in the context of climate modeling (Zanna et al. 2025). Most studies so far have focused on offline training with limited deployment in fully operational systems. An important exception is mesoscale ocean parameterizations, which have been implemented and tested in idealized configurations of large-scale ocean models (Perezhogin et al. 2024, 2025), demonstrating improvements in stability and cross-resolution generalization. However, beyond these proof-of-concept implementations, applications of hybrid modeling relevant to operational oceanography remain largely confined to model-error correction (Storto et al. 2025, Gregory et al. 2026), particularly in the context of seasonal to decadal prediction.

6. MODEL-FREE ML-BASED MONITORING AND FORECASTING

In contrast to the approaches described in the preceding sections, model-free approaches formulate ocean reconstruction and forecasting as a non-linear mapping between the input space spanned by the observations and forcings and the output space spanned by the targeted state. In this setting, a neural network approximates a mapping between sparse and sometimes irregular observations $\{\mathbf{Y}_t\}$ (and optionally forcings $\{\mathbf{F}_t\}$) and a target state $\{\mathbf{X}_t\}$, without relying explicitly on a dynamical operator.

These neural networks may be trained using real observations, simulation-based reference datasets, or combination of both. Although referred to as model-free, many of these approaches may rely on high-resolution simulation or reanalysis datasets during training, either to increase the training database or to provide a physically consistent supervision reference. In such cases, the physical model is not explicitly used during inference, but inherently defines the learned mapping.

End-to-end: directly mapping observations to ocean forecasts, bypassing intermediate physical models for streamlined prediction.

Depending on the objective, model-free ocean modeling can be categorized as follows: *Neural mapping schemes* aim at reconstructing gap-free fields from sparse observations. The underlying neural architectures vary significantly depending on the use case and may include neural data assimilation schemes which learn end-to-end data assimilation solvers and representations. This category also comprises multi-modal mapping schemes, as developed for instance for estimating subsurface states from surface variables. *Forecasting networks* aim at mapping past gappy observations to future gap-free states. Similarly to neural mapping schemes, the complexity of the underlying architectures and representations vary depending on the use-case. *Neural samplers* aim at learning representations of probability distributions of $n \times D + t$ ocean states and allow stochastic sampling, conditioned upon observations. Theses approaches can be used for both mapping and forecasting tasks.

The above approaches have been applied to the reconstruction and forecasting of surface variables, such as SSH and SST, which benefit from relatively dense satellite coverage. For instance, neural mapping schemes have been successfully deployed for reconstruction of surface variables from sparse satellite observations, including Martin et al. (2024), who introduced a DL-based mapping framework given SSH or SST observations, or Archambault et al. (2024) who proposed an attention-based encoder-decoder architecture for SSH mapping from altimeter observations, and Xiang et al. (2025b) who developed a multivariate encoder-decoder architecture for multiple surface variable reconstruction from irregular non-gridded satellite and in-situ observations. Fablet et al. (2024) introduced a neural data assimilation scheme for ocean states mapping given gridded observations, including SSH (Beauchamp et al. 2023), ocean color (Dorffer et al. 2025), and SST (Beauchamp et al. 2025). Neural samplers include probabilistic formulations for the full field reconstructions using incomplete inputs (Kim & Dean 2025), generative frameworks to sample dynamical fields from irregular observations (Chen et al. 2025) and gridded data (Martin et al. 2025a).

More recently model-free approaches have been successfully applied for the forecasting task, for instance Garcia et al. (2025) who proposed an encoder-decoder architecture for SSC prediction using NADIR and SWOT data together with buoy data, or Botvynko et al. (2025) who applied the variational data assimilation schemes for SSH forecasting given altimetry observations, and Cuervo-Londoño et al. (2025) who applied GNN to predict SST from satellite observations. Finally, with a growing amount of end-to-end approaches for monitoring and forecasting tasks, there is an emerging need for physically consistent and more explicable models. Thus, Physics-Informed Neural Networks (PINNs) is a promising venue to address these challenges, such as Ehlers et al. (2025) who explored such approach for wave-field forecasting using buoy and radar observations. Overall, these studies demonstrate how model-free end-to-end monitoring and forecasting formulations can overpass traditional interpolation- and assimilation-based approaches for surface spatio-temporal ($2D+t$) ocean states (Zhao et al. 2024).

Physics-Informed Neural Networks: a class of NNs that integrate physical priors into the loss function, ensuring outputs respect known physical laws while optimizing data-driven performance

Sea-ice constitute another active domain for model-free learning, with recent applications addressing the reconstruction and forecasting of several physical parameters. Neural mapping schemes based on convolutional encoder-decoder architectures have been successfully deployed for sea-ice charting from SAR imagery, enabling high-resolution sea-ice concentration reconstructions (Kucik & Stokholm 2023). Beyond reconstruction, substantial effort has focused on short to seasonal sea-ice predictions. A variety of DL (Kvanum et al. 2025, Zhang et al. 2025, Grigoryev et al. 2022, Koo & Rahnemoonfar 2024) and more lightweight ML approaches (Lin et al. 2025) have been proposed for short-term sea-ice forecasting. For sub-seasonal and seasonal predictions, various DL end-to-end approaches have demonstrated competitive performances compared to physical models (Yang et al. 2025b, Wang et al. 2025b, Dong et al. 2024, Palerme et al. 2025, Wang et al. 2023, Ali et al. 2021, Ali & Wang 2022). Furthermore, a neural ordinary differential equation-based framework combined with convolutional architecture has been proposed for sea-ice forecasting in polar environments (Park et al. 2025). Overall, similarly to surface ocean applications, these works show how end-to-end approaches can achieve competitive performances for $2D + t$ sea-ice reconstruction and forecasting compared to operational physical models.

In contrast, fully end-to-end approaches for $3D + t$ ocean state reconstruction and forecasting remain limited. Extending end-to-end learning to the full $3D$ ocean states is considerably more challenging due to the high scarcity and heterogeneity of subsurface observations. Some studies have explored surface to subsurface mappings, as for instance Pauthenet et al. (2022), who reconstruct temperate and salinity profiles from surface forcings using an MLP, or Cutolo et al. (2024), who proposed a convolutional architecture for salinity profile reconstructions from satellite inputs, Wang et al. (2025a), who trained a convolutional neural network for underwater sound speed profiles inversion from satellite observations, and Gao et al. (2025a) who proposed a model-free framework for vertical velocity reconstruction from sparse observations. Model-free learning approaches using satellite and/or Argo data have been explored for subsurface temperature prediction (Jiang et al. 2024, 2025, Xiao et al. 2022). Physics-informed approaches have been introduced for $3D$ chlorophyll prediction from surface observations (Sammartino et al. 2025) and for interior density reconstruction from surface data (Chen et al. 2024).

7. TRENDS AND PERSPECTIVES

Recent advancements in end-to-end model-free strategies in operational oceanography (OO) highlight two promising directions: the integration of physical prior information and the adoption of stochastic representations. Although model-free end-to-end architectures can be trained without explicitly encoding the dynamics of ocean and sea ice systems, purely data-driven formulation may struggle to ensure physical consistency, especially in highly sparse regions. Particularly, the integration of physical information is critical for inner-ocean reconstruction and forecasting due to the sparsity of its observations. The performance of model-free purely observation-based approaches strongly depends on the density and quality of available data. Surface ocean and sea-ice applications benefit from relatively dense satellite and in-situ observations, however subsurface ocean reconstruction remains under-constrained due to the sparsity and heterogeneity of in-situ measurements. In this context, physical priors can help regularize the learning process. Some studies have demonstrated the potential of leveraging dynamical constraints to learn mappings between surface observations and interior variables (Chen et al. 2024).

Additionally, in order to ensure physical consistency, several strategies may be applied to include physical knowledge into the learning process. Among the most promising methods are PINNs, where partial differential equations are embedded directly into the loss function. Such approaches enforce dynamical consistency without requiring explicit integration of a

GenAI

Generative AI (GenAI, reviewed in Bond-Taylor et al. (2022)) models provide samples from a target probability distribution. GenAI models can be trained on unconditional samples $x_i \sim p(x)$ or conditional samples $x_i \sim p(x|y_i)$. Over the past 30 years, a wide variety of GenAI model classes have found applications in probabilistic learning and across application domains, such as mixture density networks, Gaussian processes, Generative adversarial networks (GANs) (Goodfellow et al. 2014), Variational autoencoders (Kingma & Welling 2013), Normalizing Flows (Rezende & Mohamed 2015) or denoising diffusion (Sohl-Dickstein et al. 2015, Ho et al. 2020). GenAI is increasingly leveraged for inverse modeling, enabling the inference of latent system states from sparse or noisy observations (Rozet et al. 2025), and early applications to ocean state reconstructions appear promising (Martin et al. 2025b). By sampling from probabilistic distributions, GenAI may ultimately enhance our ability to represent and propagate uncertainties in monitoring and forecasting systems. However, while promising, the full potential of GenAI for ocean applications remains to be demonstrated, particularly in terms of scalability, and integration with physics-based frameworks.

full numerical model, as, for instance, Limousin et al. (2025), who explored physics-informed learning of $3D$ ocean states. Alternatively, lightweight ad hoc physical constraints can be incorporated into the training, such as conservation or balance constraints (Le Guillou et al. 2025). These simplified physical components must though remain differentiable in order to be integrated within end-to-end optimization pipelines. While incorporating physical priors during neural network optimization enhances physical consistency, it is equally important to highlight the advantages of probabilistic frameworks. Unlike deterministic approaches that predict a single system state, probabilistic frameworks learn the full distribution of possible states, thereby providing a more comprehensive and realistic representation of system uncertainties and variability. A major advantage of end-to-end neural frameworks is their flexibility in being extended to stochastic formulations (see GenAI sidebox) without fundamentally altering their architecture. Simple strategies such as noising the inputs or the latent representations during training and/or inference can improve robustness of model-free approaches. Beyond these strategies, generative models, including GANs or diffusion models, can directly learn a distribution over ocean states rather than a single deterministic estimate. For example, Martin et al. (2025b), Asefi et al. (2025), Wang et al. (2024b), Souza et al. (2025) proposed generative approaches to improve surface and subsurface reconstructions and predictions within a probabilistic framework. By sampling multiple plausible realizations, such methods may provide uncertainty estimation that is particularly valuable in highly dynamical or poorly observed regions. However, probabilistic sampling does not explicitly respond to the challenge related to the physical consistency of the reconstructed fields. Ensuring that the generated states remain dynamically coherent remains an open challenge.

The benefits of probabilistic and generative learning-based strategies in model-free approaches align with the ongoing trend of using GenAI to design autoregressive emulators. This resonance with GenAI reflects its potential to change the field, eventually through the development of foundation models (see associated side-box) in OO. Probabilistic and generative models represent a significant advancement over deterministic neural network emulators by learning the full distribution of system states, thereby enabling robust un-

Foundation models

Foundation models represent an emerging paradigm in deep learning, characterized by training large-scale models on broad, diverse datasets via self-supervision. These models are designed to be adaptable (often through fine-tuning) to a wide range of downstream tasks (Bommasani et al. 2021). Recent examples of multi-task foundation models include Aurora, which addresses ocean wave forecasts, air pollution forecasts, tropical cyclone track predictions, and global weather forecasting (Bodnar et al. 2025), and ClimaX, which supports global and regional forecasting, climate projections, and sub-seasonal to seasonal predictions (Nguyen et al. 2023). In the oceanic domain, foundation models such as those leveraging observations for reconstruction tasks (e.g., (Cutolo et al. 2024, Dawson et al. 2025)) are beginning to emerge. However, the development and maintenance of such models will require substantial collaborative effort. Given the scarcity of ocean observations, foundation models will likely need to rely heavily on physics-based simulations for training, further emphasizing the need for interdisciplinary cooperation between data scientists, oceanographers, and climate modelers.

certainty quantification, probabilistic forecasting, and enhanced data assimilation. Early contributions in this domain emerged from atmospheric science, where pioneering studies (Li et al. 2024a, Alet et al. 2025, Couairon et al. 2024, Price et al. 2025) demonstrated the feasibility of probabilistic emulation for weather systems. In sea-ice modeling, multivariable stochastic emulators have already been developed (Finn et al. 2024, 2025), showcasing their potential to capture complex, uncertain dynamics. However, generative stochastic emulators for ocean models remain an open research frontier, presenting opportunities for innovation. GenAI holds significant promise for improving uncertainty quantification in geophysical modeling. By design, GenAI captures non-deterministic relationships, enabling a more accurate and comprehensive representation of uncertainties, a critical advantage over deterministic approaches. The integration of GenAI-based emulators offers transformative potential across key applications, including uncertainty quantification, ensemble generation, and data assimilation, where generative priors enhance predictive robustness (Martin et al. 2025b, Qu et al. 2025). Additionally, GenAI extends the utility of sparse or incomplete datasets (Souza et al. 2025), further strengthening its role in operational and research contexts. As these methods continue to develop, they offer potential to address current limitations in predictive accuracy, uncertainty representation, and operational integration, contributing to the evolution of geophysical modeling systems. Moreover, GenAI holds transformative potential due to its capacity to train generic priors, foundation models, that can be adapted across multiple tasks. While this concept has yet to be fully explored in OO, it promises to enhance the versatility, scalability, and physical coherence of next-generation emulators. While data-driven emulators are unlikely to replace traditional ocean models in operational systems in the near future, their integration with physics-based approaches holds potential to significantly enhance predictive accuracy and robustness. This synergy between innovation and established methods will be critical for building the adaptive and reliable forecasting systems of tomorrow.

Differentiable programming (DP), which allow to seamlessly integrate physics-based and trainable components in end-to-end pipelines, is another emerging paradigm that holds promises in the context of operational oceanography. The relevance of differentiable programming (see the dedicated sidebox) to the design of geoscientific models is now well identified (Shen et al. 2023) and demonstrated for atmospheric modelling (Kochkov et al. 2024). By streamlining the computation of the gradients of numerical models, DP offers the possibility to optimize the parameters of trainable components of operational systems with end-to-end strategies. At the fundamental level, DP is related to variational data assimilation (Martin et al. 2025a) but in practice DP builds upon recent developments of automatic differentiation (AD) which are only readily available in modern computer languages and software libraries (as PyTorch, Julia and JAX). In principle, DP allows to define and optimize fully differentiable monitoring and forecasting systems, which may comprise physics-based components and trainable components, both embedded into the same AD framework. In the context of hybrid models described in section 4, DP is key to the deployment of online learning strategies over multiple roll-outs. This paradigm has demonstrated substantial advantages (Gelbrecht et al. 2023, Shen et al. 2023) in idealized configurations relevant to Earth System Models. In two-dimensional (and quasi-geostrophic) turbulent systems, calibrating the parametrization while running the numerical model over multiple time-steps has been shown to significantly enhance the short-term predictive skill (Kochkov et al. 2021). Beyond forecast accuracy, online learning can also improve the long-term stability of the data-driven parametrization (Frezat et al. 2022, Maddison 2024, Yan et al. 2025, Brolly 2026). Moreover, online training strategies have been found to require less training data than offline training strategies (Pahlavan et al. 2024). DP is also gaining traction for operational applications beyond hydrid modelling (Le Guillou et al. 2025, Bertrand et al. 2026), because it simplifies the optimization of the parameters of computer codes with gradient based minimization. Because it allows to compute the gradient of numerical models without the additional effort of maintaining an adjoint code, DP also holds the potential to simplify the deployment and maintenance of variational data assimilation (Solvik et al. 2025) pipelines. But, despite its promise, adopting DP in operational ocean and sea-ice models poses significant challenges. Most legacy numerical models are written in languages that are not readily compatible with modern AD frameworks, often requiring extensive refactoring or complete reimplementation. Recent collaborative efforts aim to address this limitation by developing differentiable ocean models from the ground up, such as Veros (Häfner et al. 2021) implemented in JAX and Oceananigans (Wagner et al. 2025, Silvestri et al. 2025) developed in Julia. These projects promote high-level, modular APIs that facilitate both numerical experimentation and integration with ML libraries. Early studies have already demonstrated the potential of such differentiable programming ecosystems for hybrid modeling and online learning (Meunier et al. 2025, Moses et al. 2025), suggesting a viable pathway toward embedding DP within next-generation ocean models.

Application Programming Interface (API): a defined set of rules that allows different software components to communicate and interact with each other.

8. DISCUSSION AND UPCOMING CHALLENGES

The three approaches identified in this review, namely model-based autoregressive emulators, hybrid modeling, and model-free methods, should all be considered potentially valid pathways for next-generation numerical modeling. The future preference among these approaches may differ for ocean modeling compared to other geophysical fields, owing to the intrinsic peculiarities of the ocean domain. These include the scarcity and heterogeneity of observations, the relatively short Rossby radius of deformation that constrains spatial scales of variability, and the specific characteristics of the ocean modeling community itself. As a result, the optimal path among these three approaches may be distinct, and possibly unique, for ocean modeling applications, and it is uncertain at the moment. In practice, different Earth system modeling communities are generally concerned with different spatio-temporal scales, and thus tend to favor different strategies: for instance, hybrid modeling is mostly investigated within the climate modeling, aiming at enhancing numerical stability over long integrations; autoregressive emulators are primarily developed for operational forecasting (short time scales and higher resolutions), while model-free strategies are most frequently applied to observation-mapping problems.

The preferred path for advancing numerical ocean modeling through the exploitation of AI methods, among all the emerging approaches described earlier, and their uptake into operational predictions, will not only depend on scientific and algorithmic arguments. First, the evolution of computational requirements and the associated costs, including carbon footprint, is crucially dependent on the evolution of the GPU market, particularly in the operational context where timeliness of production is a key requirement. It is unclear at the moment whether emerging industrial competitors, especially from Asia, may revolutionize the GPU market and further drive innovation and performance increase by fueling competition, and whether the increasing demand for GPUs can be thus satisfied by the market. Second, changes in geopolitical scenarios may affect the maintainability and the evolution of the current ocean observation programs, which are a key aspect to generate accurate datasets on which learning methods rely. Specificities of future observing network scenarios can lead, in turn, to the need to maximize the exploitation of historical observations and/or favor approaches not necessarily relying on high-density observing networks, or, differently, focus on the optimal exploitation of enhanced observational sampling.

The expected evolution of the ocean modeling landscape due to the new AI technologies will also feed back and influence the design of next-generation observing networks, systems, and platforms. A critical aspect for geoscientific applications is the ability of deep learning models to generalize geographically (namely, leverage spatial transfer learning) when deployed in regions whose dynamical regimes and data distributions differ from those seen during training. In practice, the model performances can degrade under changes in geographic domains, requiring in turn regional re-training and/or re-tuning (Beauchamp et al. 2023). The degree of success in such geographical transfer learning and general-

Differentiable programming

Differentiable programming (DP) is a computational paradigm that integrates automatic differentiation (AD) within computer programs, enabling gradient-based optimization of program parameters θ. DP underpins modern deep-learning frameworks and has seen many applications in scientific computing, particularly for numerical simulations governed by differential equations (see review by Sapienza et al. (2025)). To date, DP has shown promising results for learning stable parameterizations in idealized systems (see Kochkov et al. (2021), Frezat et al. (2022), Brolly (2026) for examples) and atmospheric models (Kochkov et al. 2024) although its use typically requires a full re-implementation of the dynamical core. However, recent efforts are beginning to experiment with new models for ocean and sea-ice dynamics that support DP through the Julia language or the JAX library, such as those described in Moses et al. (2025). Nevertheless, the benefits of DP for complex, fully realistic ocean and sea-ice systems remain at the time to be demonstrated.

ization will determine optimal observational sampling strategies, namely, whether it will be preferable to ensure global and nearly uniform coverage of observations or rather invest in high-density observation campaigns over selected regions and periods. Additionally, algorithmic advances in end-to-end AI predictions (from observations to forecasts, see Section 6) may guide the design of future satellite missions and in-situ platforms, prioritizing multi-variate and regular-sampling observation programs.

Fully exploiting the potential of AI methods requires a technological transition, which is now a key challenge, as the ocean modeling community may not yet be fully prepared in several aspects. This includes, in particular, the limited presence of truly multidisciplinary teams in many research institutions, which may reflect both some degree of cultural resistance to new technologies and the relatively lower attractiveness of the ocean modeling field, and research institutions more broadly, compared to industry, leading IT companies, and the private sector in general. In addition, organizational challenges within research institutions and operational centers often limit the adoption of innovation, as existing validation protocols are not always aligned with rapid technological changes or cannot handle abrupt changes in the forecast products, especially for operational centers, as those implied by AI methods. A central question is whether it is possible to significantly reduce the cycle of prototyping, testing at scale, and deployment (for operational prediction applications). This raises a fundamental dilemma between scientific rigor, exemplified by the slow and conservative peer-review processes performed by volunteer scientists, and the need for faster validation and deployment, namely an accelerated research-to-operations cycle. Fully adopting open-source practices, cloud-based infrastructures, digital twins, and the associated ecosystem of tools appears essential to support this paradigm shift, in addition to rethinking the peer-review process for rapidly evolving applications.

A useful way to accelerate progress in AI-based ocean predictions is to support community evaluation benchmarks that replicate what has proved successful in NWP (e.g., the WeatherBench framework Rasp et al. (2020, 2024)), further extending it to enable its inclusion in operational ocean forecasting chains. In practice, this means publishing a fully documented, versioned, portable and reproducible evaluation workflow that can be readily executed. Identifying and including reference verification datasets (reanalyses, in situ and satellite observation products, and any other high-quality product) in the benchmark infrastructure is another key aspect to ensure authority of the results, further to their reproducibility. Beyond traditional verification skill scores, the benchmark should incorporate metrics that test the physical consistency of the forecasts, such as, for instance, multivariate coherence (e.g., geostrophic consistency between SSH and currents, see, e.g., El Aouni et al. (2025b)), energy and conservation/closure diagnostics, and scale-aware measures (e.g., spectral diagnostics or scale-separated error measures), to reveal whether models reproduce the correct multivariate, multiscale variability. Several efforts are currently being devoted to benchmark developments (Jia et al. 2025, El Aouni et al. 2025a), favoring a routine understanding of strengths and weaknesses of AI-based predictions to guide their future evolution.

SUMMARY POINTS

1. Physics-based numerical models are one of the cornerstones of present-generation operational systems used for monitoring and forecasting ocean and sea-ice states.
2. Learning-based approaches, such as auto-regressive emulators, hybrid models, and

end-to-end model-free schemes, are calling into question the centrality of physics-based models in operational systems.
3. Learning-based approaches continue to rely on physical information, especially in contexts of sparse observational data, but integrate it in diverse ways for monitoring and forecasting.
4. Differentiable programming offers a unified framework for seamlessly integrating physics-based and learning-based approaches into optimized, end-to-end monitoring and forecasting pipelines.
5. Generative AI, which enables the representation of probabilistic parameter distributions, opens new avenues for improving uncertainty quantification in monitoring and forecasting systems.
6. The development of open benchmarks and datasets is essential to foster the evidence-based integration of learning-based approaches in operational oceanography.

FUTURE ISSUES

1. The integration of learning-based approaches into existing operational centers requires a technological transition—one that must be actively embraced by the operational community to ensure successful adoption and sustained impact.
2. The rapid evolution and diversity of approaches in this fast-moving field pose significant organizational challenges for their evaluation and integration into operational systems.
3. Among the available conceptual approaches—autoregressive emulators, hybrid models, and model-free methods—the optimal choice may vary depending on the target task, lead time, and resolution.
4. While establishing commonly agreed benchmarks is essential for fostering trust and guiding the future evolution of the field, coordinating their development remains a key challenge.
5. Beyond scientific performance, the accessibility and cost of GPUs, as well as the carbon footprint of training, must also be considered in the evaluation and adoption of new approaches.
6. The adoption of learning-based approaches may influence observational data collection strategies and will ultimately depend on the ability of trained models to generalize across diverse geographical regions.

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