Deep Learning to Infer Ocean Dynamics

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Citation:
Georgy E. Manucharyan, Scott A. Martin, Dhruv Balwada, Jinbo Wang. 2026. Deep Learning to Infer Ocean Dynamics. Annual Review of Marine Science 19:In press. https://doi.org/10.1146/annurev-marine-040324-023244

Annu. Rev. Mar. Sci. 2027. 19:1–26

https://doi.org/10.1146/annurev-marine-040324-023244

Keywords

Deep Learning, Ocean Dynamics, Neural Data Assimilation, Ocean Forecasting, Hybrid Models

Abstract

Inferring ocean dynamics remains challenging due to the complexity of multiscale nonlinear interactions, sparsity of observations, and limitations of numerical models. Deep learning (DL) has emerged as a powerful data-driven framework that exploits nonlinear dependencies across heterogeneous datasets, complementing traditional approaches. Here, we review recent progress in applying DL to ocean dynamics, including spatiotemporal interpolation of satellite and *in situ* data, estimation of unobserved ocean variables, neural data assimilation, ocean forecasting, and the development of eddy parameterizations for hybrid models. DL methods have excelled at fusing multimodal observations, reconstructing multiscale fields, learning complex distributions, and providing computationally efficient predictions that often match or exceed those of conventional statistical approaches. Despite the rapid methodological progress, opportunities remain in uncertainty quantification, ensuring physical consistency, generalization to unseen conditions, and leveraging DL beyond obtaining operational gains to advance scientific discovery and human-level understanding of ocean dynamics.

1. Introduction

Our understanding of ocean processes, advances in modeling capabilities, and the development of theories are grounded in observations. The establishment of global remote sensing and *in situ* observational platforms, combined with targeted observational campaigns, has been essential for inferring dynamical processes, including large-scale ocean circulation, meso- and submesoscale dynamics, internal waves, and mixing (Fu et al. 2010, Archer & et al. 2025, Wong et al. 2020, MacKinnon et al. 2017). Although the surface ocean benefits from relatively comprehensive remote sensing and drifter observations, the ocean interior remains sparsely observed through infrequent measurements from ships, buoys, and autonomous floats, particularly at eddy scales (Figure 1). The lack of direct observations of ocean currents, including vertical velocities, and co-located temperature and salinity measurements, limits our ability to test theories and evaluate models since process evaluation often requires higher-order statistical quantities such as vorticity and divergence, potential vorticity, kinetic energy spectrum, and spectral energy fluxes. The development of eddy parameterizations (Fox-Kemper et al. 2019) is also hindered by the complexity of observing eddy momentum and tracer fluxes, which require co-located, high-resolution measurements across a wide range of spatiotemporal scales. These observational limitations are compounded by challenges in modeling, resulting in global data assimilation models that do not constrain even the surface ocean state at scales smaller than large mesoscale eddies (Stammer et al. 2016), which limits forecast horizons, in part due to unresolved submesoscale dynamics (Sandery & Sakov 2017). These limitations have motivated the use of machine learning to augment conventional analysis methods by leveraging the rapidly growing volume of ocean data from both observations and high-resolution numerical simulations (Lai et al. 2025, Bracco et al. 2025).

Machine Learning (ML): a class of algorithms that learn statistical patterns from data without being explicitly programmed.

Deep Learning (DL): a machine learning approach that uses deep artificial neural networks with many hidden layers to learn hierarchical representations of data.

Recent advances in deep learning (DL), a machine learning (ML) approach that uses deep artificial neural networks (Goodfellow et al. 2016), have spurred rapid adaptation of these methods for ocean dynamics. DL seeks to efficiently extract information from limited, often diverse, data sources, with demonstrated advances in inference of ocean variables from incomplete or indirect observations (He & Mahadevan 2024, Martin et al. 2024), the exploration of variable co-dependencies (Sinha & Abernathey 2021, Fablet et al. 2024), data assimilation (Fablet et al. 2021, Martin et al. 2025), forecasting (Ham et al. 2019, Cui et al. 2025), and eddy parameterizations (Zanna & Bolton 2020, Bodner et al. 2025). Unconstrained by highly idealized analytical assumptions and free to exploit the intricate nonlinear dependencies in the data, DL methods are becoming complementary tools to established analysis methods and state-of-the-art numerical ocean modeling, which can omit many of the complexities of the real-world ocean in search of revealing fundamental mechanisms. This review focuses on the use of DL for inferring ocean dynamics, including studies that deduce, estimate, or reconstruct information about ocean motion and physical processes from available, often incomplete or indirect, ocean observations. We will begin the review by conceptually outlining how observations and numerical models have contributed to the development of DL frameworks, then review major applications in ocean dynamics, and discuss ongoing challenges and opportunities for future development.

2. Deep Learning Paradigms for Ocean Observations

A major application of DL is to establish non-linear mappings between inputs and outputs, including regression and classification, distribution approximation, conditional statistics,

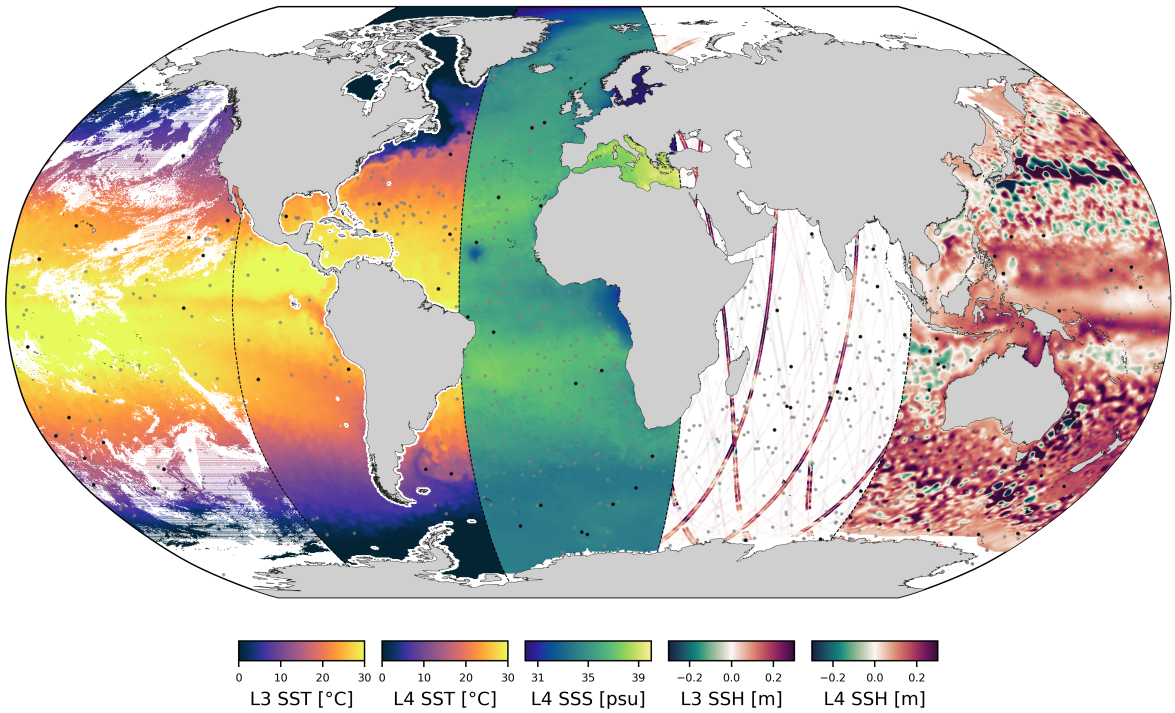

Figure 1

Multi-modal satellite observations of SST, SSH, and SSS, including sparse but higher-resolution "Level 3" (L3) and gap-filled but lower-resolution "Level 4" (L4) processing levels. From left to right: L3 SST, L4 SST, L4 SSS, L3 SSH from both nadir and wide-swath altimeters, and L4 SSH. Locations of *in situ* ARGO float profiles are shown over a preceding one-day (black points) and ten-day periods (gray points), emphasizing the sparsity of interior ocean observations for mesoscale and submesoscale ocean eddies.

and inference of time-evolution operators for dynamical ocean variables. In *supervised learning*, models are trained on paired input–output examples, such as mapping surface observations to subsurface properties, reconstructing ocean currents from satellite fields, or predicting future states from present states. These approaches require reliable targets and have been applied to a wide variety of oceanographic data, including remote sensing, in situ data, reanalyses, and numerical simulations. In contrast, *unsupervised learning* extracts structure from data alone, without labeled outputs, and is commonly used for clustering, identifying coherent patterns, or dimensionality reduction. The rapidly evolving *generative models* are designed to sample from complex, high-dimensional data distributions (e.g., ocean state variables) and can enable stochastic interpolation, uncertainty quantification, data augmentation, and acceleration of forecasting and data assimilation. The power of DL models lies in their expressivity, enabling them to represent complex, non-linear dependencies and extract information from multiple data modalities, such as remote sensing and *in situ* measurements, as well as physical and biogeochemical data, without specifying a dynamical or statistical model. DL architectures must be carefully tailored to specific datasets and tasks, with a wide range of architectures that have proven successful in processing spatiotemporally rich ocean data. This review focuses on the application of DL to

Generative Models: DL frameworks that generate samples statistically consistent with the data's probability distribution, enabling probabilistic predictions.

ocean dynamics, and we refer readers to the cited studies for details on DL architectures.

One could broadly group existing DL studies of ocean dynamics into (*i*) *conceptual studies* that test methods and explore fundamental dependencies within numerical models, (*ii*) *simulation learning*, where neural networks are exclusively trained on numerical ocean models but applied directly to observations, and (*iii*) *observational learning*, where training is fully or at least partially performed using real-world observations.

SST: Sea Surface Temperature

SSH: Sea Surface Height

SSS: Sea Surface Salinity

(*i*) *Conceptual studies* help test and develop DL methods and reveal plausible statistical relations between variables. Using ocean models of varying degrees of complexity, many studies identified mappings from well-observed surface quantities (e.g., SSH or SST) to dynamical quantities that are more challenging to observe, such as sub-surface density and currents (e.g. Manucharyan et al. 2021), surface kinematics (Xiao et al. 2023), vertical velocity (Zhu et al. 2023, He & Mahadevan 2024), or eddy fluxes (e.g. Bolton & Zanna 2019, George et al. 2021).

(*ii*) *Simulation learning* leverages ocean model simulations to provide clean, gridded training data that capture realizations of ocean dynamics and encode much of the known ocean physics. This is particularly useful when real-world observations are too sparse or low-resolution to support direct training. Here, synthetic observations are generated from ocean models to train DL models, which are then applied to real-world observations on inference (e.g. Buongiorno Nardelli et al. 2022, Febvre et al. 2024b, Lenain et al. 2026). This approach can be challenging when there are significant model errors in representing processes that affect real-world observations.

(*iii*) *Observational learning* bypasses the need for training on numerical simulations, learning directly from observations of the real ocean. Since observations generally exhibit greater complexity, sparsity, and noise contamination than ocean simulations, relatively few studies implement this learning strategy. Nonetheless, supervised or *self-supervised* learning has enabled training on the growing volume of remote sensing and *in situ* ocean observations (e.g. Ducournau & Fablet 2016, Su et al. 2020, Barth et al. 2020, Martin et al. 2023, Garcia et al. 2025). Observation learning can also be employed as a fine-tuning step, to help models pre-trained on simulation data adapt to real-world observations (e.g. Archambault et al. 2024). Despite its major benefit of not inheriting biases from numerical models, the fundamental limitation of observational learning is that it cannot be used to infer variables that were never observed.

Self-supervised learning: DL models learn to predict missing or altered components of the data by hiding or corrupting parts of the input fields.

3. Enhancing Observational Datasets using DL

Progress in physical oceanography has been propelled by the growing availability of high-quality satellite and *in situ* observations. These data, however, are heterogeneous and imperfect, affected by sparsity, measurement noise, limited resolution, and contamination by overlapping geophysical signals. Bridging incomplete observations with theory and numerical models has typically relied on hand-designed algorithms such as objective analysis and filtering. While effective, these approaches often attenuate and distort small-scale ocean dynamics. Consequently, one of the most widely explored applications of DL has been the enhancement of observational datasets, developing data-driven methods for denoising, bias removal, interpolation, and downscaling (resolution increase), and, increasingly, the inference of unobserved variables from available measurements. If DL can better preserve the small-scale dynamical signals present in raw observations, then integrating DL-enhanced datasets into downstream physical oceanography studies could offer new insights into ocean dynamics.

3.1. Denoising, bias removal, and calibration

In remote sensing, there is a delicate balance between removing sensor noise and preserving geophysically relevant signals. In recent years, DL has emerged as a denoising, bias removal, and calibration tool. By combining low-resolution SSH from nadir altimetry with high-resolution SWOT observations, Febvre et al. (2024a) proposed a method to reduce spatially correlated noise and contaminating signals without overly smoothing fine-scale SSH. Convolutional neural network denoising methods trained on high-resolution simulations are now applied to create the 'filtered' SSH variable in Level 3 SSH products from the Surface Water and Ocean Topography (SWOT) satellite mission (Gomez-Navarro et al. 2020, Tréboutte et al. 2023), though further evaluation is required to better understand if these methods attenuate or distort submesoscale SSH signals while removing noise. Cutolo et al. (2025) recently proposed a generative ensemble method trained on simulations for denoising SWOT SSH observations, which, upon application to real observations, showed significant improvement in the physical realism of the retained signal.

3.2. Spatiotemporal interpolation and downscaling

Spatiotemporal interpolation of sparse observations and downscaling of coarse observational products are central problems in physical oceanography, as analysis of ocean dynamics commonly requires gap-free fields of the highest possible resolution. Simulation-based learning provides a natural framework for method development. Using observing system simulation experiments (OSSE), Febvre et al. (2024b) showed that training 4DVarNet (see Section 4.1) on eddy-resolving simulations leads to substantial improvements in real-world SSH interpolation, outperforming objective analysis and variational data assimilation products. Performance improved systematically as more realistic, higher-resolution training simulations were used. Related approaches have demonstrated strong performance for SSH mapping from the SWOT mission (Beauchamp et al. 2023, Ballarotta et al. 2025), where the mismatch between sparse temporal and high-resolution spatial sampling makes interpolation fundamentally a dynamical problem. Simulation-trained models have also exploited multimodal synergies: combining low-resolution SSH with high-resolution SST improves the reconstruction of mesoscale and submesoscale currents (Buongiorno Nardelli et al. 2022, Fablet et al. 2024). Similarly, proof-of-concept studies suggest that simulation-trained DL methods can mitigate SST data gaps under clouds (Agabin et al. 2024, Goh et al. 2024, Beauchamp et al. 2025), although operational SST mapping remains an open challenge. These studies demonstrate the high value of using simulation data, but the resulting products could inherit model biases.

Observing System Simulation Experiments: frameworks using numerical model output as surrogate truth to evaluate observing systems and optimize data-driven methods before deployment.

An increasing number of studies demonstrate the benefits of training DL models directly on real-world observations. For example, it is possible to downscale SST and improve the representation of submesoscale features by mapping coarse-resolution microwave observations to higher-resolution infrared and *in situ* data (Ducournau & Fablet 2016, Fanelli et al. 2024). Self-supervised DL approaches for spatiotemporal interpolation of SSH leveraged additional concurrent SST observations, improving reconstructions across the wide gaps between altimeter tracks, as SST fields contain signatures of mesoscale eddy stirring (Barth et al. 2022, Archambault et al. 2023, Martin et al. 2023). Hybrid schemes combining simulation-based pre-training with observational fine-tuning have shown further gains in regional SSH mapping, highlighting the complementarity of the two paradigms (Archambault et al. 2024). Overall, DL methods show strong potential for interpolation and downscaling across a range of applications, although currently only a limited number have matured into widely used community datasets. An example of a publicly available DL dataset is Neural Ocean Surface Topography (NeurOST), which synthesized SSH and SST observations to provide global gridded SSH and surface geostrophic currents with improved mesoscale eddy dynamics (Martin et al. 2024) (see the sidebar titled "Insights into Mesoscale Eddy Dynamics Gained from a DL Dataset"). Examples beyond dynamical datasets include gridded dissolved oxygen concentration estimates (Sharp et al. 2022), enabled by DL training exclusively on *in situ* observations such as ARGO floats, while reconstructions of gap-free chlorophyll-*a* time series were enabled by learning physical-biological relations in global ocean models (Roussillon et al. 2023).

Insights into Mesoscale Eddy Dynamics Gained from a DL Dataset

With the emergence of DL-enhanced datasets, a lingering question arises: can they add new insights into ocean dynamics? Here, we provide an example based on NeurOST (Martin et al. 2024), a global DL-enabled SSH product trained exclusively on real satellite observations to predict gap-free, gridded SSH from sparse altimeter data, with SST as an auxiliary predictor to constrain small-scale structure between tracks. During training, a subset of altimeter observations is withheld from the input and used as sparse ground truth targets, enabling the model to learn from real observations without requiring high-resolution 2D ground truth (Martin et al. 2023). Gridded SSH and surface geostrophic currents from NeurOST revealed qualitatively different eddy evolution and propagation in many regions. For example, in the subtropics, the community-standard DUACS product (Taburet et al. 2019) exhibits uniformly westward-propagating, weakly interacting mesoscale eddies, whereas NeurOST reveals strongly interacting eddies with little westward propagation. The uniform westward propagation in DUACS is likely an artifact of the mean propagation velocities assumed in the covariance structure of the objective analysis method, whereas NeurOST avoids these biases by learning directly from observations (Martin et al. 2024). In the subtropical counter-current, NeurOST revealed a seasonal upscale kinetic energy cascade, with a magnitude strong enough to support the hypothesis that submesoscale eddies drive the seasonality of large mesoscale eddies, bringing SSH observations into closer agreement with high-resolution simulations (Sasaki et al. 2014). On the contrary, the kinetic energy cascade and its seasonality are largely suppressed in DUACS due to its exaggerated interpolation smoothing. As a publicly available dataset, NeurOST further enables physical insight in downstream studies, e.g., on the formation of deep submesoscale fronts by mesoscale eddies (Siegelman et al. 2025) or for isolating baroclinic tides in SWOT observations (Zaron et al. 2026).

3.3. Estimation of Unobserved Ocean Variables

We broadly split the review of DL applications for estimating unobserved variables into two categories: studies that estimate surface ocean currents from a wide range of *in situ* and satellite observations, and studies that infer the subsurface state from surface observations.

3.3.1. Surface Ocean Currents. Surface ocean currents are not currently directly observed by existing satellites and are only sparsely sampled by surface drifters. The development of DL SSH mapping methods (Section 3.2) has led to improved global observations of mesoscale surface ocean currents by applying geostrophic (or cyclo-geostrophic) balance (Martin et al. 2024). Other approaches have used high-resolution, but sparse, geostrophic currents from wide-swath altimetry as ground truth to train a DL model to estimate surface geostrophic currents from SAR observations (Sun et al. 2025). However, a substantial fraction of the surface currents, especially at submesoscales, cannot be directly retrieved from the SSH alone because they are ageostrophic (see the sidebar titled "Inference of Surface Submesoscale Dynamics from Wide-Swath Altimetry"). Several simulation-learning studies have shown that submesoscale ageostrophic surface currents can be inferred by combining SSH and SST (Sinha & Abernathey 2021, Xiao et al. 2023, Fablet et al. 2024) or by leveraging the geostationary satellite's hourly sampling of SST (Lenain et al. 2026) or ocean color (chlorophyll-a concentrations) (Ding et al. 2026). Although these methods show promising capabilities, further research is required to assess the extent to which biases from numerical ocean models used for training propagate into reconstructions of real-world observations. Several observational learning approaches (not relying on numerical ocean models for training) demonstrated that DL models can be trained on data points where high-resolution altimetry and surface drifter observations coincide (Zhou et al. 2025), or inferred currents directly from drifters by approximating the evolution equations using a sparse regression approach and using those for a physics-informed neural network (Bang et al. 2025). Generally, DL methods demonstrated a significant reduction in reconstruction errors for surface currents, enabled by synthesizing data from different sources, such as SST, SSH, and drifters, and/or using eddy-resolving numerical simulations as ground truth for training.

3.3.2. Surface-to-subsurface Inference. At mesoscales and smaller, the ocean interior observations remain sparse and intermittent, while the surface ocean is much more comprehensively observed (Figure 1). DL attempts to address this disparity by inferring interior quantities from surface observations through both simulation learning, where three-dimensional fields are available for training, and observational learning, which constructs surface-to-interior mappings using sparse *in situ* observations. Vertical velocity, for example, is essentially unobservable at global scales, but recent work has shown that three-dimensional structure can be inferred from SSH snapshots alone in controlled settings (Zhu et al. 2023), with additional SST and wind observations potentially enabling its kilometer-scale reconstructions (He & Mahadevan 2024). Such results remain largely conceptual, but they illustrate that aspects of interior ocean dynamics may be recoverable from the vast surface-confined data. Observational learning studies focused on synthesizing multimodal satellite and *in situ* observations from ARGO floats and other platforms. Meng et al. (2021) used simulation learning for subsurface temperature inference that was then fine-tuned using ARGO data, while Zhang et al. (2023b) employed a similar approach but fine-tuned on an ocean reanalysis model instead. Yu et al. (2025) demonstrated that information on surface waves significantly improves upper-ocean temperature and salinity reconstruction from surface fields. Su et al. (2020) estimated global ocean heat content and assessed its decadal variability by synthesizing multi-source satellite remote sensing data with ARGO observations. DL studies seem to converge on the notion that a substantial amount of information about the ocean interior state is indeed encoded on its surface, an idea with a long history in theoretical studies of eddy dynamics (e.g., Lapeyre & Klein 2006, Wang et al. 2013). Finally, a number of studies have explored the extent to which global-scale

Inference of Surface Submesoscale Dynamics from Wide-Swath Altimetry

Submesoscale dynamics, with waves, fronts, filaments, and fluctuations from a myriad of instabilities, lack well-established geostrophic balance relations. Because these dynamics are too large for ship surveys and too small for conventional altimetry satellites, they have historically been difficult to observe, though this is changing with the emergence of high-resolution, wide-swath altimetry from satellites like SWOT (Archer & et al. 2025). Although km-scale surface observations demonstrate the prevalence of submesoscale variability, a fundamental challenge for inferring ocean currents lies in separating the mixed imprints of balanced and unbalanced signals in sparse surface observations, a problem that is inherently underdetermined. The use of ML to disentangle these nonlinear patterns is rationalized as the textures of the balanced and unbalanced phenomena can appear visually distinct (Cheng & Ménard 2021, Skinner et al. 2025). Trained on high-resolution simulations, DL models demonstrate that an approximate pattern separation may indeed be plausible (Lguensat et al. 2020, Wang et al. 2022, Gao et al. 2024, Lyu et al. 2024, Wang et al. 2025b). However, it is unclear how well these model-based training approaches will generalize to real-world observations, as even submesoscale-resolving models overly simplify dynamics and exhibit significant biases (Uchida et al. 2022, Archer & et al. 2025). Observational DL has been used to combine high-resolution altimetry with high-frequency-radar velocity to decompose SSH into balanced and unbalanced components (Wang et al. 2025a) or with drifter observations to infer total ocean currents (Zhou et al. 2025). While demonstrating significant skills in statistical evaluations, these observation-based approaches can be biased by observational and representation errors, particularly when reconstructing submesoscale processes. Significant opportunities therefore remain in determining how best to integrate submesoscale-resolving simulations and observations to fully exploit global wide-swath altimetry data for inferring submesoscale dynamics.

flows, such as the Meridional Overturning Circulation, can be constrained by surface observables, including SSH, SST, SSS, and ocean bottom pressure (Solodoch et al. 2023, Wei et al. 2025), which led to improved understanding of its historical variability (Michel et al. 2025, Medvedev et al. 2026).

Latent space: an abstract internal space in which a neural network encodes learned representations of the input data.

3.4. Classification of dynamical features in physical and latent spaces

Partitioning the ocean into distinct dynamical features such as gyres, eddies, and fronts provides an alternative language for describing and interpreting observations. DL approaches offer objective, automated methods for such classifications. A common example of ocean classification is automated eddy detection from remote sensing observations (e.g. Moschos et al. 2020, Liu et al. 2021). However, most approaches still rely on labels generated by conventional eddy-detection algorithms and hence inherit their assumptions and limitations, unless additional supervision sources are included or only high-fidelity subsets of data are considered (Moschos et al. 2020). A more explicitly dynamics-focused example is the identification of leading-order balances and gyre boundaries based on the barotropic vorticity budget (Sonnewald et al. 2019). Learning low-dimensional representations of high-dimensional ocean data (Prochaska et al. 2023) has been used to evaluate high-resolution ocean simulations against observations in latent rather than physical space (Gallmeier et al. 2023), capturing subtle structural differences that are difficult to diagnose with traditional metrics such as power spectra. Cutolo et al. (2024) developed a DL framework that first transforms remote sensing images into fuzzy clusters to extract information on the shapes of surface ocean features, and then leverages non-local relations in this latent cluster space to interpolate surface fields and infer the three-dimensional deep ocean state. Characterizing ocean dynamics in a learned latent space remains a nascent research direction, and key questions remain about the physical interpretability and robustness of learned representations.

Variational Data Assimilation: numerical model state estimation obtained by iteratively minimizing deviations from observations and a prior state estimate.

4. Neural Data Assimilation

Data assimilation (DA) combines numerical models with observations with the aim of producing physically consistent estimates of the ocean state (Stammer et al. 2016). The widely used variational DA (Weaver et al. 2003) enables inference over unobserved variables but requires an adjoint model and is computationally intensive, thereby limiting its global-ocean applications to mesoscale-resolving or coarser models. DA with three-dimensional ocean models is poorly suited for many applications in which only small subsets of observables or subdomains are of interest, such as surface-only reconstructions. DA products can also inherit biases from their underlying ocean models. These challenges motivated the development of ML methods that do not specify a dynamical model but are in many ways similar to variational DA (Geer 2021, Cheng et al. 2023).

4.1. Variational DA–Inspired DL

The similarities between DL and DA have motivated hybrid methods that replace selected components of DA with neural networks. A prominent example in ocean state estimation is *4DVarNet* (Fablet et al. 2021), which has been applied to SSH mapping (Beauchamp et al. 2023, Febvre et al. 2024b), ageostrophic current inference (Fablet et al. 2024), and SST reconstruction beneath clouds (Beauchamp et al. 2025). 4DVarNet is inspired by the classical 4D-Var cost function (Weaver et al. 2003),

$$\mathcal{L}(x, y, \Phi) = \lambda_1 \left\| \mathcal{A}(x) - y \right\|_2^2 + \lambda_2 \sum_i \left\| x(t_i) - \Phi(x(t_i - \Delta t)) \right\|_2^2, \qquad 1.$$

where $\mathcal{A}(x)$ is the observation operator acting on the state x and compared to observations y, $\Phi(x(t-\Delta t)) \mapsto x(t)$ represents a dynamical prior (the time-evolution operator), and $\lambda_{1,2}$ are weighting coefficients. In classical 4D-Var, this objective is minimized iteratively using adjoint gradients from a known physical model Φ, whereas in 4DVarNet, the dynamical operator Φ and the gradient-based minimization procedure itself are replaced by neural networks, with the whole framework trained end-to-end. Its architecture can be further improved by regularizing Φ to capture more physically meaningful dynamics (Beauchamp et al. 2023) and enabling uncertainty quantification (Lafon et al. 2023). This approach is well-suited to simulation-based learning and has been shown to generalize to real-world data (Febvre et al. 2024b). However, it can result in blurry, physically unrealistic ocean states when only sparse or coarse observations are available, as there is no physical constraint.

4.2. Data Assimilation Using Generative DL

From a Bayesian perspective, ocean state estimation can be posed as sampling from the posterior probability distribution $p(x \mid y)$, where x denotes the considered ocean state and y the available observations, subject to some prior $p(x)$ representing physically plausible

Score-Based Diffusion Models

Score-based diffusion models are built around a simple idea: data samples, x, are gradually corrupted by noise, and a DL model is trained to reverse this process. The forward corruption process adds Gaussian noise of increasing magnitude to a data sample x_0,

$$x(\tau) = x_0 + \sigma(\tau)\,\epsilon, \tag{2.}$$

where τ indexes the corruption level and $\sigma(\tau)$ is a specified monotonically increasing noise scale of a standard normal distribution, $\epsilon \sim \mathcal{N}(0, I)$. The structure in the corrupted sample, $x(\tau)$, is progressively removed until it approaches a normal distribution. The probability flow ordinary differential equation (ODE) (Song et al. 2020, Karras et al. 2022) provides a continuous description of how samples move through intermediate noisy distributions $p(x; \sigma(\tau))$:

$$\frac{dx}{d\tau} = -\dot{\sigma}(\tau)\,\sigma(\tau)\,\nabla_x \log p(x; \sigma(\tau)), \quad x(0) = x_0, \quad \dot{\sigma} = \frac{d\sigma}{d\tau}. \tag{3.}$$

Here, $\nabla_x \log p(x; \sigma)$ is the *score*, pointing toward regions of higher probability of the noise-corrupted distribution and approximated using a neural network trained to denoise the samples (Karras et al. 2022). Integrating the ODE backward transports pure noise realizations toward plausible samples from the original data distribution. Alternative formalisms often replace the ODE with a stochastic differential equation (Song et al. 2020).

ocean states. Recently developed deep generative methods aim to generate samples from the full posterior, enabling uncertainty-aware ensemble state estimation, which is particularly pertinent for sparsely observed mesoscale and submesoscale ocean dynamics. But how can we sample from a set of physically plausible ocean states that occupies a highly structured and tiny subset of high-dimensional state space? Generative models frame this as transforming samples from a known distribution (*e.g.* Gaussian) into samples that appear to be drawn from a training data distribution. Although there are several approaches, including Generative Adversarial Networks (Goodfellow et al. 2014) and flow-based models (e.g. Papamakarios et al. 2021, Lipman et al. 2022), score-based diffusion models (see Song et al. (2020), Karras et al. (2022) and the sidebar titled "Score-Based Diffusion Models") have found prominent applications in atmospheric science (Manshausen et al. 2025) and oceanography (Martin et al. 2025, Asefi et al. 2025, Han et al. 2025). The score-based diffusion model serves as an illustrative backbone for conditional and guided unconditional generative data assimilation.

4.2.1. Conditional Generative Models for Ocean Data Assimilation.

Conditional Generative Model: generative DL model trained to condition its prediction on some input, for example, sparse observations.

Conditional generative models aim to generate plausible ocean states, x, conditioned on some observations, y. Training such models requires paired data (x, y), typically constructed by subsampling fields from GCM simulations to emulate the observing system. Within the diffusion framework, conditioning is implemented by augmenting the denoiser to take observations as input, thereby learning the conditional score $\nabla_x \log p(x \mid y; \sigma)$. This approach is particularly well-suited to underdetermined problems, such as inferring the ocean interior from surface measurements. For example, Souza et al. (2025) showed that conditioning a diffusion model on sea surface height (SSH) yields a distribution of interior states whose spread depends on observational information content: coarse SSH leads to a broad, weakly constrained posterior, while high-resolution SSH produces a much tighter distribution. Other recent applications include downscaling of surface fields (Han et al. 2025) and inference of ocean currents from drifters (Asefi et al. 2025).

Unconditional Generative Model: generative DL model trained to make predictions without reference to any input conditioning variable.

Guidance: steering the generation process of a diffusion model to produce samples that satisfy specific conditions, such as consistency with observations or physical constraints.

4.2.2. Guiding Unconditional Generative Models with Sparse Observations. Conditional generative models must be retrained when the observing system changes and do not explicitly account for observation errors. An emerging alternative is to *guide* the reverse denoising process of an *unconditional* diffusion model toward observations (Chung et al. 2022, Rozet & Louppe 2023). This guidance enables posterior sampling without retraining the generative model. Using Bayes' rule, the posterior score decomposes as

$$\nabla_x \log p(x \mid y; \sigma) = \nabla_x \log p(x; \sigma) + \nabla_x \log p(y \mid x; \sigma), \qquad 4.$$

where the first term is the unconditional score learned during training, and the second encodes the observation likelihood, which must be approximated at finite noise levels. Rozet & Louppe (2023) approximate $p(y \mid x; \sigma)$ using a Gaussian centered on the model-predicted observations, with a variance that increases with σ. By specifying the observation operator only at inference, a single unconditional model can be reused across many observing systems without retraining, a major advantage over conditional generative models.

Although the limits of likelihood approximations still need to be understood (Babu et al. 2025), this framework enables guided generation and allows incorporation of observation errors through the covariance of the assumed Gaussian. This method was applied to mesoscale eddy-resolving surface ocean state estimation from multimodal, multi-resolution satellite data (Martin et al. 2025). Trained on eddy-resolving simulations, multi-variate surface state estimation is achieved by comparing the predicted state to sparse satellite observations at each diffusion step to guide the model to maximize the observation likelihood while satisfying the learned simulation prior (Figure 2). This approach enabled inference of unobserved ageostrophic currents, downscaling of SSS from SST observations, and showed signs of learned physics consistent with cyclogeostrophy. Such real-world applications demonstrate the power of generative DA in mimicking physical realism by generating states that resemble those of a physics-based numerical model.

5. Ocean Forecasting

Ocean prediction has conventionally relied on numerical models or statistical approaches. DL offers a powerful alternative: by learning the nonlinear evolution operator directly from observations or simulations, neural networks can produce faster and often more accurate forecasts. We distinguish between two related applications: *phenomenon forecasting*, which targets specific ocean processes or variables, and *ocean state forecasting*, which aims to predict all prognostic variables, effectively emulating numerical ocean models.

5.1. Phenomenon forecasting

DL-based forecasting has been explored for many ocean processes, with notable examples including prediction of SSH (Shao et al. 2021, Chattopadhyay et al. 2024, Zheng et al. 2025b, Brettin et al. 2025), surface ocean currents (Thongniran et al. 2019, Immas et al.

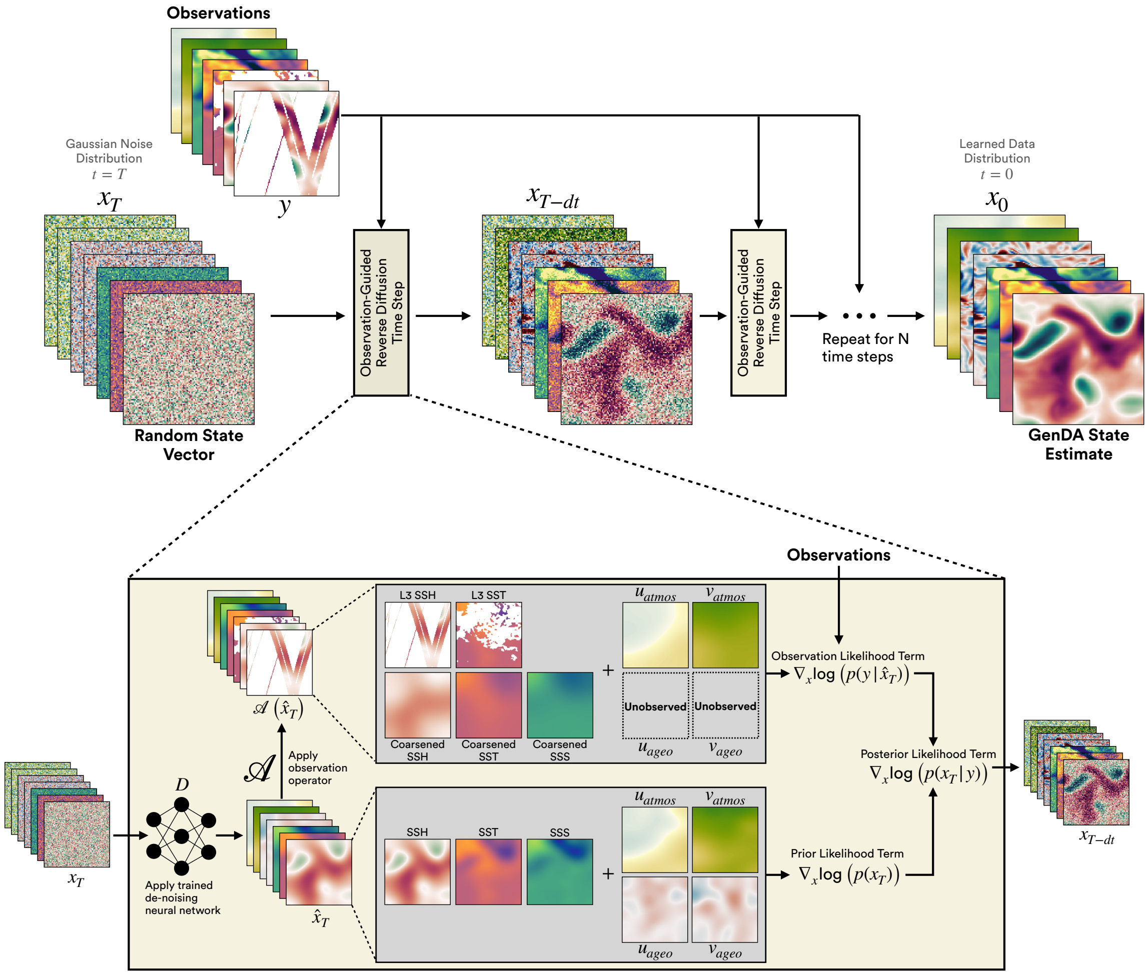

Figure 2

Schematic of surface ocean state estimation by guiding an unconditional diffusion model, $\mathcal{D}$, with observations, y. Repeated observation-guided denoising steps transform random noise into a realistic ocean state. An expanded view shows how an observation operator, $\mathcal{A}$, is applied to the unconditional diffusion model output to estimate the observation likelihood, which is then combined with the prior term to sample from the posterior. Figure from Martin et al. (2025).

2021, Garcia et al. 2025), SST and subsurface temperature anomalies (Zhang et al. 2020), and surface waves during storms (Wei 2021). Although architectures and pipelines are often tailored to specific datasets and tasks, the main challenge is the limited information in observable predictor variables. For example, relying solely on past observations to forecast SST is insufficient, as SST's evolution is directly influenced by atmospheric winds, heat fluxes, and ocean circulation, which are often unobserved. Consequently, neural forecasts can suffer from poor generalizability and exhibit increasingly unphysical evolution over time, even though they remain more skillful than numerical ocean models for longer. To improve realism, studies have introduced higher-order statistical constraints on the generated ocean

Autoregressive Forecasting

Neural forecasting is typically formulated as supervised learning where a neural network, $\mathcal{F}_\theta$, with parameters θ, predicts the future state $\boldsymbol{X}^{t+1}$, given N past times and auxiliary variables or boundary conditions, $\boldsymbol{\tau}$:

$$\boldsymbol{X}^{t+1} = \mathcal{F}_\theta(\{\boldsymbol{X}^{t-N}, .., \boldsymbol{X}^{t}\}, \boldsymbol{\tau}^{t}). \qquad 5.$$

Here $\boldsymbol{X}$ represents variables of interest, which, for ocean state forecasting, include three-dimensional temperature, salinity, and velocity, as well as SSH. The parameters of $\mathcal{F}_\theta$ are optimized by minimizing a loss function, $\mathcal{L}$, where the predicted state $\boldsymbol{X}^{t+1}$ is compared to the true state $\hat{\boldsymbol{X}}^{t+1}$:

$$\mathcal{L} = \overline{(\hat{\boldsymbol{X}}^{t+1} - \boldsymbol{X}^{t+1})^2} + \sum_j \lambda_j L_j(\hat{\boldsymbol{X}}^{t+1}, \boldsymbol{X}^{t+1}), \qquad 6.$$

commonly involving a weighted mean-square-error (overline) and additional components L_j, weighted by hyperparameters λ_j, to include physics-inspired constraints or improve specialized metrics. Training may use gridded time series from ocean models, observations, or reanalyses; predictions over longer horizons are made autoregressively, feeding past predictions back as inputs. These networks can take relatively large time steps that would not be possible in traditional numerical models because of the stability requirements of their integration schemes. An alternative formulation is to learn the time-evolution operator, $\dot{\boldsymbol{X}} = F_\theta(\boldsymbol{X}, \boldsymbol{\tau})$, and advance the state through numerical integration (Chen et al. 2018, Chattopadhyay et al. 2024).

state. For example, loss function terms that enforce realistic kinetic energy spectra (Chattopadhyay et al. 2024) or spectral energy fluxes (Zheng et al. 2025b) improve the predicted mesoscale eddy field and achieve better generalization.

Neural forecasting is also increasingly deployed for climate-scale ocean variability, including sea-ice evolution (Kim et al. 2020, Andersson et al. 2021), marine heatwaves (Sun et al. 2024, Shu et al. 2025), and ENSO (Tangang et al. 1998, Ham et al. 2019). Several methodological themes emerge across these applications. Pretraining on climate simulation ensembles followed by fine-tuning on observations has proven effective at mitigating observational sparsity (Andersson et al. 2021). Bias correction of physical models offers another path to improved skill (Sun et al. 2024), while hybrid approaches that learn only the unknown terms in conservation laws, with forecast target as objective, can improve dynamical consistency (Shu et al. 2025). DL models have demonstrated significant ENSO forecast skill, outperforming numerical models (Ham et al. 2019, Wang et al. 2023, Chen et al. 2025), and subsequent work has developed explainable architectures to identify physically interpretable precursors (Zhao et al. 2024).

5.2. Ocean state forecasting

DL is also used to predict the full set of prognostic variables, effectively learning to evolve the entire three-dimensional ocean state (e.g. Xiong et al. 2023, Wang et al. 2024, Cui et al. 2025). These approaches offer advantages over numerical ocean models. A striking result across many studies is that neural forecast models run orders of magnitude faster and, on standard skill metrics, outperform the very numerical ocean models that generated their training data, including reanalyses used to supply initial conditions. The speedup arises because these models run efficiently on GPUs and can take large time steps, whereas ocean models are constrained by the stability limits of their discretization schemes. The improved accuracy is possible because these models do not need to satisfy dynamical equations at each step, giving them the flexibility to approximate the evolution operator in ways that minimize predictive error by capturing empirical regularities in ocean variability.

As a well-defined, quantitatively measurable task, ocean state forecasting provides a natural testbed for systematic method comparison and improvement. Progress from early conceptual models (Xiong et al. 2023) to more recent systems has required avoiding model-train/model-predict bias by validating against satellite and *in situ* observations (Yang et al. 2024, Cui et al. 2025, Zheng et al. 2025a, Huang et al. 2025). Benchmarking initiatives such as OceanBench (El Aouni et al. 2025) demonstrate the value of shared protocols and standardized metrics. Several methodological advances have improved on the basic autoregressive formulation (see the sidebar titled "Autoregressive Forecasting"), including loss function terms that emphasize eddy features through tendency correlations (Zheng et al. 2025a), training strategies that first predict single steps then fine-tune on multiple steps to reduce error accumulation (Huang et al. 2025), direct multi-step prediction for long-term stability (Dheeshjith et al. 2025, Guo et al. 2025), and improved time integration schemes (Chattopadhyay et al. 2024). Metric choice also requires care: commonly used mean squared error (MSE) overemphasizes large-scale features, while continuous ranked probability scores may be more appropriate for eddy-resolving ensemble forecasts (Cui et al. 2025). Although current work focuses on improving forecasting accuracy metrics, with further development, these models can ultimately serve as "foundation" or "backbone" models for a wide range of downstream applications beyond forecasting (Xiong et al. 2023). Their internal encoders and decoders could be repurposed or fine-tuned for tasks such as state estimation, downscaling, extreme-event prediction, bias correction, and sensitivity analysis. Coupling separately trained DL ocean and atmosphere models is emerging as a viable path toward fully data-driven Earth System Models that reproduce coupled ocean–atmosphere variability (Cresswell-Clay et al. 2025, Duncan et al. 2025).

Foundation models: general-purpose DL models trained on diverse data sources to learn transferable representations used in downstream applications without retraining from scratch.

However, neural forecasting, whether targeting specific phenomena or the full ocean state, comes with important limitations. The generated evolution is not guaranteed to be physically sound and may include artifacts such as spontaneous warming/cooling or unforced changes in currents; importantly, it is not yet common practice to quantify how unphysical these predictions are, which limits their scientific applications. Model generalizability is also limited, especially for rare or unseen (long-tail) events. Most approaches produce deterministic trajectories, which are poorly suited for chaotic, eddy-rich regimes where generative ensembles are preferred to quantify uncertainty. Operationally, forecasting models depend on external state estimation and atmospheric boundary conditions from conventional data-assimilation systems, highlighting the absence of mature neural data assimilation and fully coupled atmosphere–ocean forecasting. Caution is also needed when evaluating ocean-only models (e.g. Wang et al. 2024, Cui et al. 2025, Dheeshjith et al. 2025), as prescribed atmospheric boundary conditions encode significant information about the ocean interior, obscuring whether skill arises from learned dynamics or surface-subsurface inference. More fundamentally, without mechanisms for continual model improvement using real-world observations, the over-reliance on imperfect numerical ocean models during training can lead to their biases being inherited and even amplified.

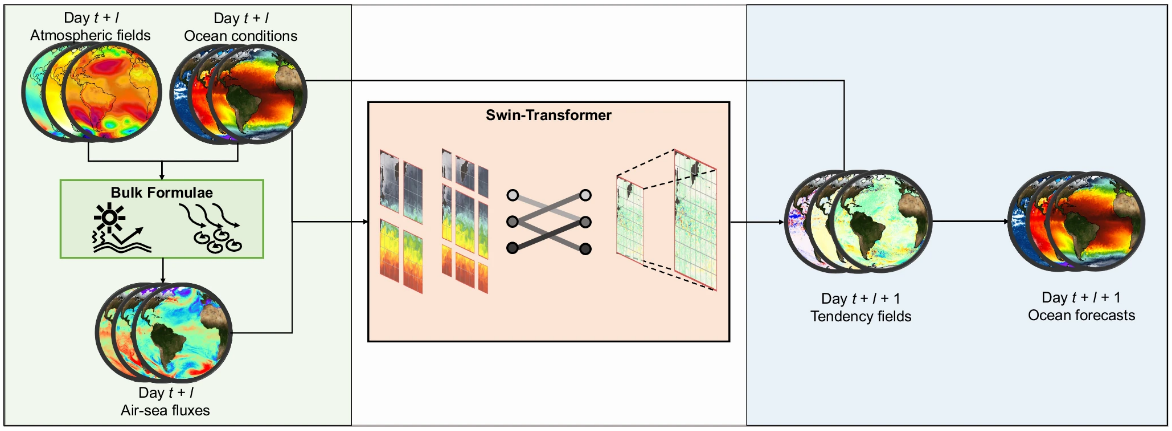

Figure 3

A DL global ocean forecasting system, WenHai (Cui et al. 2025), targeting mesoscale eddy variability over daily to weekly lead times. The air-sea momentum, heat, and freshwater fluxes are first computed using the bulk formulae (green block) for a given initialization date t and forecast lead time l in one-day intervals. The ocean variables and air-sea fluxes are used as inputs to a deep neural network (red block) that is trained to forecast the temporal tendency of ocean variables, from which the ocean forecast is derived (blue block). Forecasts over multiple days are made autoregressively. Figure from Cui et al. (2025).

6. Hybrid Modeling

Since numerical ocean models only resolve processes over a limited range of scales, the impact of unresolved (sub-grid-scale) processes is missing and must be parameterized or represented in terms of the resolved variables (see the sidebar titled "Sub-Grid Parameterizations"). Traditional approaches in oceanography have addressed this closure problem through physically motivated parameterizations that aim to capture the highly idealized representation of the bulk effects of the missing processes (Fox-Kemper et al. 2019). ML-based parameterizations can potentially learn the intricate details of realistic situations, where bulk eddy effects are influenced by the spatial and temporal variability of the mean flow and its instabilities, stratification, external forcing, and bathymetry and coastline effects. Deployed in numerical models, ML parameterizations form hybrid models that rely on the dynamical core for the resolvable dynamics and ML for the unresolved effects (Irrgang et al. 2021, Zanna et al. 2025).

Although early applications of neural networks for ocean parameterizations, in particular for air-sea flux parameterizations, date back nearly two decades (Bourras et al. 2007), their rapid adoption for other processes only started a few years ago (Bolton & Zanna 2019). Given this recency, only a limited number of processes have been targets for ML parameterizations so far. The major focus has been on parameterization of mesoscale eddies in the open ocean (Bolton & Zanna 2019, Zanna & Bolton 2020, Guillaumin & Zanna 2021, Perezhogin et al. 2024, Zhang et al. 2023a, Srinivasan et al. 2024, Ross et al. 2023, Perezhogin et al. 2025, Balwada et al. 2025). More recently, boundary layer turbulence (Ramadhan et al. 2020, Sane et al. 2023, Zhu et al. 2022, Lee et al. 2025), air-sea fluxes (Wu et al. 2025, Busecke et al. 2025), submesoscale turbulence (Bodner et al. 2025, Zhou et al. 2024, Feng et al. 2025), and mesoscale turbulence near continental shelves (Xie et al.

Sub-Grid Parameterizations

As an illustrative example of what sub-grid terms correspond to, consider the momentum conservation law:

$$\frac{\partial \boldsymbol{u}}{\partial t} + (\boldsymbol{u} \cdot \nabla)\boldsymbol{u} = -\frac{1}{\rho_0}\nabla p + \boldsymbol{F}(\boldsymbol{u}), \tag{7}$$

where $\boldsymbol{u}$ is the velocity field, ρ_0 is a reference density, p is the pressure field, and $\boldsymbol{F}$ represents sources and sinks (dissipation) of momentum computed from ocean state variables. Applying a linear averaging operator (overbar) yields the evolution of filtered variables, which may be representable in a coarse-resolution numerical model:

$$\frac{\partial \bar{\boldsymbol{u}}}{\partial t} + (\bar{\boldsymbol{u}} \cdot \nabla)\bar{\boldsymbol{u}} = -\frac{1}{\rho_0}\nabla \bar{p} + \overline{\boldsymbol{F}(\boldsymbol{u})} + \boldsymbol{S}, \text{ where } \boldsymbol{S} = (\bar{\boldsymbol{u}} \cdot \nabla)\bar{\boldsymbol{u}} - \overline{(\boldsymbol{u} \cdot \nabla)\boldsymbol{u}}. \tag{8}$$

Here $\boldsymbol{S}$ is the acceleration from unresolved or sub-grid momentum flux divergence. Generally, $\overline{\boldsymbol{F}(\boldsymbol{u})} \neq \boldsymbol{F}(\bar{\boldsymbol{u}})$ due to nonlinearities in the mixing and boundary fluxes (Busecke et al. 2025). A traditional or ML parameterization solves the closure problem by representing $\boldsymbol{S}$ and $\overline{\boldsymbol{F}}$ in terms of the filtered variables.

2023) have also been targeted. In addition to targeting specific processes or scales, some studies have also explored approaches that directly target the error in a coarse-resolution model by trying to match its state with a more truthful model state from a reanalysis or high-resolution model (Meunier et al. 2025, Frezat et al. 2022, Yan et al. 2024) or by learning errors that are diagnosed by a data assimilation system (Du et al. 2025, Verma et al. 2025).

The neural parameterizations differ in a number of ways, including definition of the terms or dynamics being parameterized, architectural choices and optimization objective, sources of training data, and intended deployment strategies, in which existing parameterizations can be either augmented or entirely replaced. When individual processes are targeted, training data may be obtained from more realistic high-resolution simulations (e.g. Perezhogin et al. 2025, Balwada et al. 2025), idealized LES-simulations meant to produce specific processes (e.g. Ramadhan et al. 2020), or from reduced-order models (e.g. Sane et al. 2023). When the scaffolding of traditional parameterization is presumed to provide benefits, neural parameterizations replace its components or estimate its parameters; when the structural errors or biases of traditional parameterizations are too large, completely new models are designed. Architectural choices include multi-layer perceptrons, convolutional and residual layers, and alternative approaches such as equation discovery via sparse regression. A complementary thread embeds physical structure into the architecture itself: Zanna & Bolton (2020) demonstrate the value of conservation laws as structural constraints, an approach extended by more recent nascent attempts to leverage fully differentiable ocean models (e.g. Mrozowska et al. 2025, Meunier et al. 2025). Across many of these efforts, skill tends to plateau, suggesting that eddy parameterization may be an inherently underdetermined and/or stochastic problem that likely cannot be fully resolved by deterministic ML models alone, and there may be a need to advance towards ML-based probability models Wu et al. (2025). While many proof-of-concept studies have demonstrated success, only a fraction of neural parameterizations have so far been incorporated into full-complexity ocean circulation models (e.g. Sane et al. 2023, Perezhogin et al. 2025, Balwada et al. 2025).

7. Perspectives

7.1. Synthesis

In this review, we have provided examples of rapidly growing research applications that use data-driven DL methods to infer ocean dynamics from multivariate and heterogeneous ocean observations and numerical simulations. Conceptual DL studies using numerical simulations reveal that interconnections between dynamical variables can be used to infer the unobserved ocean state. Surface footprints of mesoscale and submesoscale turbulence on dynamical variables such as SST and SSH, as well as on biological tracers such as chlorophyll, have been shown to contain significant information about the interior ocean state, enabling reconstructions of subsurface hydrography and vertical velocities. DL has demonstrated its advantage in extracting task-specific information from diverse data modalities, including observables not represented in ocean models. Tailored DL denoising and spatiotemporal interpolation models for sparse observations have yielded datasets that better preserve smaller-scale features than conventional objective mapping techniques. In blending numerical models and observations, DL methods have also made significant progress, with neural data assimilation methods, particularly generative models, enabling more accurate, high-resolution state estimation than conventional variational methods for specific surface variables and regional applications. Similar progress has been made in neural ocean forecasting, targeting either a specific phenomenon or the entire ocean state, where DL models outperform numerical forecast models on standard skill metrics. The development of hybrid models, in which DL replaces specific sub-grid-scale parameterizations, enabled more accurate and faster low-resolution simulations. These examples point to the growing role of DL as a tool to address practical problems with well-defined quantitative objectives. Beyond the scientific promise demonstrated by these examples, the rapid uptake of DL has also been enabled by the maturity of modern software stacks (*e.g.*, PyTorch, JAX), which are largely problem-agnostic and impose a low barrier to entry — a trend now further accelerated by the rise of agentic coding tools.

The same accessibility that has driven this rapid adoption, however, also makes it easy to deploy DL models without commensurate scrutiny, and several fundamental challenges limit their current impact on the physical understanding of ocean dynamics. DL models remain weakly constrained by physical principles because incorporating hard dynamical constraints into flexible neural architectures is non-trivial, and insufficient emphasis has been placed on this problem. It is not common practice to systematically assess the dynamical consistency of DL-generated ocean states, leaving concerns about the realism of the inferred dynamics unaddressed. Perhaps as a consequence of reliability concerns, the use of DL datasets in research has been limited, even as the field grows with the emergence of publicly accessible DL-enhanced datasets. The widespread reliance on simulation learning, in which DL models are trained on numerical simulations and then applied to observations, has proven effective for ocean state estimation and forecasting. However, robust uncertainty quantification of simulation errors that are inherited and perhaps even amplified by imperfect training remains poorly established. More broadly, existing literature mostly emphasizes task-specific benchmark gains rather than advancing human-level understanding of ocean dynamics. Consequently, DL has so far contributed more to improved data products than to the discovery of new processes or mechanisms via a hypothesis-driven approach.

7.2. Challenges and opportunities

While rapidly advancing DL methods have shown substantial potential for inferring ocean dynamics, significant challenges and opportunities remain.

7.2.1. Balancing realism, physical consistency, and accuracy. A fundamental tension in DL for ocean dynamics resides in balancing three competing objectives in the predictions: realism (matching data statistics), physical consistency, and prediction accuracy. Unlike numerical models built on conservation laws and dynamical equations, which are designed to ensure physical consistency within the constraints of numerical schemes, DL models optimize loss functions that may not encode key physical principles. As a result, they can achieve high prediction skill while violating basic principles such as conservation of mass, momentum, or energy, or suppressing small-scale variance. Generative models offer one path forward by explicitly learning to sample from the data distribution, potentially capturing physical structure implicitly when trained on physics-constrained data. Alternatively, physical constraints can be selectively enforced during training, although determining which constraints to enforce and how to weight competing objectives remains an active area of research.

7.2.2. Generalization to out-of-distribution conditions. DL models often fail when faced with conditions outside their training distribution. This arises in simulation-based learning, where gaps exist in modeled dynamical regimes, and in observational learning, where sparse sampling underrepresents many ocean states. Although performance is typically strong on in-distribution test data, it can degrade rapidly when applied to rarely observed states or regions with different dynamical balances. Addressing this is particularly important for long-term ocean predictions under climate variability and change, where statistics may drift toward states that have never been observed before. Embedding known conservation laws and dynamical constraints using physics-informed neural network approaches may improve generalization and physical consistency. However, enforcing dynamical constraints requires explicit access to a computationally demanding three-dimensional ocean state, while ocean observations are strongly surface-focused, providing limited constraints on subsurface processes. In addition, simplifying assumptions introduced to approximate complex conservation laws in physics-informed formulations may break down in real ocean settings, leading to degraded performance. Developing robust physics-informed approaches for real-world ocean dynamics, therefore, remains a largely open research frontier.

7.2.3. Validating and improving simulation-based learning and hybrid models. The widespread use of numerical simulations to train DL models raises concerns about how model biases propagate through learning and affect downstream applications. Even state-of-the-art ocean models exhibit systematic biases in representing mesoscale eddies, submesoscale dynamics, internal gravity waves, and mixing. DL models trained on such simulations risk inheriting or amplifying these biases, a concern extending to hybrid models with DL components that replace traditional parameterizations. A critical challenge is developing systematic validation frameworks and metrics that go beyond pointwise error statistics to assess whether DL-enhanced datasets and hybrid models capture correct physical processes, rather than merely achieving low prediction errors. Process-oriented evaluation, informed by targeted observations and mechanistic understanding, will be essential to ensure that DL augments rather than obscures understanding of ocean dynamics.

7.2.4. Moving toward continual learning and multitask models. The prevailing paradigm of isolated, task-specific DL models, rarely reused beyond their original publications, limits knowledge integration across the community. DL models are typically abandoned, with no mechanism for continual learning as new data accumulates. A major opportunity lies in developing continually learning models that improve operationally by ingesting diverse data streams and cross-learning across applications. Such models would replace the publish-and-abandon pattern with living systems that accumulate knowledge over time, potentially through multi-task learning. This evolution could also enable adaptive observing systems, where DL models guide autonomous platforms to optimally sample the ocean in real time.

7.2.5. Leveraging DL for scientific discovery and understanding. Although DL excels at optimizing well-defined objective functions, advancing scientific understanding of ocean dynamics requires open-ended, hypothesis-driven inquiry that is difficult to formalize. Recent progress has emphasized operational gains (*e.g.*, improving forecast skill) rather than uncovering new dynamical mechanisms or testing physical hypotheses. To realize DL's potential as a scientific tool, the field must move beyond merely demonstrating that neural networks can outperform traditional methods on benchmark metrics to asking how DL can accelerate discovery and advance human-level understanding. This requires careful problem formulation explicitly aimed at physical insight.

FUTURE ISSUES

1. DL methods lack the analytical constraints and well-understood limitations of physics-based approaches, leaving us without well-developed tools to characterize their failure modes. It is thus important to develop analysis tools that can distinguish genuine physical insights from artifacts of the learning process.
2. The current paradigm of isolated, task-specific DL models that are rarely reused limits knowledge integration across the communities. A major challenge is developing general models that can continuously learn and operationally improve by ingesting diverse data streams and solving a wide range of problems.
3. Much of the recent progress has been methodological. It is now time to innovate on how DL can be used to accelerate scientific discovery and advance human-level understanding of ocean dynamics, building on traditional hypothesis-driven research.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

The authors greatly acknowledge the research efforts of the scientific community using DL for ocean dynamics, only a fraction of which was cited. G.E.M. and S.A.M. were funded by NASA Award 80NSSC21K1187, D.B., NASA Awards 80NSSC20K1142 and 80NSSC24K1664, and J. W., NASA Award 80NSSC25K7643 and 80NSSC26K0212. Support was provided to DB by Schmidt Sciences, LLC.

AUTHOR CONTRIBUTION STATEMENT

All authors contributed to conceptualization, literature synthesis, and writing. Generative artificial intelligence tools were used to improve the writing clarity in parts of the article.

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