Recent Developments in Artificial Intelligence in Oceanography

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With the availability of petabytes of oceanographic observations and numerical model simulations, artificial intelligence (AI) tools are being increasingly leveraged in a variety of applications. In this paper, these applications are reviewed from the perspectives of identifying, forecasting, and parameterizing ocean phenomena. Specifically, the usage of AI algorithms for the identification of mesoscale eddies, internal waves, oil spills, sea ice, and marine algae are discussed in this paper. Additionally, AI-based forecasting of surface waves, the El Niño Southern Oscillation, and storm surges is discussed. This is followed by a discussion on the usage of these schemes to parameterize oceanic turbulence and atmospheric moist physics. Moreover, physics-informed deep learning and neural networks are discussed within an oceanographic context, and further applications with ocean digital twins and physics-constrained AI algorithms are described. This review is meant to introduce beginners and experts in the marine sciences to AI methodologies and stimulate future research toward the usage of causality-adherent physics-informed neural networks and Fourier neural networks in oceanography.

1. Introduction

The depth of outer space is vast, and there are tens of trillions of stars in the observable universe alone; however, the ease at which these observations are currently routinely made is often overlooked. The secrets of Earth’s global ocean are paradoxically less well understood due to the extreme environment that characterizes it. The phrase “We know more about the moon than the (deep) ocean” comes to mind [1–3]. Since the first documented exploration of the ocean by the HMS Challenger from 1873 to 1876, techniques to characterize the ocean’s physical, chemical, and biological properties have evolved from simple Secchi disks, Nansen bottles, and lengths of rope to measure the ocean depth to encompass multiton research vessels, remotely operated airborne and submersible vehicles, buoys, and high-frequency coastal radar and satellites that orbit the planet several times within a single day.

The rapid development of powerful computers, algorithms, and data capacities has allowed mankind to process petabytes of data, giving rise to big data, i.e., data described by five characteristics: velocity, volume, veracity, variety, and value, and new understandings of the ocean. These understandings are encompassed in the development and deployment of a host of numerical models that can successfully simulate problems on spatiotemporal scales ranging from entire ocean basins if not the entire planet and centuries to thousands of years all the way down to the submesoscale (turbulence!) with phenomena occurring in fractions of seconds. Despite these advances, a new problem has emerged: how can increasing volumes of complex data be processed so that hindcasts, nowcasts, and, most impor-
tantly, forecasts be performed rapidly and with minimal computational expense? Moreover, due to spatiotemporal insufficiencies in oceanic observation sampling rates and model resolutions, much information is lost, negatively affecting progress in gaining even deeper insights and hampering efforts to effectively forecast either low-frequency, high-impact phenomena such as tropical cyclones (TCs) or the long-term effects of global warming, sea level rise, and climate change.

To overcome these and other issues, artificial intelligence (AI) tools are being increasingly leveraged. However, as is common in science, solving one problem often leads to many others. As they are inherently and solely dependent on the input data from which they learn, data-driven tools are an important limitation of current AI systems. Thus, partial differential equations (PDEs), the bedrock of modern science and advanced numerical models, cannot be incorporated. Progress in solving this new problem is migrating toward the usage of physics-informed neural networks (PINNs)—neural networks trained to solve supervised learning tasks while obeying all the laws of physics described by PDEs. This paper is geared toward not only providing a comprehensive review of AI tools in oceanography but also introducing physics-informed neural networks (PINNs) and deep learning (DL). Consequently, the remainder of this review is structured as follows. In Section 2, the usage of AI methodologies in oceanic phenomena detection is described. In Section 3, a similar description is given for dynamic ocean parameter forecasting. In Section 4, applications on the estimation of dynamic oceanic and meteorological parameters are presented, and in Section 5, an outlook on physics-informed deep learning and physics-informed AI and a retrospective with applications in ocean digital twins and physics-constrained AI are given. In Section 6, this review is concluded with a summary and two paths for future research. To enhance readability, the various sections are given below in Table 1.

2. AI-Based Identification of Oceanic Phenomena

Due to the rapid development of AI algorithms, they are being increasingly used in diverse fields, leading to deeper intersections between oceanography and AI. Oceanographic phenomena such as mesoscale eddies, internal waves, sea ice, and marine algae are crucial to a host of fields concerning the Earth’s climate, marine biogeochemical cycles, ocean health, and human activities and are reviewed here.

With the rapid development of AI algorithms, they are being applied in various fields, resulting in a deeper combination of oceanography and AI. There are many special phenomena with physical, ecological, and environmental significance in the ocean, such as oceanic eddies, internal waves, oil spills, sea ice, and marine algae. It is of great theoretical significance and application value to identify these features from satellite data and other resources. Traditional identification methods are based on physical or mathematical algorithms, which are greatly limited in terms of accuracy and timeliness. In this section, the development of AI-based identification of ocean features from ocean remote sensing data is introduced.

2.1. Eddy Detection. Mesoscale eddies are ubiquitous features in the ocean that play important roles in global energy and matter transport as well as the distribution of nutrients and phytoplankton in the ocean (e.g., [4–7]). Eddies can be subdivided into cyclonic and anticyclonic eddies. Under the action of the Coriolis force induced by Earth’s rotation, cyclonic eddies rotate counterclockwise (clockwise) in the northern (southern) hemisphere, and anticyclonic eddies rotate clockwise (counterclockwise) in the northern (southern) hemisphere. Eddies carry tremendous quantities of kinetic energy, moving water in their areas of effect several times or an order of magnitude faster than the average ocean velocity. Their high rotational speed and accompanying strong shear make eddies highly nonlinear; thus, they retain their own memory and conservation characteristics. It is for these and other reasons that the study of ocean mesoscale eddies is of paramount scientific significance and has large application potential.

Based on the available type of data, a series of eddy detection methodologies has been developed. These can be classified as Euler [8, 9], Lagrangian [10], and hybrid [11, 12] methodologies. Despite their widespread usage, they all suffer from one fundamental limitation: dynamic eddy detection methodologies are slow when datasets are large. In recent years, DL algorithms have matured and can now be used for mesoscale eddy detection. If oceanic feature parameters, such as the sea surface height anomaly (SSHA) and sea surface temperature (SST), are considered as images, ocean eddies can be identified by semantic segmentation in DL. Lguensat et al. [13] applied a DL algorithm based on U-Net under the classical semantic segmentation framework to identify cyclones and anticyclones from SSHA data. However, the network structure adopted was relatively simple, and the quantitative characteristics of the detected eddies were not analyzed. Franz et al. [14] also used the encoder-decoder network to detect ocean eddies based on SSHA data; more network parameters were introduced, but convolution modules and upsampling modules were simply superimposed. Du et al. [15] used a deep learning algorithm to automatically detect ocean eddies from synthetic aperture radar (SAR) images by extracting high-level features and fusing multiscale features. Xu et al. [16] identified ocean eddies using the pyramid scene parsing network (PSPNet) under the framework of semantic segmentation. This network included dilated convolution and pyramid pooling modules to capture more context relations by making full use of global and local information. Duo et al. [17] proposed the ocean eddy detection network (OEDNet) based on a target identification network, which combines the advantages of deep residual networks and pyramid networks. Oceanic eddies were detected by enhancing and optimizing SSHA training datasets for small samples and complex terrain. Santana et al. [18] analyzed the performance of several convolutional neural networks for eddy detection based on SSHA data. Xu et al. [19] used three AI-based algorithms of semantic segmentation (PSPNet, DeepLabV3+, and
BiSeNet) to identify oceanic eddies (as shown in Figure 1) and made a series of comparisons and analyses using the results from the three algorithms. Liu et al. [20] proposed a DL model to detect oceanic abnormal eddies (cyclonic warm eddies and anticyclonic cold eddies) based on the combination of SSHA and SST. The number of abnormal eddies accounted for one-third of the total number of global eddies, and they were more active in equatorial current and highly unstable current regions.

2.2. Internal Waves. Internal waves are those that occur within the ocean where the density is stable and stratified. These waves occur throughout all ocean depths and are distinct from other waves in that they play an important role in transferring the energies of mesoscale and large-scale motions. They also repeatedly lift seawater from deep to shallow layers and, as such, promote photosynthesis for phytoplankton and improve oceanic primary productivity. Internal waves also have important implications for ocean acoustics, offshore engineering, and submarine navigation.

Although internal wave amplitudes cannot reach the sea surface, seawater oscillations can modulate surface waves and force local convergence and divergence. As such, satellites can be used to study internal waves. Both SAR and visible spectral remote sensing imaging have become effective tools in the study of these waves. Satellite images can be used to obtain the distribution, generation, propagation (reflection, refraction), and other characteristics of waves in different regions (e.g., [21–24]). Amplitude inversion of internal waves from satellite images is mostly based on the Korteweg–de Vries (KdV) equation and half-wavelength characteristics of internal waves [25].

Currently, ML tools have been applied to the study of ocean internal waves due to their strong nonlinear mapping and multidimensional information processing advantages. Pan et al. [26] used the back propagation (BP) algorithm to intelligently invert the amplitude of ocean internal waves based on texture features and ocean environmental parameters of remote sensing images, and the inversion results were in good agreement with the observation data. Li et al. [27] used the improved U-Net model to extract internal wave features from Himawari-8 images taken around the Dongsha Atoll in the northern South China Sea. Wang et al. [28] proposed four internal wave amplitude inversion models in the frameworks of support vector machine (SVM), random forest (RF), convolutional neural network (CNN), and multilayer perceptron (MLP) based on the relationship between the characteristic parameters of remote sensing images obtained in the simulation laboratory and the amplitude of ocean internal waves. The results showed that SVM is the best framework for the inversion of internal wave amplitude. Vasavi et al. [29] applied U-Net for the segmentation and feature extraction of internal wave parameters and used the Korteweg–de Vries (KdV) solver to simulate their velocity and density. Zhang et al. [30] established an AI-based ocean wave amplitude inversion model with a transfer learning method using laboratory experiments and satellite in situ observation data. The wave amplitude information was more accurate than that based on the traditional KdV equation, as shown in Figure 2.

2.3. Oil Spills. With the continuous development and utilization of petroleum resources, marine oil spills have become more common and serious and are responsible for large-scale marine pollution and endangering the marine ecological environment, fisheries, wildlife, and tourism [31]. In recent years, large-scale oil spills have occurred one after another, such as the explosion of a semisubmersible drilling platform in the Gulf of Mexico in April 2010 and the sinking of the Sanchi oil tanker after a collision in the region east of the Yangtze Estuary in 2018 that spread oil over an area of approximately 58 km². Therefore, timely and effective oil spill detection can not only help disaster managers with targeted responses but also help scientists predict the

<table>
<thead>
<tr>
<th>Heading</th>
<th>Topic(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>AI-Based Identification of Oceanic Phenomena</strong></td>
<td>Oceanic eddy, Internal waves, Oil spills, Sea ice, Marine algae</td>
</tr>
<tr>
<td><strong>Oceanic Phenomena Forecasting</strong></td>
<td>Significant wave height, ENSO, Strom surge</td>
</tr>
<tr>
<td><strong>AI-Based Estimation of Dynamic Oceanic and Meteorological Parameters</strong></td>
<td>Physics- and data-driven ocean model parameterizations, AI ocean turbulence parameterization schemes, AI estimation and parameterization of moist physics</td>
</tr>
<tr>
<td><strong>Outlook: Physics-Informed Deep Learning</strong></td>
<td>Physics-informed artificial intelligence and machine learning, Retrospective Applications (digital twins and data-driven forecasting)</td>
</tr>
</tbody>
</table>
Figure 1: Ocean mesoscale eddies identified by a traditional method (VG) and three AI-based algorithms (PSPNet, DeepLabV3+, and BiSeNet), adapted from Xu et al. [19].

Figure 2: Internal wave amplitude inversion based on transfer learning-based model in the Anderman Sea, adapted from Zhang et al. [30].
movement and dispersal of oil spills. SAR is an effective resource for oil spill monitoring because oil film restrains the surface roughness and appears as dark lines in SAR images [22, 32]. In addition, the oil spill area modulates the surface signals received by polarimetric SAR [33], which ensures the ease of oil spill detection using this methodology.

Due to the increasing popularity of NN and machine learning (ML) algorithms, AI technology has been gradually integrated into oil spill detection. Topouzelis et al. [34] proposed a fully connected feedforward neural network to monitor an oil spill area and achieved high detection accuracy. Taravat and Oppelt [35] used a Weibull multiplication filter to suppress speckle noise in SAR images, enhanced the contrast between the target and background, and used a multilayer perceptron neural network to monitor oil spills from filtered SAR images. Subsequently, Taravat et al. [36] combined the Weibull multiplication model with a pulse-coupled neural network to monitor oil spills from SAR images. Singh [37] used an ANN to identify the features of oil spills; while this method improved detection accuracy to a certain extent and suppressed the influence of speckle noise on feature extraction, it still failed to achieve high detection accuracy and robustness. To suppress the speckle noise of SAR images, Teng et al. [38] proposed an oil spill segmentation algorithm based on hierarchical clustering that could effectively maintain the shape characteristics of oil spills in SAR images, but weak boundary region identification was not ideal. Chen et al. [39] employed a stacked autoencoder (SAE), deep belief network (DBN), and other DL algorithms to reduce the feature dimension by hierarchical unsupervised pretraining and optimizing the feature set of polarized SAR images. Oil spill monitoring and classification using polarimetric SAR images were carried out. The results showed that the oil spill classification effect of the deep network was better than that of SVM and traditional ANNs. Guo et al. [40, 41] obtained good results in monitoring oil spills based on CNN and subsequently adopted the SegNet semantic segmentation model, which could not only accurately identify the oil spill area in SAR images but also had high robustness under high noise and fuzzy boundary conditions. Combining the feature pyramid network with transfer learning, Yekeen et al. [42] proposed an instance segmentation mask R-CNN model to recognize oil spills. Matias et al. [43] evaluated six machine learning algorithms, including ANNs, random forest (RF), naive Bayes (NB), decision tree (DT), linear discriminant analysis (LDA), and logistic regression (LR), to distinguish between natural and anthropic oil slicks from SAR images. RF performed the best and achieved the maximum accuracy. Basit et al. [44] developed a new loss function, namely, the “gradient profile” loss, based on a CNN and hybrid models to classify oil spills from SAR images. The new loss function offered significant improvement in the multiclass classification of natural sea surface, land, ship, and look-alikes, as shown in Figure 3.

2.4. Sea Ice. Sea ice, which is a general term for all the ice in the ocean, affects many important physical processes and plays important roles in the global climate system. The long-term change in sea ice cover is an indicator of global climate change, with crucial implications for polar maritime transport and human activities. Long-term monitoring of sea ice cover parameters is required to gain a more detailed understanding of the various interactions and feedback mechanisms among the atmosphere, sea ice, and ocean that influence the global climate. Satellite remote sensing,
including optical remote sensing, microwave radiometers, and SAR, has become the most effective method for monitoring polar sea ice [45]. Due to its high spatial resolution, wide coverage, and ability to penetrate clouds, SAR images have been a major source used for sea ice monitoring and classification. The key to sea ice detection from SAR images is how to develop a robust model to distinguish sea ice and open water according to backscattering signals. At present, many sea ice detection models, such as those based on the backscattering threshold method [46] and Bayesian technology [47], have been developed. In the 21st century, NNs [48, 49], SVMs [50–52], and random forest classifiers [53] have become very popular in terms of usage.

Xu and Scott [54] used the early CNN model AlexNet to classify sea ice and open water. Li et al. [55] used a CNN model to classify sea ice and open water from China Gaofen-3 satellite images. Gao et al. [56] combined transfer learning with DenseNet to form a multilevel fusion network (MLFN) for sea ice and open water classification. Boulze et al. [57] proposed an algorithm based on CNN for sea ice classification using Sentinel-1 SAR images. With high calculation time efficiency and low sensitivity to SAR data noise, their algorithm performed better than the random forest model. Ren et al. [58] used the U-Net algorithm combined with a dual attention mechanism to detect sea ice based on SAR images. The algorithm was able to achieve pixel-level sea ice classification, and the dual attention mechanism could be used to further improve classification accuracy. Gonçalves and Lynch [59] proposed an improved U-Net with a ResNet encoder to extract fine-scale sea ice from very-high-resolution multispectral satellite imagery (Wordview-3). Zhang et al. [60] combined the DL model MobileNetV3 with a multiscale feature fusion method to propose a multiscale MobileNet (MSMN) model and used dual-polarization SAR data from the Gaofen-3 satellite to classify sea ice in the Arctic in winter (Figure 4). Its accuracy was superior to those of the CNN and ResNet models on average.

Figure 4: Sea ice classification results from the MSMN model based on SAR images with the different polarization combinations. (a) Original SAR image and results from (b) VV polarization, (c) VH polarization, and (d) dual polarization, adapted from Zhang et al. [60].
2.5. Marine Algae. Within the global ocean, there are more than ten thousand known species of plant, with the overwhelming majority of them being micro- and macroalgae. Among them, the macroalgae Enteromorpha and Sargassum, classified as green and brown algae, respectively, are very common. While they are important aspects of the marine ecosystem, their excessive proliferation can lead to damage to the environment and human health [57] and socioeconomic losses [62, 63]. This necessitates close monitoring, forecasting, and, where possible, remediation [64–66].

Due to the aggregation and dispersion of marine algae, sea surface reflectance is modulated and thus can be observed through satellite remote sensing platforms and instruments [67]. Classically, the normalized difference vegetation index (NDVI) and floating algae index (FAI) are commonly used indices in optimal remote sensing images [32, 68]. SAR imagery, by contrast, relies on grayscale and backscattering coefficient differences to identify possible algal blooms. Despite the wide array of technologies available to monitor the occurrence and spread of algal blooms, DL techniques have recently been applied for their intelligent identification and forecasting abilities. Arellano-verdejo et al. [69] designed a deep neural network, ERISNet, using convolutional and recurrent neural networks for intelligent monitoring of Sargasso on the Gulf Coast from MODIS images. Frias et al. [70] compared three CNNs (MobileNetV2, ResNet18, Xception) based on the classification of five macroalgal species in high-resolution images, and ResNet18 achieved the best performance. Gao et al. [71] developed an expandable DL model, AlgaeNet, for green algal identification based on moderate resolution imaging spectroradiometer (MODIS) and SAR images. This model was designed on the basis of the classic U-Net model, and the input of the model was multichannel multisource remote sensing data. Moreover, a new loss function was introduced to solve the problem of sampling imbalance. The results of the model reduced the possible deviation of threshold selection in the traditional threshold-based segmentation process.

Inspired by the idea of transfer learning, Cui et al. [72] proposed SRSε-Net, a deep semantic segmentation network suitable for large-scale green tide extraction (Figure 5). First, a superresolution model was pretrained with high spatial resolution GF1-WFV images, and then the model representation learned was transferred to the MODIS image domain. This model introduced a dense connection mechanism, replacing the convolution operation with a dense block, and effectively obtained detailed green tide boundary information by strengthening the propagation and reuse characteristics. Experimental results showed that SRSε-Net is able to obtain more accurate segmentation with fewer network parameters. Shin et al. [73] trained three machine learning models with Rayleigh-corrected reflection images and a ground truth map obtained from Geostationary Ocean Color Imager-II (GOCI-II) imagery during the agglomeration of Sargassum along the northern Jeju coast in Korea in 2021, including fine tree, fine Gaussian support vector machine (SVM), and gentle adaptive boosting (GentleBoost). Among these, the authors determined that GentleBoost was best at detecting the location of Sargassum (Figure 5).

As DL algorithms become more widely applied in ocean feature detection, new problems have emerged. First, ocean feature identification relies heavily on a large volume of labeled feature data, and these are obtained either manually or semiautomatically based on transmission or dynamic methods. The continued reliance on human-derived professional knowledge to label data ensures that bias will occur, necessitating the combination of knowledge from different expert groups. Second, the intelligent identification of ocean features is currently limited to the surface, with only rare examples of subsurface feature detection available in the literature.

In the aspect of target recognition, non-AI-based approaches mainly include human visual interpretation and traditional dynamic methods. The former relies on expert experience, bringing subjectivity and error. The latter is computationally inefficient in processing large amounts of data. Therefore, AI-based methods can efficiently identify objects accurately and objectively from a large amount of data, even when there are missing or small errors in the data.

3. Oceanic Phenomena Forecasting

In the forecasting of oceanic variables, methodologies broadly fall into two types. The first type of methodology
includes traditional numerical models that rely on expert knowledge to develop complex dynamic and thermodynamic equations. The second type of methodology includes AI methods that are largely driven by data. Unlike numerical models, AI models do not depend on specialized knowledge and can make accurate forecasts by learning the fundamental properties and rules of a given dataset. In this section, AI-based methodologies are used for forecasting the significant wave height, El Niño-Southern Oscillation (ENSO), and storm surges.

3.1. Significant Wave Height. Ocean surface gravity waves (hereafter, waves) exhibit a high degree of nonlinearity and are of principal importance in ocean engineering, marine renewable energy, maritime transport, and other nearshore, coastal, and offshore applications. Over the last few decades, traditional wave prediction models have been regularly updated and modified. For example, the WaveWatch III (WW3) model from the National Environmental Prediction Center in the United States and the Simulating Waves Near-shore (SWAN) model from the University of Delft in the Netherlands are now among the most extensively used models. Traditional numerical wave prediction models are based on solving the wave action balance equation through the use of discrete calculations rather than differential equations, and as such, numerical errors inevitably arise. Additionally, the usage of numerical models leads to high computational costs and long model run times. Consequently, in emergency situations, it is often impractical to rely upon them for rapid forecasting applications.

To overcome these and other limitations, AI has been introduced for significant wave height prediction; although, most studies focus on single-point forecasts. In an early study, Deo and Naidu [74] used an ANN for 3- to 24-hour wave predictions and found that the predictions were in satisfactory agreement with the observations. Later, Londhe and Panchang [75] also used an ANN for significant wave height predictions and discovered that forecasts within six hours were very accurate with regard to the observations, and the correlation coefficient between the forecast and observations in a twelve-hour time frame was 67%, which is still acceptable. More recently, Kaloop et al. [76] combined wavelet analysis, particle swarm optimization (PSO), and extreme learning machine (ELM) to create a joint wavelet-particle swarm optimization (wavelet-PSO-ELM, WPSO-ELM). In the case of low complexity and few input variables, this method had high prediction accuracy. Emmanouil et al. [77] improved the numerical prediction of SWH using a Bayesian network (BN). Using a special cyclic NN structure, the long short-term memory (LSTM; [78]) network can avoid the problem of long-term data dependence and is very suitable for wave height prediction problems. Lu et al. [79] combined an LSTM network and multiple linear regression to establish an M-LSTM hybrid prediction model, which optimizes wave height prediction by restricting a single predictor. Fan et al. [80] combined LSTM and SWAN for single-point prediction and found that the model had better prediction performance than models such as ELM and SVM. In the joint SWAN-LSTM model, the prediction accuracy was improved by approximately 65% over the SWAN model. Mandal and Prabaharan [81] used a recurrent neural network (RNN) to predict wave heights after 3, 6, and 12 hours, and the correlation coefficients between the predicted and observed values were 0.95, 0.9, and 0.87, respectively. Gao et al. [82] used LSTM to forecast wave heights at different buoy locations in the Bohai Sea. Zhou et al. [83] proposed a single-point wave prediction model based on the EMD-LSTM algorithm and applied it to the forecast of buoy data in the Caribbean Sea (CS); it showed better results than the singular LSTM network. Later, considering the large number of TCs in the CS, Bethel et al. [84] also considered the usage of LSTM for point predictions but used time series of both the significant wave height and surface wind speed to predict hurricane activity. It was determined that although truncated time series led to phase shifting, within a six-hour time frame, errors were minimal, and the forecasted significant wave height remained highly accurate in terms of both correlation and the root-mean-square error.

Despite these advances, single-point forecasts, by their very nature, cannot be used on larger, regional scales. To demonstrate this, the mechanics of LSTM is briefly reviewed. Within this neural network, information flow within cells is governed through the usage of input (i_t), output (o_t), and forget (f_t) gates. Current information, which is saved in the input gate i_t ⊗ g_t, takes the values of h_{t-1} and x_t, applies the sigmoid function to them, and determines the value to be updated. The output gate determines the information flow to the next cell. To represent the strength and direction of current information storage, i_t ranges from 0 to 1, and g_t ranges from -1 to 1. The forget gate, as the name implies, selectively forgets information that is being transferred between cells; decisions on which information to forget are determined based on the value obtained by applying the sigmoid function after receiving h_{t-1} and x_t. The output of the sigmoid function ranges from 0 to 1; thus, if the value is 0, the information of the previous state is completely forgotten, and if the value is 1, the information is completely retained. Follow this, the value computed with the tanh function and Hadamard product operator (⊙) is sent from the input gate. The cell (c_t) and hidden (h_t) states enable LSTM to learn long-term information while simultaneously avoiding dependence problems on the same long-term scales. Note the following equations that govern the operation of LSTM:

\[
\begin{align*}
    f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f), \\
    i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i), \\
    o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o), \\
    g_t &= \tanh(W_{xg}x_t + W_{hg}h_{t-1} + b_g), \\
    c_t &= f_t \odot c_{t-1} + i_t \odot g_t, \\
    h_t &= o_t \odot \tanh(c_t),
\end{align*}
\]

where W is each layer’s assigned weight, x_t is the input time step, b is the bias, and tanh is the hyperbolic tangent function.
Although the above equations are well suited for time series data, if extended to a two-dimensional (2D) field, the computational expense would be greatly increased while still being unable to capture the spatial characteristics of a given field. To advance the state of the art, Shi et al. [85], in a landmark study, replaced the matrix multiplication of Hochreiter and Schmidhuber [78] with a convolutional operation, thus giving rise to the following equations:

\[
\begin{align*}
    f_t &= \sigma(W_x f_t + W_h f_t - 1 + b_f), \\
    i_t &= \sigma(W_x i_t + W_h i_t - 1 + b_i), \\
    o_t &= \sigma(W_x o_t + W_h o_t - 1 + b_o), \\
    g_t &= \tanh(W_x g_t + W_h g_t - 1 + b_g), \\
    c_t &= f_t \odot c_{t-1} + i_t \odot g_t, \\
    h_t &= o_t \odot \tanh(c_t),
\end{align*}
\]

where $\odot$ is the convolutional operator.

The use of Equations (7)–(12) gives rise to the convolutional LSTM (convLSTM) model, which has been widely applied in 2D forecasts of the significant wave height. For example, Choi et al. [86] used convLSTM on raw ocean images derived from the National Data Buoy Center dataset for the real-time prediction of the significant wave height. The authors found that their model could achieve an accuracy of 84% with minor errors. Zhou et al. [87] used convLSTM to forecast significant wave heights in the eastern and southern waters of China with minimal computational expense (Figure 6). Bai et al. [88] used the CNN algorithm to forecast the significant wave height in the South China Sea and obtained the optimal input variable duration of the 12h prediction model through 56 sets of sensitivity experiments.

Considering its importance as one of the bulk wave parameters (alongside the wave period and wave direction), research on AI forecasting of the significant wave height accounts for the largest proportion of studies by far. However, several studies have attempted to forecast the remaining two wave parameters, and others are strongly related to bulk wave parameters such as surface winds. For example, Feng et al. [89] used a multilayer perceptron to forecast significant wave height and peak wave periods while considering the effects of both wind and ice cover on wave generation in Lake Michigan. The authors found that this ML approach could forecast wave conditions in $1/20,000^{th}$ to $1/10,000^{th}$ of the computational time necessary to run SWAN, a physics-based model. In a similar study, Hu et al. [90] used XGBoost and LSTM in the predictions of the significant wave height and peak wave period and found that XGBoost led to superior forecast results over LSTM, but both ran significantly faster than WW3. Bethel et al. [91] showed that due to the strong causal link between significant wave heights and surface wind speeds, each can be forecasted from its counterpart with a high degree of accuracy, and this is even possible under extreme conditions, as may be forced by TCs.

Figure 6: Wave height prediction results during the typhoon period, adapted from Zhou et al. [87].
Despite the aforementioned advances, the current accuracy and model training speed of prediction for oceanic variables using artificial intelligence (AI) techniques are still limited by the resolution and accuracy of labeled data. By introducing physical mechanisms, it may be possible to accelerate the convergence of AI models and break through labeled data bottlenecks to improve forecast accuracy.

3.2. ENSO. Statistical and coupled air-sea dynamic models are currently used to anticipate ENSO. Dynamic models solve the physical equations of the air-sea system to forecast ENSO, while statistical models provide predictions by creating linear or nonlinear correlations between ENSO signals and predictors. Coupled air-sea dynamic models employed in ENSO forecasting are superior to statistical models due to continual adjustment of the parameterization scheme and initial conditions, although even the most sophisticated dynamic forecast model is not optimal for ENSO forecasting for more than one year. The predictive power of both models will be greatly reduced due to the presence of the spring predictability barrier (SPB; [92, 93]). As a result, multyear ENSO forecasting remains a serious challenge.

In recent years, many ENSO forecasting methods based on AI methodologies, such as those performed by Petersik and Dijkstra [94], have applied a Gaussian density and quantile regression NN ensemble. Both models are capable of assessing the uncertainty of predictions through Gaussian distribution and quantiles. These models have a high correlation over a longer forecast time. Mahesh et al. [95] proposed an RNN-based ENSO forecasting method that can predict monthly ENSO temperatures with different forecasting times. Zhou and Zhang [96] proposed a hybrid NN for ENSO predictions using a joint principal oscillation pattern (POP) analysis and convLSTM model, giving rise to POP-Net. Gupta et al. [97] used convLSTM to forecast the monthly average Niño3.4 index one year in advance in the prediction of extreme El Niño events. To better explain the prediction of the NN, Cachay et al. [98] applied the spatiotemporal graph NN to the prediction of ENSO. Compared with the CNN, the model can better utilize the spatiotemporal information in the input data. Based on the Liang–Kleiman information flow (IF), Liang et al. [99] generated a new AI model, and by carefully selecting predictors using an IF causal analysis method, ENSO could be accurately forecasted ~10 years in advance. A representative study on the usage of AI in ENSO predictions was provided by Ham et al. [92]. Using a CNN, the authors identified that predictions of the Niño 3.4 index can be achieved with a higher correlation coefficient than the traditional dynamic model 17 months in advance (Figure 7).

3.3. Storm Surges. The two types of classical storm surge forecasting methodologies are empirical forecasting and numerical forecasting [100]. Changes in coastal water levels and their floodplain processes are the parameters that must be forecasted. Forecasters’ subjective experience and empirical statistical forecasting methods are commonly referred to as empirical forecasting methods. Numerical model prediction and early warning technology have become increasingly popular technological advances. The National Oceanic and Atmospheric Administration (NOAA), National Hurricane Center (NHC), and other departments have utilized the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model to study different paths and storm surge disasters caused by tropical cyclones with intensity levels and provide storm surge probability products and maximum possible water enhancement products to provide decision support for governments and other departments [101]. In fact, since the 1970s, the international community has focused on the development of numerical forecasting and early warning technology for marine dynamic disasters, and a relatively complete forecasting model and system with good numerical forecasting capabilities for storm surges, tsunamis, and other natural disasters has gradually been built [102].

The rise of AI algorithms has also brought more methods for forecasting storm surges ([103]); although due to the dearth of spatiotemporal data, current AI-based storm surge forecasting is limited to single-point forecasting, with little research available on 2D scales. Lee [100, 104] proposed a storm surge forecasting method based on ANN and BPNN using inputs of wind speed, wind direction, air pressure, and tide level harmonic analyses to predict storm surge events. Rajasekaran et al. [105] applied SVR and found that it was useful in predicting not only storm surges but also biases. You and Seo [106] proposed a joint ANN-cluster analysis model to forecast storm surge events in South Korea. To provide a 5-day surge forecast for the Mediterranean Sea, Bajo and Umgisier [107] combined hydrodynamic models and ANNs. More recently, Kim et al. [108] introduced more predictors (i.e., latitude, longitude, moving speed, heading direction, central pressure, radius of strong wind speed, and maximum wind speed) into the forecast model and used the model to analyze six sites in South Korea; the correlation coefficient of the predicted values had a minimum value of 0.861 and a maximum value of 0.979. Chao et al. [109] used ANNs and effective typhoon parameters (i.e., the central pressure deficit, maximum wind speed, relative location (described by the distance and angle), radius of the typhoon, and forward speed and direction) to reevaluate storm surge forecasts, improving forecast accuracy under long forecast durations (Figure 8). Jiang [110] used the beetle antenna search algorithm to optimize a BP NN storm surge forecast at the next moment based on 20 prediction parameters; this algorithm had higher accuracy than a single BPNN algorithm. Tiggeloven et al. [111] used ANN, LSTM, and convLSTM to construct NN ensembles at 736 global tide stations for the prediction of sea levels. The authors found that LSTM outperformed the other two approaches, but when more predictor variables were added to the forecast models, the computational time correspondingly improved. The authors also identified that performance improvements were still not able to sufficiently capture dynamics for some reasons, as, for example, modeling surges in the tropics were insufficient to capture intra-annual sea level variability.
4. AI-Based Estimation of Dynamic Oceanic and Meteorological Parameters

4.1. Physics- and Data-Driven Ocean Model Parameterizations.

Ocean numerical models are an indispensable means of studying various ocean phenomena, and within them, many parameters, such as subgrid processes, e.g., turbulence, which cannot be resolved by discrete grids, are estimated by experience. These processes are often parameterized based on a combination of theory and observational data. The selection and usage of parameterization schemes are key factors in the usage of ocean numerical models, and as such, a wide range of schemes are available. Common vertical mixing schemes include MY [112], PP [113], K-profile parameterization (KPP; [114]), hybrid [115], and Fox–Kemper parameterization schemes [116], among others. Horizontal mixing schemes include the Smagorinsky [117] and GM schemes [118].

Often, increasing the spatial resolution of a numerical model is sufficient to realize the simulation of turbulent processes; however, this comes at the expense of dramatically increased computational costs [119]. Traditionally, parameterization schemes are based on semiempirical and semiphysical principles, which can improve climate simulations. These methodologies are largely physics-driven, and while they offer the advantage of interpretability, they are nevertheless imperfect and may lead to large biases in ocean circulation, air-sea heat flux, and ocean carbon absorption simulations [120]. To overcome these limitations, the introduction of data-driven methods has been proposed to eliminate the need to make physical assumptions about a physical process that is to be parameterized. Data to produce
these new schemes can be obtained from high-resolution numerical models, observations, or a combination of the two, and then DL algorithms can be used to derive dynamic parameters directly from the data. Data-driven parameterization has been applied in some ideal models [121–123], and some progress has been made in turbulence models [124]. ML algorithms can also improve the computational efficiency and universality of data-driven parameterization schemes. This was demonstrated by Zhu et al. [120], who combined a high-resolution numerical model and observation data and showed that a data-driven parameterization scheme can improve ocean model simulations and calculate ocean dynamic parameters more thoroughly. Data-driven methodologies can find rules from a large number of parameter experiments and predict the value of optimal parameters [33, 125] or find rules from massive observation data or high-resolution model results and establish new parameterization schemes [126]. It should be pointed out that most current studies focus on the parameter optimization of atmospheric general circulation [33] or typhoon prediction models [125]. Research on ocean model parameterization schemes using ML schemes has only recently begun [120, 123].

### 4.2 AI Ocean Turbulence Parameterization Schemes

The interaction between oceanic small- and large-scale processes and consequent energy cascades is of great significance to understanding a host of phenomena [127–131]. Consequently, the use and selection of parameterization schemes for subgrid processes in numerical models have important implications for model results. Presently, there are many ML algorithms (e.g., linear expression, random forests, and support vector machines) that can be applied to the problem of supervised regression required for parameterization. With the continuous development and progress of DL, NNs can be better applied in the construction of ML-driven parameterization schemes. At present, computing resources allow for the simultaneous training of thousands to millions of

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**Figure 8:** Long lead time storm surge predictions obtained by different combinations of controlling parameters from the Krosa event, adapted from Chao et al. [109].
NNs, each with many different architectures (deep fully connected networks, deep belief networks, RNNs, and revolutionary NN-CNNs) [132]. For example, the power and success of CNNs are derived from the fact that convolutional layers—which usually extract the most important information from two-dimensional spatial fields—learn from data. Compared with simple physics-driven parameterization schemes, the disadvantage of CNNs is the computational cost involved in forecasting. Despite this, the computational cost of parameterization using CNNs is still lower than that of running high-resolution numerical models.

One of the earliest data-driven turbulence parameterization schemes initially appeared in numerical models run by Tracey et al. [133] and Ling et al. [134, 135]. In these studies, the spatial scale involved in turbulent processes was several orders of magnitude smaller than that of climate models. For example, Ling et al. [135] used a deep fully connected NN to estimate the eddy momentum parameterization of an anisotropic stress tensor. The authors introduced physical constraints into DL to ensure a specific symmetry for data-driven parameterization. They found that only after applying physical constraints can deep NNs be competent for linear regression models. Integrating physical principles into data-driven algorithms is very important for fidelity and can also improve the prediction skills for the parameterization of results. In addition, NNs have also been used to parameterize the eddy momentum flux in the free attenuation two-dimensional turbulence model [136–139] and large eddy simulation [140]. As a case in point, Maulik et al. [138] parameterized the eddy momentum flux using NNs and then applied the data-driven parameterization scheme to the original model. They used the traditional Smagorinsky and Leith eddy viscosity functions [117, 141] as the input characteristics of one of the NNs. The results showed that the ML-driven parameterization scheme does not improve the computing power of the NN, but it does improve the stability of the turbulence model after its implementation. Based on the above work, Maulik et al. [138] removed the upper gradient momentum flux to enhance the stability of the numerical model and thus changed the physical properties of the turbulent process. Nevertheless, applying the combination of a physical model and mathematical characteristics to DL is an important step to make parameterization physically consistent and improve its computational performance in climate models [142, 143].

For the parameterization of ocean turbulence processes, there have been some studies using CNNs. Bolton and Zanna [126] and Zanna and Bolton [144] parameterized an ocean mesoscale eddy in an idealized ocean model and showed that the results can even be extended to oceans with different dynamic states. Salehipour and Peltier [145] showed that CNNs can be used to parameterize the ocean vertical mixing rate. Zhu et al. [120] designed an ocean vertical mixing parameterization scheme based on DL under physical constraints by using turbulence observation data in the tropical Pacific Ocean and applied this parameterization scheme to the climate model. It was found that the data-driven turbulent mixing parameterization scheme can better simulate the vertical heat flux of the upper ocean and improve the temperature simulation results of the Tropical Pacific Ocean (Figure 9).

Regarding the accuracy achieved in parameterization, in a numerical model, the ocean vertical hybrid parameterization scheme based on deep learning of physical constraints is adopted. The model results show that the performance is significantly better than the current parameterization scheme based on physical relations [120]. In addition, AI parameterization has significant advantages in computing resources and computing speed [144].

4.3. AI Estimation and Parameterization of Moist Physics. Moist physical processes in atmospheric models are mainly concerned with clouds and convection. Clouds play an important role in the radiation budget and hydrological cycle of the Earth’s system [146, 147]. The latent heat release and convection of clouds interact with atmospheric circulation and affect the transport and distribution of global matter and energy. However, clouds and convection are the most difficult processes in climate models [142, 143]. The spatial scale of cloud-related processes can range from the micron scale of cloud droplets to the thousands of kilometer scale of tropical disturbances, in which cloud microphysical processes must be parameterized [148]. Current atmospheric general circulation models cannot distinguish the convective process because of coarse resolutions; so, the convective process also needs to be parameterized [149, 150]. At present, the parameterization of convection and clouds has become the research core of atmospheric general circulation models [31]. The convection parameterization scheme is based on limited observations and some empirical relationships [149, 150]. In these parameterization schemes, convection and clouds are individually idealized on a single kilometer scale. Although most convective parameterization schemes can qualitatively reflect the convective transport, condensation, and heating of heat and water, many important convective characteristics have not been represented [142, 151].

Since the 1980s, cloud resolving models (CRMs) have been used to simulate convection and convective processes in general circulation models (i.e., hyperparameterization). Using the National Center for Atmospheric Research (NCAR) Community Atmospheric Model (CAM), Khairoutdinov et al. [152] developed a superparameterized community atmosphere model (SPCAM), which performs better in terms of representing the convective characteristics of the atmospheric general circulation model. However, and rather obviously, if a century of time is required to make estimates of the future climate using traditional numerical models, computational costs will be too high. To overcome this, data-driven ML has been applied in the atmospheric sciences. Krasnopolsky et al. [153] developed a stochastic convection parameterization scheme for numerical weather prediction and climate models based on NNs using the tropical western Pacific data output by the CRM. The parameterization scheme can simulate the main characteristics of diabatic heating and cloud distribution in NCAR CAM4. Gentine et al. [154] developed a deep NN to predict cloud
and radiation processes trained on SPCAM data. Rasp et al. [155] successfully coupled an NN-based parameterization scheme to an atmospheric general circulation model and carried out a multiyear prediction simulation, which reproduced the simulation results of the SPCAM well. O’Gorman and Dwyer [156] developed a convective parameterization scheme based on a random forest decision tree using the output data of the general circulation model integrated into a conventional convective parameterization scheme. Han et al. [157] used the deep convolution residual NN (ResNet) to simulate moist physical processes with the actual global distribution of land and ocean in the SPCAM. The annual average precipitation estimated by ResNet (Figure 10(b)) was found to be very consistent with the SPCAM simulations on a global scale (Figure 10(a)). The main precipitation characteristics, such as the tropical convergence zone (ITCZ), the South Pacific convergence zone (SPCZ), the tropical monsoon system, and storms in mid-latitudes, were simulated well, but the ITCZ and SPCZ in the southeastern United States and South America were slightly underestimated, and precipitation over the Tibetan Plateau was overestimated (Figure 10(c)). In terms of the global average, there was a small negative deviation because the negative deviation in the tropics offsets the positive deviation in the high latitudes.

5. Outlook: Physics-Informed Deep Learning

Generally, both CNNs and NNs can estimate the spatiotemporal variability of subgrid processes within numerical models (e.g., eddy kinetic energy forcing). However, the primary disadvantage of NNs and DL methods is that there are no physical constraints in data-driven processes. Although Bolton and Zanna [126] processed the input field or output field learned by CNN to meet the physical constraints, this method introduces a few biases. These biases can be mitigated, if not avoided, in several ways.

First, the most traditional method requires the usage of DL to optimize unknown coefficients used in physics-driven parameterization [158]. This method requires the assumption that the structural form of the used parameters is the correct representation of a given process; although, this assumption comes at the benefit of not requiring additional parameterization. Unfortunately, Zanna et al. [159]...
showed that these assumptions are not valid in ocean models because their parameterizations are often uncertain or unknown.

Second, in DL model optimization, loss functions can be changed. Loss functions can be augmented to include additional constraints such as the global conservation of mass, momentum, salinity, or energy. This simple approach helps to ensure that systems dependent on learning from data can tend to obey conservation laws [160]. Despite this, unless rigid constraints are used, adherence to conservation laws may not be strictly enforced and only approximately satisfied.

Third, the structure of NNs can be modified [134, 144]. Zanna and Bolton [144] used images of analytical velocity components as CNN inputs to analyze subgrid eddy momentum forcing horizontal and vertical components. To dynamically constrain the DL scheme, the authors used a specifically constructed convolutional layer with fixed parameters. This allowed for the direct integration of physical principles with data-driven algorithms. Compared with purely physics-driven parameterization methods, this method allows for machine learning parameterization with more physical robustness and hence better results. This comes at a major disadvantage: this approach requires practitioners to have a great breadth of knowledge, as expertise in DL and physics is needed.

5.1. Physics-Informed Artificial Intelligence and Machine Learning. Within the realm of applications of AI in oceanography, several hurdles exist. These include ensuring that ML schemes are correct, can be ported to other fields, and have capabilities that can be expanded. It is not difficult to

Figure 10: Global distribution of annual average precipitation from (a) SPCAM data, (b) ResNet estimation, and (c) their differences, adapted from Han et al. [157].
understand that a new model must be developed specifically and trained to identify target objects and to initiate forecasting of required variables. As such, these models must be retrained for the same target objects but in different geographical locations. In this sense, the use of AI in oceanography differs from their standard usage scenarios. For example, when facial recognition is the goal, a single model can be efficiently applied to different individuals in differing task scenarios. This is currently not feasible with AI schemes in oceanography. Here, models face the dual problem of the paucity of data and the complex situations in which they are applied.

Essentially, an ML model extracts information and relationships from input data and uses them for inferences and predictions. The applications mentioned in the previous sections are all conventional data-driven models. As the collected data used to derive mapping relationships between inputs and outputs are often incomplete, these relationships can only provide correct object identification and variable forecasting within certain limits. Complete governing equations cannot be developed, and convergent results cannot be guaranteed. Therefore, such mapping relationships can only be regarded as an empirical equation, which fails to satisfy known physical constraints such as even basic conservation of energy laws. These and other problems have become a bottleneck that restricts the development of AI methods in oceanography. One way to break this bottleneck is to embed discipline knowledge into the neural network. This will allow the avoidance of problems associated with pure data-driven NNs and lead to the further development of physics-constrained NNs. In recent years, research on embedding physics into ML has matured into enabling networks to meet the needs of governing equations, giving rise to the usage of AI to solve partial differential equations (PDEs; [161, 162]). For example, AI models can be used to solve Navier–Stokes equations [163, 164] and obtain extremely accurate solutions at speeds that far exceed those of traditional numerical models. Therefore, in future model development, the usage of AI in solving governing equations can lead to the creation of pure AI-based models.

In this section, there will be discussions along two paths: retrospective and application prospects. First, the development history of physics-constrained NNs will be reviewed, and then their existing applications in oceanography will be introduced. Finally, possible directions for future development will be described.

5.2. Retrospective. Since the recent introduction of the PDE functional identification of the nonlinear dynamics (PDE-FIND) algorithm by Rudy et al. [165], a wave of PDE neural network solvers have been introduced. In the previously mentioned study, the authors presented a sparse regression approach for model training that employs variables acquired from discretely solving the original equations as training data and then used iterative optimization to discover the PDE that corresponds to that data. To complete the solution of the governing equation, all feasible partial differential operators for the same variable are considered candidates, and a tree traversal algorithm is used to filter them out one by one. Strictly speaking, this does not introduce too much physical interference into the NN process or its output. Rather, it merely introduces operators based on human understanding to enable the network to solve governing equation coefficients, thereby yielding the governing equation.

Recently, Raissi et al. [166] introduced physics-informed neural networks (PINNs), which have since been widely used to solve a variety of tasks [167]. In some respects, PINNs are similar to the PDE-FIND algorithm in that they also require the fundamental form of a given equation ahead of time, i.e., the form of the equation that we want the network to learn from the data. In contrast to PDE-FIND, PINNs allow for incorporating physical constraints into neural networks to ensure that model training outcomes conform to established physical principles. These physical constraints are added to the NN’s loss functions so that physics equations are included in the model training. Here, the NN optimizes not only its loss functions but also the differences between the physical equations and the original boundary conditions during each iteration in the training process. The results output by the NN incrementally approach the physical restrictions as the number of iterations increases, and the loss functions are tuned. The introduction of PINNs alleviated some bottlenecks in the simulation of high-dimensional physical problems while reducing the requirement to generate complex networks and allowing noisy data to be incorporated into current algorithms. This approach is distinct from traditional numerical modeling approaches that rely on the discretization of PDEs, and PINNs can even outperform these standard methodologies when addressing PDE inverse problems [167]. In the context of inferring solutions of PDEs using PINNs, consider PDEs taking the form:

\[ u_t + N[u] = 0, \quad t \in [0, T], \quad x \in \Omega. \tag{13} \]

These are subject to the following initial and boundary conditions:

\[ u(0, x) = g(x), \quad x \in \Omega, \]

\[ \mathcal{B}[u] = 0, \quad t \in [0, T], \quad x \in \partial\Omega, \tag{14} \]

where \( N[\cdot] \) is a linear or nonlinear differential operator, and \( \mathcal{B}[\cdot] \) is a boundary operator corresponding to Dirichlet, Neumann, Robin, or periodic boundary conditions. The unknown latent solution governed by the PDE system in Equation (1) is given by \( u \).

Following the original work of Raissi et al. [166], the unknown solution \( u(t, x) \) is represented by a deep NN \( u_\theta(t, x) \), where \( \theta \) denotes all tunable parameters of the network (e.g., weights and biases). Consequently, a physics-informed model can be trained through the minimization of the following composite loss function:
\[ \mathcal{L}(\theta) = \lambda_c \mathcal{L}_c(\theta) + \lambda_{bc} \mathcal{L}_{bc}(\theta) + \lambda_r \mathcal{L}_r(\theta), \]
\[ \mathcal{L}_{bc}(\theta) = \frac{1}{N_{bc}} \sum_{i=1}^{N_{bc}} |\mathcal{B}[u_i^\theta](t_{bc,i}, x_{bc,i})|^2, \]
\[ \mathcal{L}_r(\theta) = \frac{1}{N_r} \sum_{i=1}^{N_r} \left| \frac{\partial u_i^\theta}{\partial t}(t_i, x_i) + N[u_i^\theta](t_i, x_i) \right|^2, \]

where \( \{x_i^\theta\}_{i=1}^{N_{bc}}, \{t_{bc,i}\}_{i=1}^{N_{bc}}, \) and \( \{t_i\}_{i=1}^{N_r} \) can be set as the vertices of a fixed set or a randomly sampled set of points at each iteration of a gradient descent algorithm. Here, it is important to note that all required gradients with respect to the input variables or network parameters \( \theta \) can be efficiently computed through automatic differentiation [168]. The hyperparameters \( \{\lambda_{bc}, \lambda_c, \lambda_r\} \) ensure flexibility in assigning different learning rates to each individual loss term, thereby balancing their interactions when a PINN is trained. Note that during model training, weights may be user-specified or automatically tuned [28, 169].

They can also be adjusted through the training phase so that an explicit convergence at a solution that follows basic physics can be attempted. Although the model output can be changed to approximately satisfy physical rules by manipulating soft penalty restrictions and this approximation does not guarantee that the output will always respect actual physical laws, it does provide an extremely flexible platform for estimating departures from these physical laws as integrals, differentials, or even fractional equations. Representative studies of this type of method include the deep Galerkin method [170] and some variants of PINN [171–174]. Through the proper selection of loss functions, constraints, and inference algorithms, PINNs mainly learn bias, thereby allowing the model to learn functions, vector fields, and operators that reflect a dataset's governing physical laws. Unfortunately, copious amounts of data are frequently required to reinforce these biases and yield predictions that satisfy certain symmetries and conservation principles [51, 52, 175–177]. In oceanography, the extreme expense of collecting data significantly inhibits further research [178, 179]. Consequently, large-scale numerical models are used to generate the required data, but these naturally give rise to how simulations can be validated and the introduction of false signals avoided.

Models that have methods that learn either from data or bias are classified as those with “soft constraint” methods, which, on average, ensure that ML models conform to physical mechanisms but do not ensure that every data point satisfies the required laws of physics. Therefore, there is another school of thought that aims to constrain ML models in a “harder” way. In principle, this is to make ML models strictly meet physical constraints and is a more intuitive approach, as it is often integrated into ML model architectures by means of mathematical or “hard” constraints. For example, Mohan et al. [180] embedded the concept of incompressible fluids into a CNN and applied it to 3D coarse-grained turbulence simulations. Chen and Zhang [181] developed a network using projections dependent on field-specific knowledge. Chen et al. [182] used hard con-
DGM based on concomitant PDE is able to correct the numerical discretization error as expected, which can significantly affect the performance of the LES.

To summarize, there are five primary techniques to apply machine learning with physical constraints: based on data bias, building learning bias based on loss function, utilizing specific model structure, forming hard constraints based on special activation function, and a combination of these schemes.

5.3. Applications. Here, it can be understood that physics-constrained ML tools have been applied to both the atmospheric and oceanic sciences, but currently, research remains relatively limited, and as such, application scopes and potentials require further study. Digital twins and data-driven forecasting may be two potential applications for solving PDEs using AI and incorporating physics-constrained ML into oceanographic research.

5.3.1. Digital Twins. Strictly speaking, a “digital twin” is a digital simulacrum of a real-world living or nonliving physical entity [196]. The real-time collection of data from installed sensors and numerical model outputs is used to produce short- and medium-term forecasts. Both externally and internally generated big data are produced and analyzed through the usage of Internet of Things (IoT) technologies to transfer data to cloud storage. However, there are numerous challenges to overcome before digital twins can be used for the real-world ocean. Primarily, the problems of missing and erroneous observational data remain persistent and are symptomatic of the extreme costs associated with designing, installing, and maintaining observation platforms for temperature, salinity, density, current flow, sea surface height, and wave measurements, among other variables. Even in ideal circumstances, data transfer from observation stations may be inconsistent. Second, numerical models rely heavily on time-consuming preprocessing and calibration procedures (such as grid creation or initial and boundary calibrations), which makes them unsuitable for use in real-time decision-making. Furthermore, many physical models for complex marine systems can only partially follow conservation rules and, as such, cannot produce a closed group of equations that, ordinarily, must be supplemented with appropriate assumptions. Physics-constrained ML models that minimize the requirement for generating numerical grids allow for the presence of noisy data, and the integration of physical models with real data may overcome these flaws. Consequently, further developing an ocean digital twin may lead to numerous leaps in our understanding of the real ocean.

5.3.2. Data-Driven Forecasting. Both traditional numerical model forecasting and existing data-driven forecasting still
have several shortcomings. Traditional numerical models are limited by computational cost, difference format errors, high-resolution grid construction, subgrid parameterization, etc. They also face bottlenecks in improving the resolution and accuracy of the model. However, the prediction of pure data-driven machine learning methods may have disadvantages such as poor interpretability, inconsistency with physical laws, and weak extrapolation abilities. Physics-constrained ML models are expected to further improve data-driven forecasting by incorporating the advantages of numerical models and data-driven forecasting tools while simultaneously avoiding the disadvantages of either. Physics-constrained ML methods do not need to build a network to solve a target equation. Automatic differential solution methods avoid truncation errors, and solutions from data-driven methods can be obtained from the data. Revealing subgrid hidden information and the introduced physical constraints can improve the extrapolation ability of the network and make the results conform to the laws of physics. Importantly, models are no longer black boxes and should be readily interpretable [197]. Despite these advances, there are several shortcomings. For example, for multiscale problems, it is difficult for the network to learn high-frequency components, and the network is often impossible to train [28, 169]. High learning costs are potentially unavoidable [198, 199]. By developing new techniques to help networks learn and address current challenges, physics-constrained machine learning approaches will hopefully produce more interpretable, data-driven forecasting models with higher accuracy and resolution. As a result, physics-constrained ML models are expected to improve numerical simulations of the oceans and forecasting tools and, as such, possess great prospects for AI applications within the oceanographic sciences.

6. Summary

In this era of a confluence of petabytes of observations, numerical model outputs, and high-performance computers, increasingly advanced AI algorithms are being operationalized within the oceanographic sciences, leading to new breakthroughs in humanity’s theoretical foundations and opportunities to reduce losses of life and property due to extreme weather and climatic events. In this review, the development and application of AI algorithms primarily within the marine sciences were primarily considered. Given the large number of oceanic phenomena waiting to be observed and understood, developing the tools needed to examine the ocean on a variety of spatiotemporal scales is a priority. Traditionally, ocean phenomena have been observed by in situ and remote sensing techniques and simulated through numerical models. However, as previously described, the current trend is to feed AI algorithms with (big) data derived from these sources. In this review, the usage of AI algorithms for the detection of ocean mesoscale eddies, internal waves, sea ice, oil spills, and marine algae was discussed. AI methodologies used in the forecasting of significant wave heights on 1D and 2D scales, ENSO, and storm surges were also described. Furthermore, the emerging fields of physics- and data-driven ocean model parameterizations, where ocean turbulence and moist physics processes are studied, were considered, and this was followed by a review of studies that considered physics-informed deep learning and AI tools and a brief description of the physics-constrained NN development history and current applications in oceanography. The methodology underlying PINN algorithm development and its usage was also described. Finally, two future research directions were reviewed, digital twins and data-driven forecasting, and their relative advantages and disadvantages were described.

Although not specifically reviewed here, several studies (e.g., [169]) have suggested that to overcome current PINN limitations in simulating dynamical systems whose systems exhibit multiscale, chaotic, or turbulent behavior, PINNs should be made to adhere to physical causality during model training. This can be accomplished by introducing loss functions that explicitly account for physical causality through model training. Similarly, Fourier neural networks (FNNs; [51, 52]) were not discussed within this review, as no example of their usage can be found with regard to oceanographic sciences. Consequently, future studies can consider the usage of either causality-adherent PINNs or FNNs in the oceanographic sciences to see if their promises of improved PDE calculations can be realized and better oceanic phenomena detection, forecasting, and parameterization algorithms can be developed and utilized.

Data Availability

No datasets were created or used in this review paper.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors’ Contributions

The authors confirm contribution to the paper as follows: study conception and design were contributed by CD, GX, HG, BJB, WX, SZ, GX, HG, BJB, WX, and SZ. Analysis and interpretation of results was contributed by CD, GX, HG, BJB, WX, and SZ. Draft manuscript preparation was contributed by GX, HG, BJB, WX, and SZ. All authors reviewed the results and approved the final version of the manuscript.

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