Frontier Interdisciplinary Strategy

An assessment study of Artificial Intelligence Oceanography

Artificial Intelligence Oceanography Research Team

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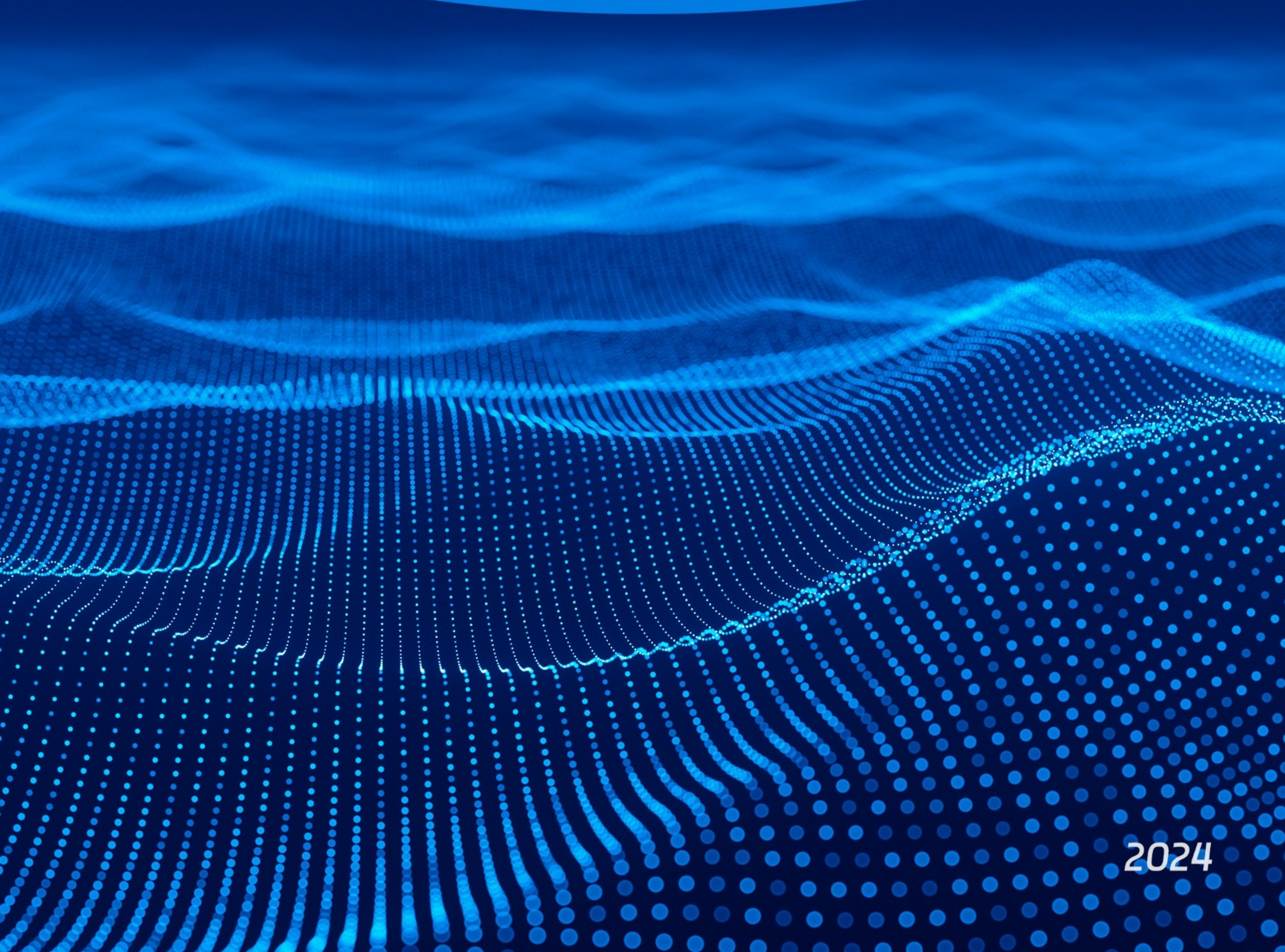

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Abstract

With the advent of the era of ocean big data and the flourishing development of artificial intelligence (AI) technology, AI oceanography has emerged as a new interdisciplinary science. By deeply integrating marine sciences with AI technology, it can provide strong support to the field of oceanography in a totally unprecedented manner. However, AI oceanography is still in its infancy and is facing many challenges, such as the lack of clarity in the direction it goes, in the scientific problems it addresses, and in the planning of its development pathways.

This study reviews the current state of AI oceanography, including new advancements in the establishment of ocean big data systems, the development of relevant AI algorithms, and the construction of the digital twins of the ocean. It is found that AI oceanography is rapidly advancing in the areas of data integration, storage and analysis, accumulating not only vast data resources but also rich experience in data processing. Via cutting-edge technologies such as deep learning and machine learning, AI oceanography enables more intelligent analysis and application of ocean data, proving new research opportunities and possibilities.

In terms of applications, AI oceanography has made significant strides in research areas such as intelligent recognition of ocean features, intelligent prediction of ocean phenomena, and intelligent estimation of model parameters. Intelligent recognition of ocean features allows for a more accurate understanding of dynamic processes, providing precise safeguards for marine environment. AI-based intelligent models can enhance the prediction accuracy for ocean meteorology and marine ecosystems, offering reliable support for marine environment protection and sustainable resource utilization. Intelligent estimation of model parameters can largely increase models' computational efficiency as well as their simulation and forecast ability.

Looking ahead, we need to develop customized natural language processing technologies (i.e. Ocean ChatGPT), to build AI-based Earth system big models, to further solidate the framework and database for the digital twins of the ocean, and to work

collectively on computing power scheduling, hardware construction, computing efficiency and stability, providing a robust foundation for AI oceanography, a truly revolutionary branch of ocean sciences. With the rapid development of AI technology and the continued growth of research teams, AI oceanography will go far beyond our imagination, providing powerful intelligent support for us to explore the mysteries of the ocean and address critical issues such as global climate change.

Content

I. Current Development Status of AI Oceanography

The journey of artificial intelligence (AI) began in the 1950s, but it wasn't until the early 21st century that we saw a surge in its growth. This was thanks to advancements in big data, deep learning, and increased computing power. As a result, AI has penetrated into fields such as healthcare, finance, manufacturing, and has become a core technology driving scientific research and socio-economic development, shaping the future and exerting a revolutionary impact on the progress of human society. AI oceanography is an emerging interdisciplinary field integrating marine science and AI, which has developed rapidly in recent years. Its role in the marine domain is mainly manifested in the following five aspects.

1. Establishment of Marine Big Data Systems

The characteristics of marine big data are summarized as the typical 5Vs: large Volume, high Velocity of growth, Variety of types and sources, high Value density, and Veracity (Mayer-Schönberger et al., 2013). These five characteristics reflect the complexity and challenges of data processing in the marine domain.

With the rapid development of marine observation technologies in recent decades, the storage volume of marine data has reached the petabyte scale, marking that ocean science has entered the era of big data. Existing ocean data used for intelligent algorithm development mainly include satellite remote sensing observation data, numerical model data and reanalysis data (Qian et al., 2022).

Traditional ocean remote sensing data relies on manual processing and interpretation with professional knowledge, which has problems such as accuracy being affected by human factors, time-consuming, and consuming human resources. In AI oceanography, intelligent processing of ocean remote sensing data has become an important research direction. With the help of AI technology, especially machine learning and deep learning algorithms, automatic processing and analysis of ocean remote sensing data can be realized, and the speed and accuracy of data processing can be improved.

Marine numerical models are based on equations of ocean dynamics, continuity, thermodynamics, etc., used to simulate and predict changes in the dynamic characteristics of seawater motion, temperature, salinity, etc. These models continue to generate large-scale marine data, simulate the complexity of marine systems, predict changes in the marine environment, and provide important bases for scientific research and decision-making.

Ocean reanalysis integrates various observational data and numerical models through coupling, utilizing data assimilation techniques to generate high-quality datasets for the analysis and reconstruction of past and present ocean states. For marine scientific research and initialization of prediction models, gridded ocean reanalysis products are one of the most important data supports.

In addition to the 5V characteristics of big data, ocean data also has the characteristics of high dimensionality, heterogeneity, and high sparseness in space and time. These characteristics bring challenges to the processing and analysis of ocean data, requiring specific methods and technologies to process and extract useful information.

2. Development of AI Algorithms for Marine Big Data

Marine big data encompasses variables related to multiple research areas such as physical oceanography, marine remote sensing, marine chemistry, marine biology, marine geology, and marine ecology, providing critical information services and decision support for marine environment forecasting, disaster prevention, operational production, and economic policy formulation. Marine big data not only covers a wide range of research fields but also exhibits complex spatiotemporal correlations among various marine elements.

To eliminate the isolation of ocean data and enhance its usability and value, it is necessary to integrate heterogeneous ocean data from multiple sources. First, data is obtained from different sources, preprocessed and cleaned to ensure data accuracy and consistency. The data is then stored and managed efficiently for quick access and retrieval. In the data integration and matching stage, the structural and format differences of heterogeneous data are resolved to ensure that the data can be effectively integrated. At the same time, in order to control data quality, a corresponding evaluation system needs to be established to ensure the credibility of the data.

In the research on integrating ocean multi-source heterogeneous datasets using AI algorithms, Zhang et al. (2023a) employed an ensemble learning approach based on a spatiotemporal ecological ensemble model to construct monthly phytoplankton community products at a global scale from 1997 to 2020 (Figure 1). The study indicates that AI algorithms exhibit unparalleled advantages in integrating ocean multi-source heterogeneous data, warranting further exploration of related technical methods and application scenarios.

Faced with the sparsity of ocean data, researchers are actively exploring data fusion and assimilation techniques, integrating data from different observation sources and merging them through numerical models to fill data gaps and improve the spatial and temporal continuity of data. Among them, data assimilation is an important technique that combines observational data with numerical models to output data products that are finer than observations and more accurate than models. AI technology has now begun to be applied to the fusion and assimilation of ocean big data, promising to provide more complete and timely data for ocean research and forecasting, as well as more reliable scientific basis for policymakers.

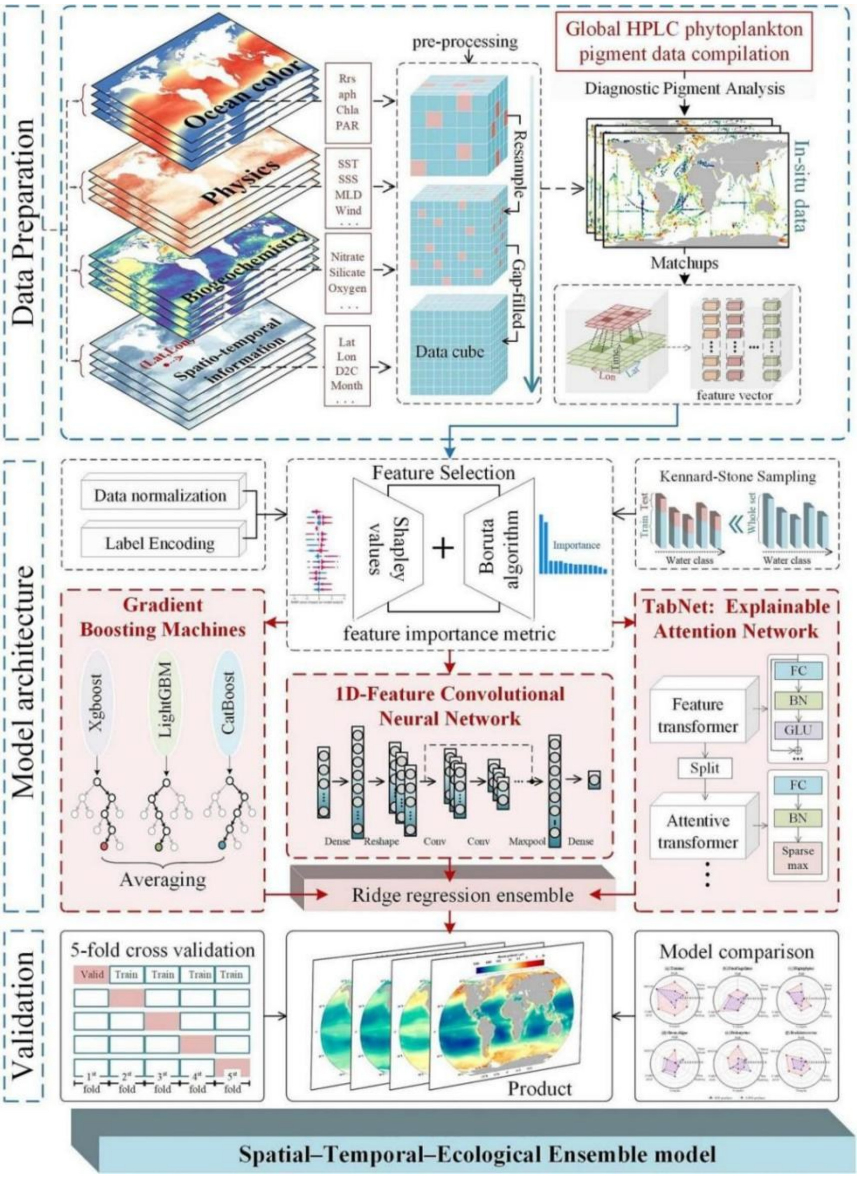

Figure 1. Utilizes an ensemble learning method based on the Spatial-Temporal-Ecological Ensemble (STEE) model, incorporating data on watercolor, physical oceanography, biogeochemistry, and spatiotemporal information from major global marine regions, to generate a schematic of the monthly phytoplankton group product on a global long-term scale from 1997 to 2020. (Zhang et al., 2023a)

3. The Application of AI in Oceanography

3.1 Intelligent Recognition of Marine Features

Intelligent recognition of marine features involves the rapid and accurate identification of physical, biological, and geological characteristics in the ocean using AI technology, which is of great significance for the in-depth understanding of ocean systems. Below, we will systematically review the research progress on intelligent identification of ocean eddies, ocean internal waves, ocean oil spills, offshore vessels, ocean algae, ocean corals and deep-sea sediments.

(1) Oceanic eddies

Oceanic eddies are closed-loop rotating water bodies widely present in the oceans, playing a significant role in the transport of matter, energy, and heat in the global oceans. As early as 2016, foreign scholars successfully employed machine learning methods for the first time in the detection of oceanic eddies, with an identification accuracy as high as 97%, far exceeding traditional identification algorithms (Ashkezari et al., 2016). This marks the first successful application of AI in the field of automated identification of oceanic eddies. Subsequently, deep learning models such as U-net based on encoder-decoder framework, REDN, and other models have also been introduced into the intelligent identification research of oceanic eddies, further enhancing the accuracy and efficiency of identification (Franz et al., 2018; Santana et al., 2022). Meanwhile, domestic scholars have also actively engaged in related research work, not only improving the model structure to enhance the accuracy of eddy recognition (Duo et al., 2019; Xu et al., 2019, 2021; Sun et al., 2021), but also utilizing AI models that integrate multi-source remote sensing data to reveal new discoveries in the ocean (Liu et al., 2021a, Figure 2). However, oceanic eddies possess complex three-dimensional structural features (Zhang et al., 2016), and it is difficult for existing intelligent recognition methods to reveal the complete shape of eddies. In the future, through highly integrated ocean knowledge and AI algorithms, it is expected that intelligent recognition of the three-dimensional structure of eddies could be further achieved through increasing training data.

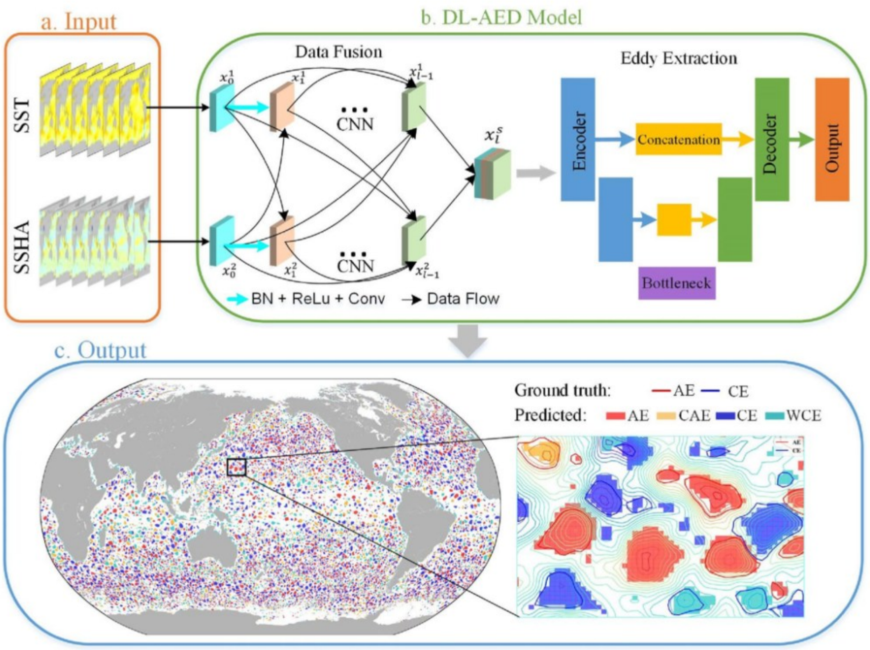

Figure 2. Deep learning model for oceanic eddy detection based on sea surface height anomalies and sea surface temperatures. (Liu et al., 2021a)

(2) Internal waves

Internal waves(IW) is a common natural phenomenon in the ocean, with significant implications for ocean acoustics, seawater mixing, nearshore engineering, and underwater navigation. Satellite observation is the only means to conduct large-scale, long-term observations of internal waves, and it has become the primary approach for studying the spatial-temporal distribution, propagation, and evolution of internal waves (Li et al., 2008). Since the 21st century, international scholars have begun to use traditional image processing methods to extract internal wave information from satellite images (Simonin et al., 2009). However, these traditional methods are susceptible to image noise interference. In contrast, machine learning methods have demonstrated more reliable performance in extracting internal wave information from satellite images (Li et al., 2020). Zhang et al. (2022) designed IWE-Net based on deep learning networks. Based on the model structure and loss function of internal wave characteristics, it realized the automatic extraction of internal wave information from remote sensing images with different loads and different resolutions, achieving high accuracy (Figure 3). Deep learning models can significantly improve the accuracy of internal wave signal extraction under challenging imaging conditions, supplementing field observations and promoting research on the generation, propagation, evolution, and dissipation of internal waves. However, the accuracy of deep learning models in a few marine areas still has room for improvement, and in the future, this can be addressed by training on more images containing rich internal wave features.

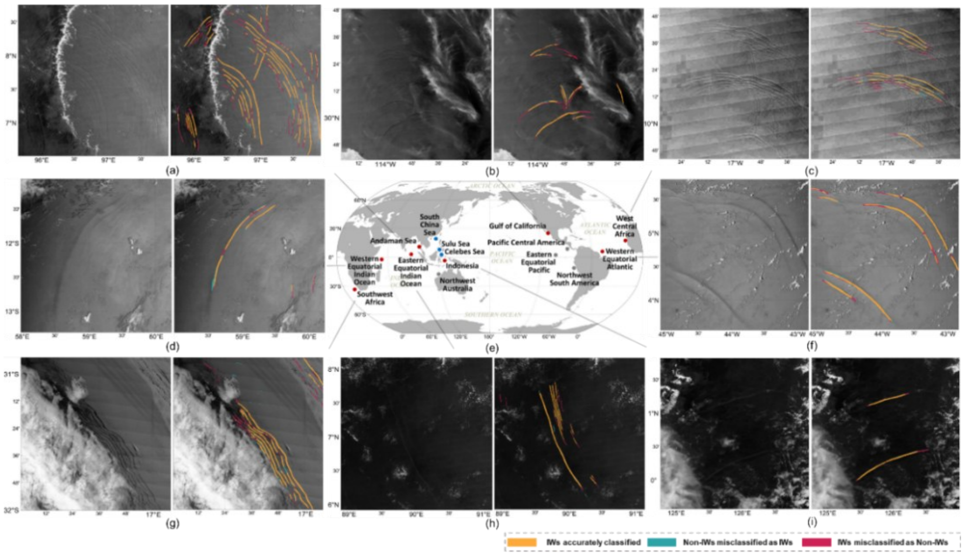

Figure 3. Eight examples of MODIS images applied globally by IWE-Net (Zhang et al., 2022).

(3) Oil spill at sea

Oil spills at sea are typical marine pollution events, often triggered by accidents involving ships, explosions at offshore oil rigs, ruptures in oil pipelines, and other causes. These incidents can have serious environmental and economic impacts on areas such as marine fisheries, aquaculture, ecosystems, maritime tourism, and transportation (Crone et al., 2010; Li et al., 2021). Satellite remote sensing imagery is widely used for detecting offshore oil spill events. Through different deep learning models, the oil film features in images can be deeply mined, which can not only quickly identify the characteristics of oil spills on the sea surface (Krestenitis et al., 2019; Yekeen et al., 2020), but also classify oil spill areas based on the texture and shape of the images (Bianchi et al., 2020, Figure 4). Instance segmentation models perform better than semantic segmentation models in intelligent oil spill recognition. Domestic scholars are also actively engaged in research on intelligent recognition of offshore oil spills. By improving model structures or introducing more feature information, they can effectively extract detailed features of oil spills on the sea surface from the imagery (Wang et al., 2022) and have successfully achieved accurate identification of irregularly shaped oil spill events (Dong et al., 2023). The quality of satellite remote sensing imagery is crucial for the accurate identification of offshore oil spill events. In the future, by improving imaging and preprocessing technologies for optical and synthetic aperture radar, and adopting advanced deep learning algorithms, it is expected to further enhance the performance of intelligent oil spill recognition models.

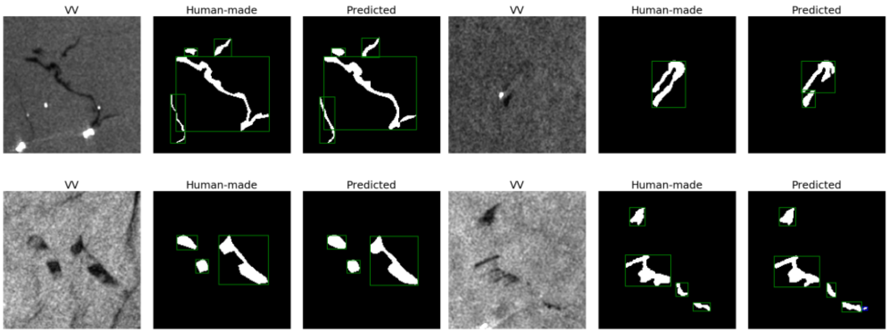

Figure 4. Results of the intelligent oil spill recognition model on the validation set. From left to right: VV polarization input, manual labeling, model output. Green boxes indicate parts recognized by both manual and model, blue boxes indicate parts recognized only by the model, and red boxes indicate parts recognized only manually. (Bianchi et al., 2020)

(4) Sea vessels

Ship detection is an important task in maritime surveillance, with significant implications for enhancing maritime defense warning capabilities and strengthening maritime monitoring and management. Synthetic Aperture Radar (SAR) is widely used in maritime ship detection due to its all-weather, all-day monitoring capability (Zhu et al., 2010; Ouchi et al., 2004). Scholars have proposed a series of algorithms for ship detection in SAR images, which can be classified into two main categories: traditional methods and AI methods. Threshold segmentation-based methods are a traditional approach to ship detection, which involves searching for pixels with significant brightness differences and utilizing filter statistics for modeling. However, the main drawback of traditional methods is the need for prior knowledge to manually design parameters and features, which is a common challenge in many fields in the era of big data (LeCun et al., 2015). In comparison to traditional methods, deep learning can automatically extract ship features and detect ships more quickly and accurately. For example, methods such as DRBox (Liu et al., 2017) based on deep learning and rotated bounding boxes, and Faster-RCNN (Deng et al., 2019, Figure 5) based on fast region convolution, have been applied to ship detection. Ship detection models based on deep neural networks greatly simplify the feature extraction process and offer higher precision and stability. In the future, utilizing intelligent models to further detect parameters such as ship types and geometric dimensions from SAR images or optical images will contribute to a more comprehensive understanding of the characteristics of maritime ships, thereby improving the efficiency and accuracy of maritime surveillance and management.

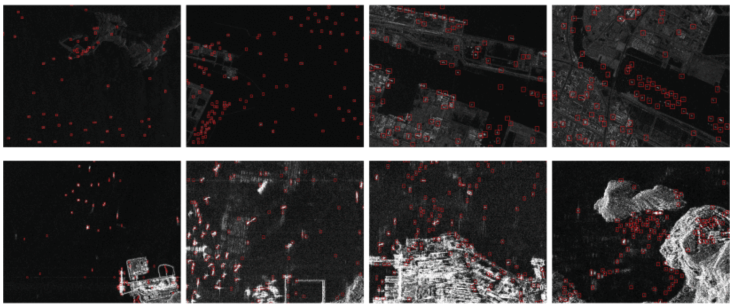

Figure 5. Ship detection results from multiple SAR images using Faster R-CNN (Region-based Convolutional Neural Network). (Deng et al., 2019)

(5) Marine algae

Marine algae play a vital role in ecosystems, but in recent years, harmful algal bloom events caused by massive reproduction in a very short period have had significant negative impacts on marine ecosystems and human societies. Therefore, intelligent detection of marine algae is crucial for preventing and controlling algal bloom disasters. Satellite remote sensing, capable of monitoring the ocean extensively and periodically, is the primary technical means for algal bloom monitoring. Meanwhile, deep learning has shown great potential in the identification of algae in optical and SAR remote sensing images. Arellano-Verdejo et al. (2011) proposed an ERISNet model based on onedimensional CNN for extracting large-scale kelp along the Mexican coastline, achieving an accuracy of up to 90.08%. Guo et al. (2022) proposed a GA-Net model for detecting green algae in SAR images (Figure 6). Compared to classical deep learning models, this model comprehensively considers normalized radar cross-section and texture information, resulting in higher accuracy and generalization ability. Optical and SAR images, due to their different imaging mechanisms and spatiotemporal resolutions, exhibit consistent overall distribution characteristics in algae identification. However, the distribution details often differ significantly. For instance, optical MODIS images frequently miss fine algal strips, while SAR images can identify more algal details simultaneously (Gao et al., 2022). In the future, by integrating algae features obtained from different satellites into the input data or considering different types of loss functions comprehensively, it is expected to further improve the accuracy and robustness of the models in algae identification.

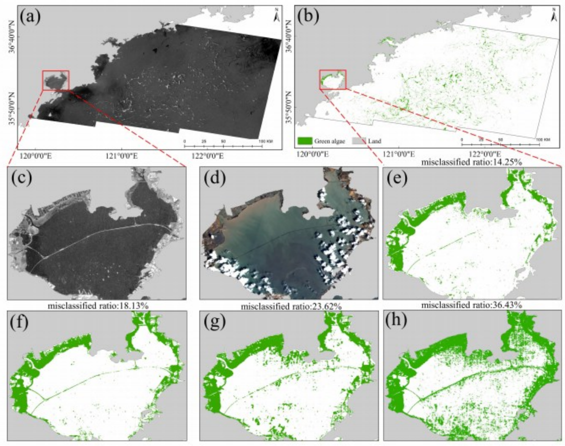

Figure 6. Identification of green algae based on SAR imagery on June 23, 2019. (a) SAR image in VV polarization under UTM projection. (b) Detection results of the GA-Net model. (e)-(h) represent the identification results of GA-Net/VGG-16/AlgaeNet/U-net models in this area. (Guo et al., 2022)

(6) Marine coral

Coral is an important part of the marine ecosystem and an indicator of climate and environmental changes. Identifying its distribution and changes is crucial to protecting marine ecology and coping with climate change. However, traditional methods of biological identification based on morphology and molecular genetics are limited in practical marine environments. With the advancement of computer vision and deep learning techniques, scholars have undertaken intelligent recognition research on marine corals. Jaisakthi et al. (2019) proposed a convolutional neural network-based method for locating and detecting different types of benthic organisms. However, achieving high-precision real-time detection with such traditional detection architectures is challenging, which is crucial for practical applications. To address this issue, Li et al. (2020a) utilized deep learning networks to achieve intelligent recognition of corals (Figure 7). They constructed a video dataset of different types of corals through frame-by-frame processing and manual annotation, standardized, cropped, and enhanced the images to improve the robustness and accuracy of the model. Liu et al. (2024), using deep-sea image data, further improved the accuracy of fine-grained recognition. The diversity of coral morphologies and species richness makes high-fidelity classification detection difficult, while the exceptionally complex and unique imaging environment of the ocean makes achieving high-precision real-time detection challenging. In the future, by optimizing data augmentation algorithms for the special and complex imaging environment of the ocean and expanding the number of coral samples to obtain high-quality datasets, it is expected to further improve the accuracy and granularity of marine coral identification.

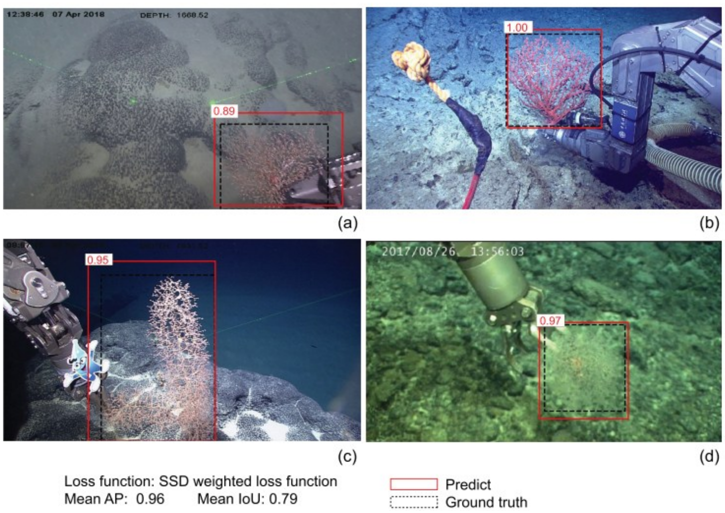

Figure 7. Different types of corals identified based on the VGG model. The numbers in the white boxes represent the confidence levels of recognition for each type of coral. (Li et al., 2020a)

(7) Deep sea sediment

The deep-sea sediment harbors vast resources and records the history of Earth's environmental changes. The widespread distribution and diversity of sediments make their identification a challenging task (Figure 8). In recent years, the identification of deep-sea sediments has started to shift toward deep learning techniques. For instance, Jiang et al. (2020) proposed a sediment testing system based on deep learning, which utilizes neural networks for error correction of data and achieves intelligent identification. Ruan et al. (2022) designed a sampling system based on image recognition technology, utilizing intelligent identification model frameworks to enhance identification accuracy. In the future, through optimizing feature extraction and data augmentation algorithms, transforming sample data into high-dimensional feature spaces, and applying advanced AI algorithms, it is expected to further improve the accuracy of deep-sea sediment identification, promoting a deeper understanding of deep-sea environments and resources to support related scientific research and applications.

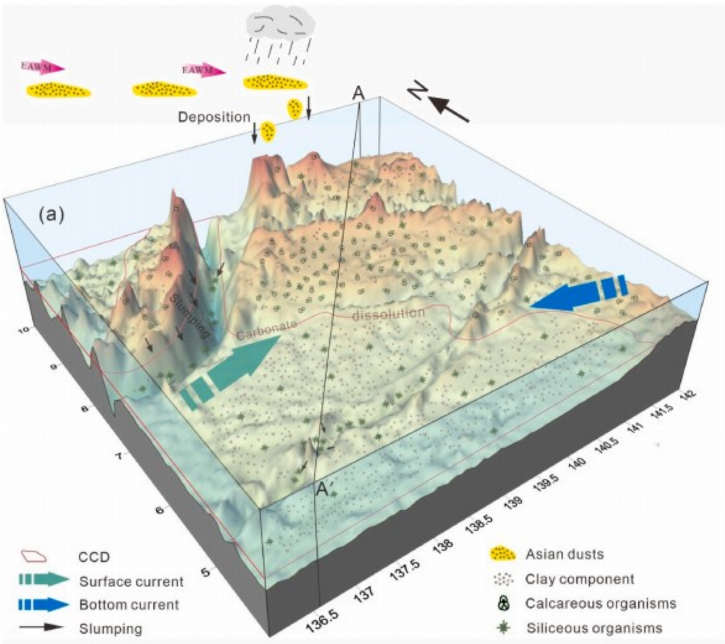

Figure 8. Spatial distribution of sediment components in the tropical western Pacific Ocean. (Guo et al., 2023)

3.2 Intelligent Forecasting of Marine Elements and Phenomena

The data-driven ocean intelligence model, utilizing AI technology, learns the inherent characteristics and patterns of oceanic changes embedded within the data, enabling forecasts of various oceanic elements and phenomena. It is currently applied in numerous fields ranging from short-term climate variations to mesoscale oceanic processes.

(1) Intelligent ENSO forecasting

In recent years, significant progress has been made in the application of AI technology to predict the El Niño-Southern Oscillation (ENSO). Ham et al. (2019) developed a CNN-based ENSO prediction model capable of forecasting the Nino3.4 index 17 months in advance, with significantly higher correlation coefficients compared to traditional dynamical models. Gupta et al. (2020) utilized Convolutional Long Short-Term Memory networks (ConvLSTM) to predict the monthly average Nino 3.4 index a year in advance, even forecasting extreme El Niño events. To better interpret the neural network's prediction outcomes, Cachay et al. (2021) applied spatiotemporal graph neural networks to ENSO prediction. Compared to traditional CNNs, this model can make fuller use of the spatiotemporal information of the input data and improve the accuracy of ENSO prediction. Liang et al. (2021) employed a causally interpretable AI model based on Liang-Kleeman information flow, successfully reproducing ENSO events with a lead time of 12 years. Zhou et al. (2023) devised a spatiotemporal 3D convolutional neural network model, TS-3DCNN, for predicting La Niña conditions from 2020 to 2021 (Figure 9). Prediction results indicate that deep learning-based models can capture La Niña events over a span of 2 years to a certain extent. Wang et al. (2023) developed an interpretable deep learning ENSO prediction model, which for the first time, utilized AI technology to discover regions globally correlated with ENSO as forecast lead time varies. The effective ENSO prediction length reached 22 months, with the model being largely unaffected by the spring predictability barrier.

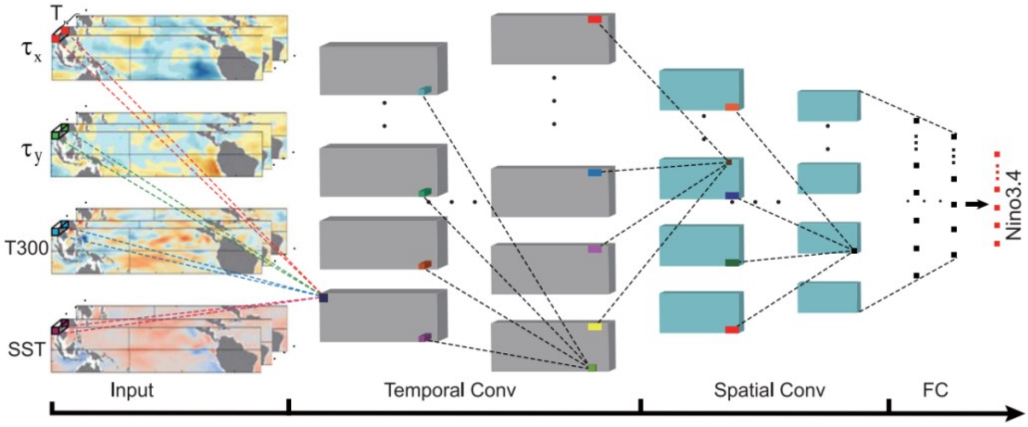

Figure 9. TS-3DCNN Model for Prediction of NINO3.4 Sea Surface Temperature Anomalies. (Zhou et al., 2023)

(2) Intelligent storm surge forecasting

Storm surge is a phenomenon of rapid rise in tidal levels in a sea area caused by intense atmospheric disturbances. Whether it becomes a disaster largely depends on whether the storm surge coincides with the tidal cycle of astronomical tides. In recent years, the rise of AI technology has added new momentum to the development of storm surge prediction research. Some studies such as Lee (2006), Rajasekaran et al. (2008), and Hashemi et al. (2016) use typhoon elements such as wind speed, wind direction, and atmospheric pressure as inputs, employing artificial neural networks (ANNs) or support vector machines to predict storm surges. Based on Long Short-Term Memory (LSTM), Liu et al. (2020) established a short-term forecast model of storm surges at individual stations using meteorological elements and pre-tidal time series. This model simultaneously considers combinations of four different input parameters, predicting and analyzing tidal heights for the next 1 to 3 hours. Xie et al. (2022) directly extracted features of two-dimensional wind fields and pressure fields using a CNN model, and fused them with tidal time series to predict water level sequences at storm surge stations (Figure 10). Compared with station observations, the correlation coefficient of the storm surge water level predicted by the model within 24 hours exceeds 0.95, indicating good performance of the model in storm surge prediction. Furthermore, Xie et al. (2023)

applied the ConvLSTM model to the intelligent prediction of storm surge inundation processes. Compared with traditional dynamical numerical forecasts, the ConvLSTM model has higher computational efficiency and can achieve prediction results comparable to numerical simulations in short-term forecasts.

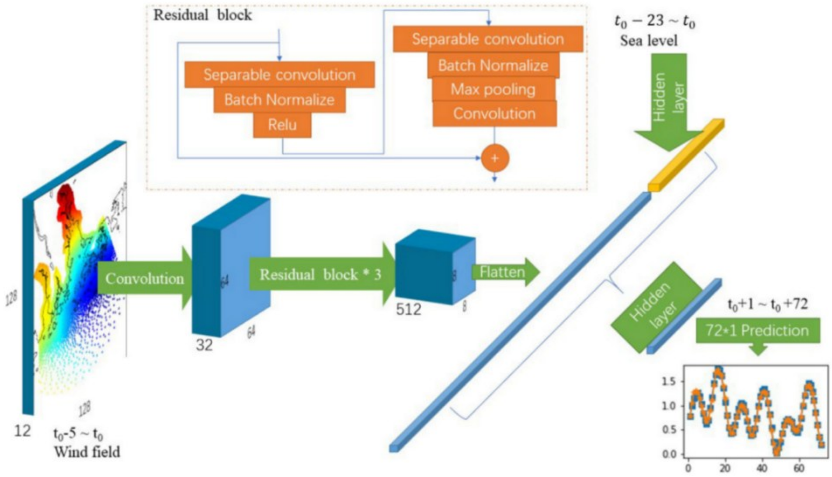

Figure 10. Intelligent prediction model for storm surge site water level based on CNN. (Xie et al., 2023)

(3) Intelligent ocean wave forecasting

The waves have strong nonlinear characteristics, which have significant impacts on ocean engineering, offshore operations, and transportation. A considerable amount of research has utilized AI techniques to predict wave characteristics at single points. Londonhe and Panchang (2006) employed Artificial Neural Networks (ANN) for intelligent prediction of significant wave height. The results showed that the model accurately predicts significant wave height for the next 6 hours, with a 67% correlation for the next 12 hours. Fan et al. (2020) combined Long Short-Term Memory (LSTM) with the SWAN model for wave height prediction. Compared to predictions using only the SWAN model, the SWAN-LSTM model improved prediction accuracy by about 65%. Zhou et al. (2021a) proposed an LSTM algorithm based on Empirical Mode Decomposition (EMD) for single-point wave prediction, achieving superior accuracy compared to the LSTM algorithm when compared with buoy observations in the

Caribbean Sea. Research on intelligent prediction of two-dimensional wave fields typically utilizes reanalysis data as labeled data to train models. Zhou et al. (2021b) used the Convolutional LSTM (ConvLSTM) algorithm to predict regional significant wave heights in the eastern and southern waters of China (Figure 11), with a maximum forecast duration of up to 24 hours. Subsequently, Bai et al. (2022) employed the CNN algorithm to predict regional significant wave heights in the South China Sea, and through 56 sets of sensitivity experiments, determined the optimal input variable duration for the 12-hour prediction model.

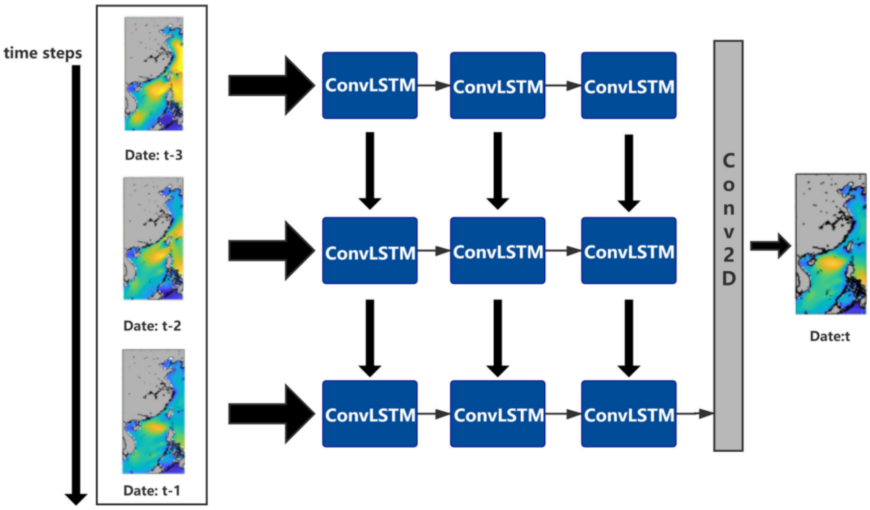

Figure 11. Effective significant wave height prediction model based on ConvLSTM. (Zhou et al., 2021b)

(4) Intelligent forecasting of sea surface temperature

An in-depth understanding and accurate forecast of the spatiotemporal changes in Sea Surface Temperature (SST) are of great significance to many fields such as oceanography, meteorology, and navigation. Currently, SST prediction methods mainly fall into two categories: numerical models and data-driven intelligent approaches. In recent years, due to the adaptive feature learning capability of deep learning, especially recurrent neural networks and their extensions such as LSTM and gated recurrent units, utilizing deep learning for accurate prediction of oceanic elements and phenomena has become a research hotspot. However, single recurrent neural network prediction models suffer from weak learning capabilities and are prone to overfitting. Studies have shown that hybrid models can help improve prediction accuracy. To solve this problem, researchers try to combine recurrent neural networks with other forecast models to improve forecast accuracy. For example, Xiao et al. (2019a) constructed a combination model of LSTM and AdaBoost to forecast SST in the East China Sea. Addressing the limitation of recurrent neural networks in considering only temporal characteristics while neglecting spatial characteristics, Xiao et al. (2019b) combined CNN with LSTM, further improving SST prediction accuracy (Figure 12). On the other hand, considering the nonlinearity and multi-noise characteristics of ocean data, scholars have also attempted to introduce data preprocessing modules into ocean prediction models to eliminate noise, thereby improving prediction accuracy.

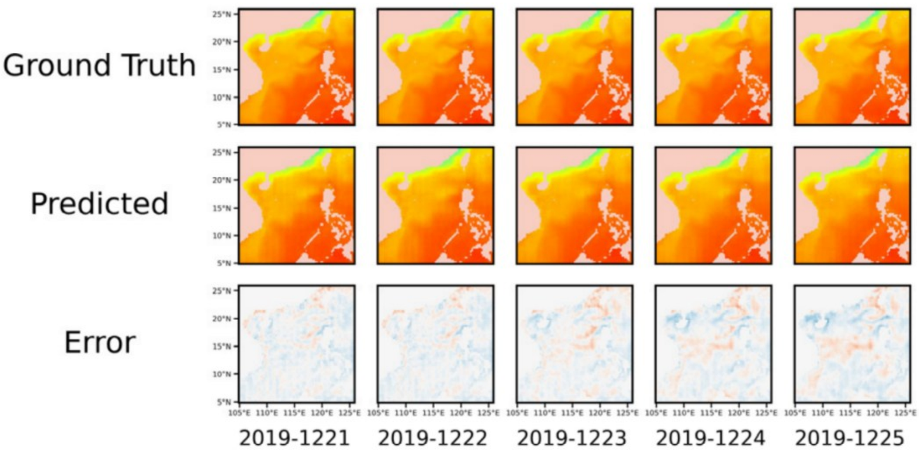

Figure 12. Prediction of future 5-day sea surface temperatures based on ConvLSTM. (Xiao et al., 2019b)

(5) Intelligent forecasting of sea surface wind speed

The prediction of sea surface wind speed using different neural network algorithms has achieved better results than traditional methods. A common method is to adopt a decomposition ensemble framework, which enhances the prediction accuracy of wind speed by extracting sub-sequences with periodicity and trendiness (Jiang et al., 2021). Another method is to employ a composite weighting framework, where the same data is first predicted using different models to generate diverse predictions. Subsequently, a weighted algorithm or optimization algorithm is utilized to combine all the results to obtain the final wind speed prediction (Niu et al., 2019). Nie et al. (2021) utilized the ICEEMDAN decomposition method to process wind speed data. Subsequently, they employed Bi-LSTM, ELM, and BP neural networks to predict the sub-sequences, and fused the prediction results of the sub-sequences using a multi-objective optimization algorithm to obtain the final wind speed prediction. Similarly, Wang et al. (2021) employed ELM, BPNN, and wavelet neural networks to predict wind speed data separately, and then utilized the grey wolf optimization algorithm to obtain the final prediction result. Furthermore, some new techniques, including physical information methods (Geng et al., 2021), graph neural networks, and graph attention mechanisms, have also been applied to wind speed forecasting research. In the future, by continuously enriching and improving the toolbox of forecasting techniques, it is expected to further enhance forecasting capabilities.

(6) Intelligent forecasting of sea ice

The mainstream methods for Arctic sea ice forecast include numerical models and statistical models. In comparison with numerical models, statistical models are more flexible and user-friendly as they start from the data itself to explore and fit the changing patterns of sea ice, especially when facing complex factors and unclear impact patterns (Horvath et al., 2020). Deep learning methods are essentially an emerging statistical approach. By constructing various deep neural network models, researchers can extract patterns from historical spatiotemporal sequences of sea ice, based on which they achieve forecasts of multiscale sea ice spatiotemporal changes and significantly improve the prediction accuracy (Chi and Kim, 2017; Choi et al., 2019; Liu et al., 2021b). Deep learning is capable of capturing the changing patterns of sea ice and enhancing the predictability of key parameters such as sea ice concentration. However, purely data-driven intelligent models often struggle to accurately forecast anomalous sea ice changes, as they involve multiscale physical processes, particularly during the summer and autumn seasons when melt pond phenomena are severe and the influences of thermal and dynamic factors are more complex. Combining deep learning with physical mechanisms of sea ice change is a research question that needs to be addressed in the future.

(7) Intelligent forecast of marine heat wave

Marine heat waves are typically defined as prolonged periods of extreme high sea surface temperatures lasting for at least five days. With global climate change, the intensity and frequency of marine heat waves are gradually increasing, significantly impacting marine environment and ecosystems. Recently AI has also been applied in prediction of marine heat waves. Sun et al. (2023) proposed a method that combines U-Net and ConvLSTM networks for predicting marine heat waves in the South China Sea region. They utilized the U-Net model to forecast the intensity of marine heat waves and employed the ConvLSTM model to predict their occurrence probabilities. Despite a gradual decrease in prediction accuracy with increasing lead time, the model's accuracy remains above 80% for a forecast lead time of 7 days (see Figure 13). In the future, with continuous advancements in AI technology and accumulation of ocean data, further improvements in the prediction accuracy are expected. This will help us better predict and understand the formation and evolution of marine heat waves, thus enhancing our ability to create a sustainable marine ecosystems effectively.

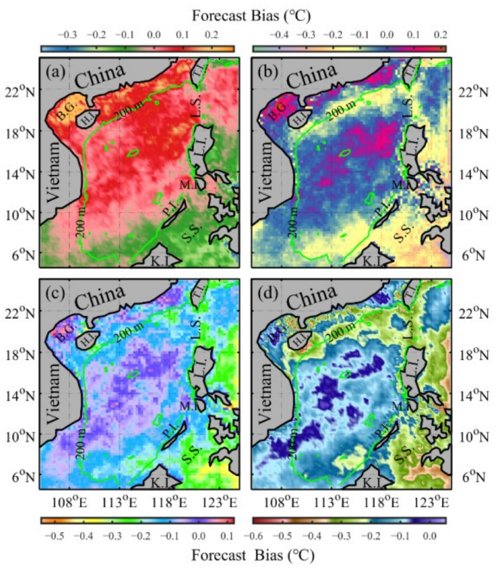

Figure 13. Spatial distribution of forecast errors in heatwave intensity for lead times of 1 day (a), 3 days (b), 5 days (c), and 7 days (d). (Sun et al., 2023)

3.3 Intelligent Estimation of Model Parameters

Parameterizing sub-grid processes in numerical models is a challenging task, and computing these parameters typically requires substantial resources. Parameterization based on data-driven AI methods do not require any physical assumptions, and the calculations are straightforward once the model is established. Such AI-based parameterizations have been applied in some idealized models (Berloff, 2005; Zanna et al., 2017; Duraisamy et al., 2019). By identifying patterns and estimating optimal parameter values from extensive experiments (Zhang et al., 2016; Han et al., 2022), or by identifying patterns from vast observational data or high-resolution model outputs and establishing new parameterization schemes (Bolton and Zanna, 2019), the intelligent parameterizations can enhance numerical models' capabilities in simulation and prediction. Current research mostly focuses on atmospheric circulation models (Zhang et al., 2016) or typhoon prediction models (Jiang et al., 2018), while research on ocean model parameterization combined with machine learning is just beginning.

Deep learning-based turbulence parametrization scheme was first applied to numerical models by Tracey et al. (2015) and Ling et al. (2016). Ling et al. (2016) utilized deep fully connected neural networks to parametrize the turbulent momentum of the anisotropic stress tensor, and they found that incorporating physical constraints into the network was necessary to achieve results better than linear regression models. Additionally, some studies have used neural networks to parametrize turbulent momentum fluxes in freely decaying two-dimensional turbulence models (Maulik and San, 2017; Cruz et al., 2019) and large eddy simulations. In the field of oceanography, researchers have utilized CNN models to parametrize mesoscale eddies and vertical mixing rates, and pointed out that such intelligent parametrizations can be generalized in ocean numerical models under different dynamic conditions. Zhu et al. (2022) designed the first deep learning-based parametrization scheme for oceanic vertical mixing using turbulence observations in the tropical Pacific (Figure 14) and applied their scheme to ocean circulation and atmosphere-ocean coupled numerical models. They found that data-driven turbulence mixing parametrization schemes can effectively simulate the vertical heat flux in the upper ocean, thereby improving the accuracy of simulating sea surface temperatures in the tropical Pacific.

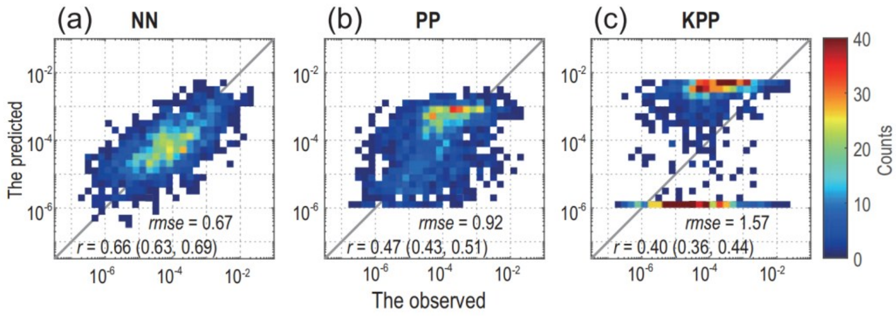

Figure 14. Histogram of two-dimensional comparison between observed and estimated vertical eddy diffusivity coefficients using different methods. NN denotes neural network, PP denotes PP parameterization scheme, and KPP denotes KPP parameterization scheme. (Zhu et al., 2022)

3.4 Intelligent Correction of Modeling Results

Numerical models are the primary tools for climate prediction today. Due to parameterization of physical processes and discretization of differential equations, numerical models inherently contain biases. Compared with traditional statistical correction methods, deep learning-based correction models can more effectively capture the nonlinear relationship between numerical model forecasts and actual observations, thus yielding more accurate model correction results. Chapman et al. (2019) corrected the water vapor transport in the Eastern Pacific and western United States outputted by the GFS model using CNN, resulting in a reduction of 9%-17% in root mean square error and an increase in correlation of 0.5%-12%. Sayeed et al. (2021) used deep CNN to correct the forecast results of the WRF model, showing that the forecast accuracy of wind speed, relative humidity, and hourly precipitation at over 90% of sites was significantly improved. Zhang et al. (2022) used linear regression, LSTM-FCN, and LightGBM, to correct the 2-meter temperature forecast of the GRAPES-3km model. The results showed that all three machine learning methods could effectively correct the temperature forecast results, with root mean square errors decreased by 33%, 32%, and 40% respectively. The accuracy of the LightGBM method after correction was over 84%. Son et al. (2022) combined CFS-v2 with image super-resolution deep learning technology to construct a hybrid wildfire weather forecasting system, significantly improving the accuracy of wildfire weather prediction with a lead time of up to 7 days and spatial resolution increased to 4 kilometers.

Due to limitations in ocean observation data, correction of ocean numerical models mainly focuses on ocean wave, salinity, and temperature. Makarynskyy (2004) used ANN to forecast wave parameters for the next 24 hours and corrected the initial forecast values to further improve forecast accuracy. Londhe et al. (2016) used historical forecast errors of wave height from the INCOIS model as input to correct wave forecast data for the 24th hour. Gracia et al. (2021) combined multilayer perceptron and LightGBM to reduce the forecast error of parameters such as significant wave height and wave period outputted by numerical models by 36%. Jang et al. (2021) improved SMAP sea surface salinity (SSS) products using ANN, random forest, and support vector regression. Their results show that intelligent models can effectively reduce the error in SSS products, with the random forest model outperforming the other two models. Choi et al. (2022) proposed a real-time correction system for ocean temperature based on deep generative image networks, satellite data, and initial fields of ocean numerical models. This system reduced the forecast error of sea surface temperature (SST) by 0.5°C, which effectively reduced the discrepancies between data assimilation and forecasting, as well as improved the accuracy for deep-sea forecasting. Yuan et al. (2023) proposed a SST bias correction and downscaling integration model based on generative adversarial networks and conducted experiments on monthly-scale ENSO and IOD events as well as daily-scale marine heat wave events (Figure 15). The model reduced the prediction error by approximately 90.3% while increasing the resolution to 0.0625°×0.0625°, which broke through the limitation of observation data resolution and achieved a structural similarity to observation results as high as 96.46%.

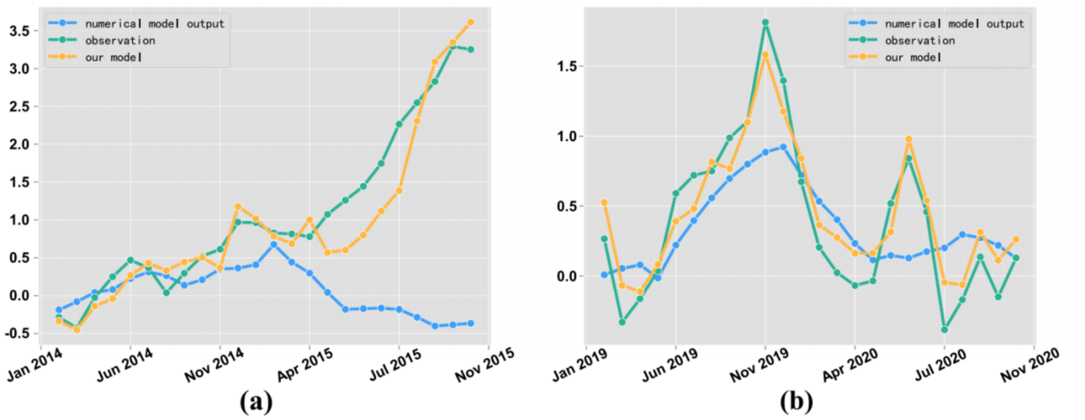

Figure 15. Comparison of (a) NINO3.4 and (b) DMI between intelligent correction and numerical model and observational values. (Yuan et al., 2023)

3.5 Intelligent Solution of Partial Differential Equations

Partial Differential Equations (PDEs) play a crucial role in modeling physical phenomena and capturing the behavior of complex physical systems. Physics-Informed Neural Networks (PINNs) incorporate the PDEs of physical systems into the loss function as regularization terms (Raissi et al., 2019), thus holding a significant potential of solving key dynamical problems with machine learning applications. However, PINN, as an alternative to traditional numerical methods (such as finite difference or finite volume), still faces some unresolved issues, thereby limiting the accuracy when applying to fields such as ocean science (Zhu et al., 2022).

Solving PDEs involves the discretization of multiple coupled equations in high-dimensional coordinate space by numerical solvers, such that rendering the nonlinear mapping relationship between inputs and outputs is highly intricate. To better solve nonlinear PDEs applicable to real-world scenarios, scholars have attempted to use neural operators with stronger generalization capabilities to obtain approximate solutions. For instance, DeepONet (Lu et al., 2021), Fourier Neural Operator (Li et al., 2020b), and Koopman Neural Operator (Xiong et al., 2023a, Figure 16) are widely used neural operators. However, learning a single neural operator still struggles to fit complex nonlinear mapping relationships, and these deep neural network models typically operate in high-dimensional coordinate spaces, making it challenging to enhance model generalization capabilities. To avoid redundant and high-dimensional coordinate spaces, Wu et al. (2023) proposed a spectral model that projects the original high-dimensional data into a spectral feature space, where complex nonlinear mappings can be approximated as a sum of multiple basis operators linearly weighted. Additionally, Rao et al. (2023) introduced a more generalizable and noise-resistant deep learning framework based on physics-encoded recursive convolutional neural networks for solving nonlinear PDEs. This approach encodes prior physical structural knowledge of given PDEs, initial conditions, and boundary conditions into the recursive convolutional neural network.

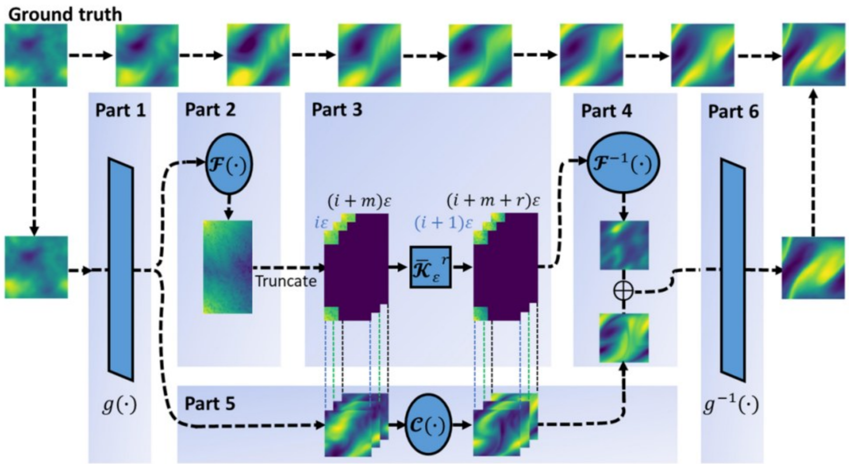

Figure 16. Network architecture of the Koopman Neural Operator. (Xiong et al., 2023a)

The intelligent solution of partial differential equations holds broad application prospects in oceanography and meteorological forecasting. However, in order to obtain high precision, robustness, interpretability, and generalizability in simulation and forecasting results, how to use AI models to efficiently achieve accurate solution of partial differential equations in scenarios with relatively sparse observation data requires further exploration.

4. Development of AI Big Models

AI big models are models pre-trained on massive datasets. In recent years, remarkable achievements have been made in the development of meteorological big models, particularly in the field of short-term precipitation forecasting. In March 2020, Google introduced the MetNet model (Sønderby et al., 2020, Figure 17), which marked the first attempt of big models in meteorological forecasting. The forecast takes only a few seconds, which is much faster than numerical models. Institutions such as NVIDIA led the development of the FourCastNet model (Pathak et al., 2022), which completed forecasts of key meteorological elements globally for 10 days at a temporal resolution of 6 hours and spatial resolution of 0.25°×0.25°(Figure 18). In November, Huawei unveiled the Pangu meteorological big model (Bi et al., 2023, Figure 19), with the capability of global meteorological prediction in seconds. In December, DeepMind and Google collaborated to release the GraphCast Big Model (Lam et al., 2022), with 99.2% of its results exhibiting higher prediction accuracy than the Pangu Big Model.

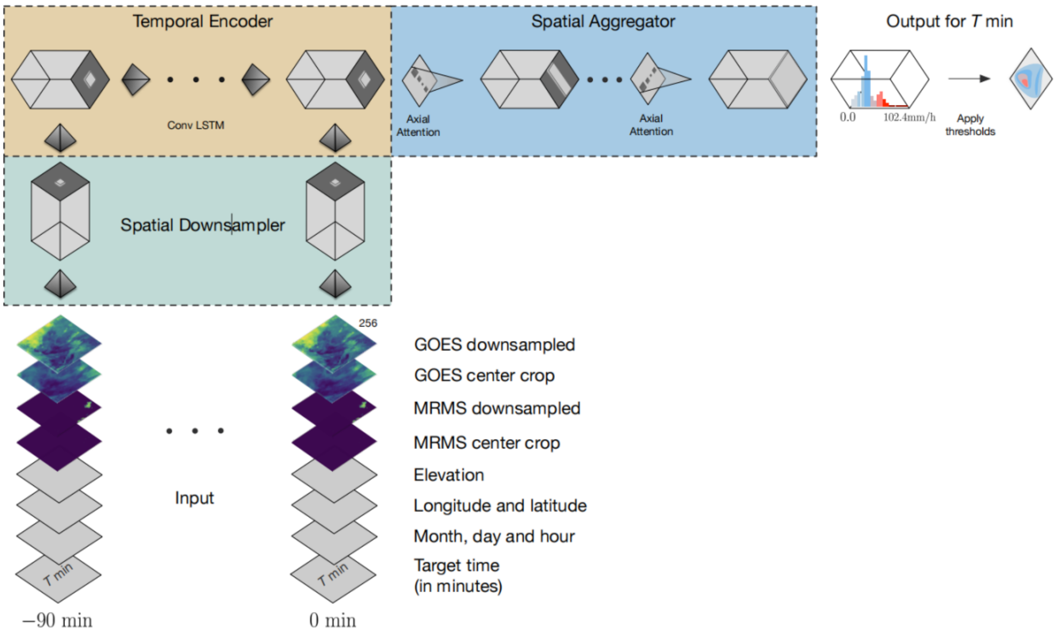

Figure 17. Framework of the MetNet model. (Sønderby et al., 2020)

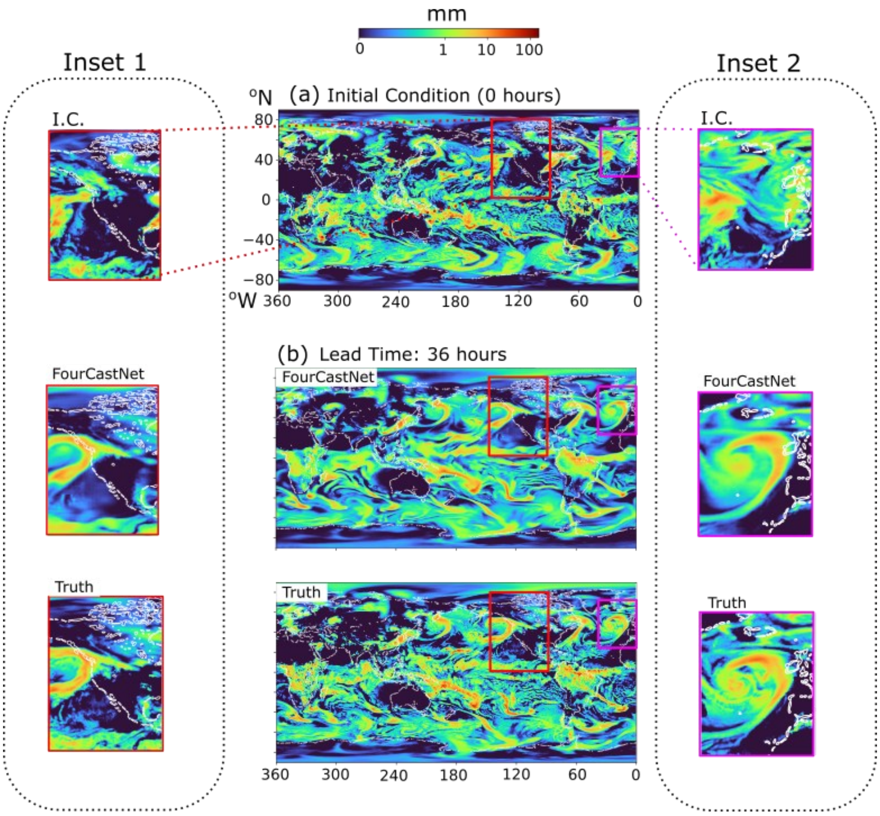

Figure 18. Global total precipitation predicted using the FourCastNet model. (Pathak et al., 2022)

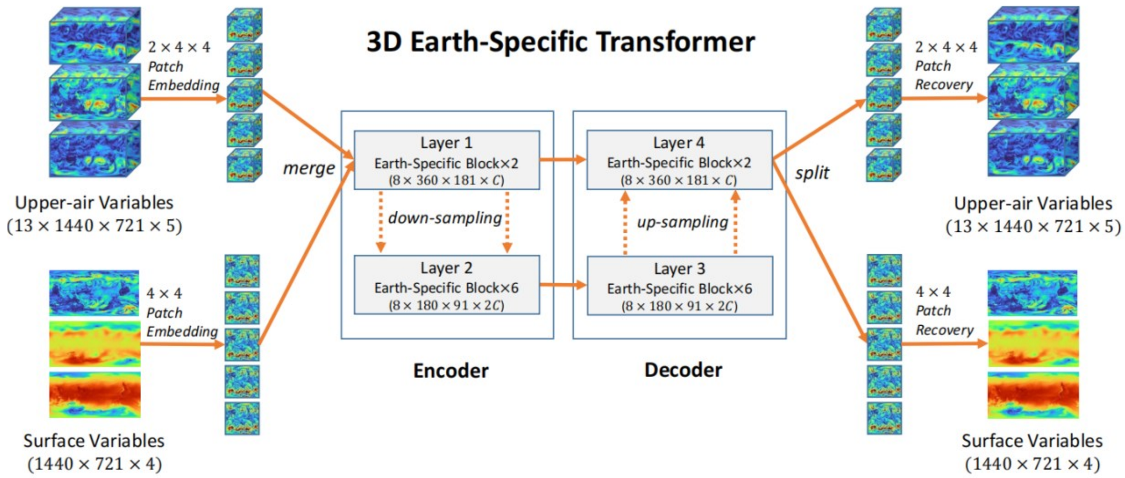

Figure 19. Network architecture of the 3DEST model in the Pangu Meteorological Grand Model. (Bi et al., 2023)

In January 2023, the ClimaX Big Model—the world's first AI big model capable of spanning weather and climate scales—was proposed (Nguyen et al., 2023). In April, institutions including the Shanghai AI Laboratory unveiled the global medium-term weather forecast big model "Fengwu" (Chen et al., 2023a), with forecast lead time exceeding 10 days for the first time. Subsequently, the "Fuxi" meteorological big model was also released (Chen et al., 2023b), extending the forecast lead time of big models to 15 days for the first time. In July, the NowcastNet Big Model was proposed (Zhang et al., 2023), extending the lead time for short-term precipitation forecasting to 3 hours for the first time, addressing the shortcomings of extreme precipitation forecasting.

Unlike meteorology data which is more abundant, ocean data particularly subsurface data is highly sparse, and consequently big ocean models are still in their infancy. In August 2023, the Department of Earth System Science at Tsinghua University introduced the AI-GOMs Ocean General Circulation Model (Xiong et al., 2023b, Figure 20), designed to predict fundamental ocean variables, including regional downscaling, wave forecasting, and biogeochemical coupling modules. AI-GOMS features a spatial resolution of 0.25°×0.25° and 15 vertical layers, demonstrating outstanding performance in 30-day forecasts of global ocean basic variables. Additionally, AI-GOMS successfully simulates mesoscale eddies in the Kuroshio region at a spatial resolution of 9 km×9 km and ocean stratification in the tropical Pacific.

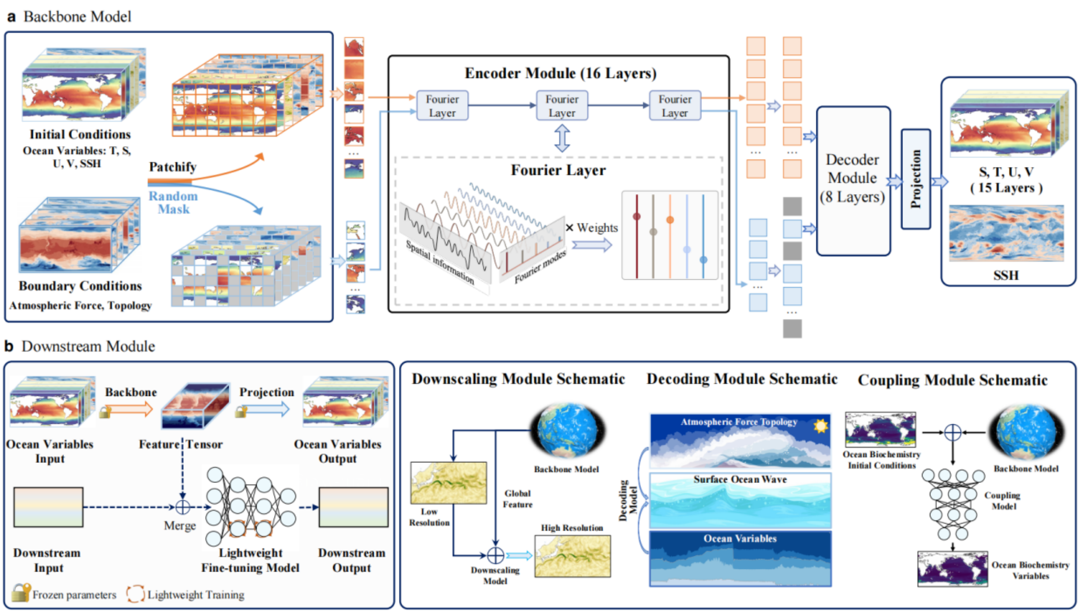

Figure 20. Framework of the AI-GOMS ocean big model. (Xiong et al., 2023b)

5. Construction of Ocean Digital Twin System

Digital twin technology was initially mainly applied in the industrial field, creating virtual models of physical entities through digitization to simulate the behavior of physical entities in real environments. Internationally, research and applications in the field of digital twins have been developed early. The United States NASA constructed a digital twin model of spacecraft in 2011, marking the first practical application of digital twins in the industrial sector (Tuegel et al., 2011). In 2022, NOAA announced a collaboration with NVIDIA and Lockheed Martin to launch the Earth Observations Digital Twin project, aiming to monitor the global environment and conduct high-resolution real-time simulations for polar regions, land, weather, and oceans.

Although China's marine digital twin technology started relatively late, it is currently keeping pace with international standards. Some research institutions are actively conducting research on marine digital twins, carrying out a series of preliminary work in areas such as building the foundation of marine big data, developing intelligent marine models, and intelligent prediction of ocean and climate. Tsinghua University's Shenzhen International Graduate School has made breakthroughs in the integration of three-dimensional geographic information and marine information technologies, constructing a digital marine model based on BIM and GIS. Laoshan Laboratory has funded several important projects, including the digital twin research project on Yellow Sea cold water mass seafloor sediment hazards, and the demonstration of key technologies and applications of AI-based twin ocean. The Southern Marine Science and Engineering Guangdong Provincial Laboratory (Zhuhai), in collaboration with Tencent, released the world's first marine digital twin engine on September 8, 2023, and applied it to the Guangdong-Hong Kong-Macao Greater Bay Area.

With the rapid development of cloud computing technology, the twin ocean data pool adopts a design that separates computation from storage. This design not only meets the demand for sudden resource peaks but also helps improve overall resource utilization, thereby achieving intensive management of ocean big data resources. Although the twin ocean system has made preliminary progress in information mining and forecasting technology, there is still considerable room for improvement in aspects such as the accumulation and timely acquisition of basic data, the combination of AI algorithms and numerical models, and the efficiency and accuracy of system operation. The foundation of the twin ocean entity is built on the integration of multi-source observation and simulation data, which not only requires the presentation of global large-scale ocean dynamic processes but also necessitates real-time mapping of local and small-scale ocean and meteorological processes relevant to humans. Therefore, establishing a global ocean observation network and a refined regional ocean observation system, integrating various traditional numerical models and AI forecasting technologies, and enhancing the intelligence, openness, and interactivity of service platforms and toolkits are imperative for the development of ocean digital twin systems.

II. Key Directions of AI Oceanography

1. Intelligent Warning and Forecasting of Marine Hazards

Marine hazards include dynamic hazards (such as storm surges, rogue waves, etc.), ecological hazards (such as red tides, green tides, and coral bleaching), and geological hazards (such as deep-sea mudslides, submarine earthquakes, and volcanic eruptions), posing a significant threat to marine environments and the safety of people's lives and property. In recent years, significant progress has been made in deep learning-based intelligent forecasting and early warning systems for marine hazards, which to a certain extent, have compensated for the shortcomings of traditional operational numerical prediction systems in terms of timeliness and convenience. This advancement is of great significance for enhancing the defense capability against marine hazards and ensuring the safety of coastal areas.

The current intelligent forecasting and warning of marine hazards mainly rely on purely data-driven models, which not only lack scientific basis but also require massive amounts of training data. In order to improve the reliability and interpretability of forecasts, and reduce dependence on training data volume, the introduction of physical constraints into intelligent models is gradually becoming a new research direction. These physical constraints not only help better characterize the complexity of ocean dynamic processes but also contribute to improving the credibility of forecast results. Additionally, because marine hazard warning and forecasting are typically conducted at relatively simple coastal ocean stations in terms of hardware conditions, it is necessary to develop lightweight intelligent forecasting models to effectively address marine hazards in different regions.

2. Ocean ChatGPT

GPT stands for Generative Pre-Trained Transformer, which is a significant technology based on deep learning and the Transformer architecture, and has become a powerful tool for handling natural language tasks. Although general-purpose GPT models possess continuously improving language understanding and generation capabilities, they often perform poorly in specific professional domains. With the emergence of simplified versions of open-source large language models such as Meta LLaMa and fine-tuning techniques, large language models are gradually transitioning from general-purpose to domain-specific. Through domain-specific training, large language models tailored to different fields or based on domain knowledge in natural language processing are emerging, providing more accurate services for various professional domains.

Therefore, it is necessary to develop an ocean-oriented large language model called Ocean ChatGPT. This model should be capable of developing deep understanding of oceanography, marine humanities, marine environment, marine geography, and providing services including knowledge Q&A, data processing, technical support, policy interpretation, tourism recommendations, as well as solutions for environmental protection and sustainable development in the marine domain. To enhance the adaptability and generalization of the model, it is essential to extensively and deeply collect data from international oceanographic data centers, public publications, government reports, etc., and to conduct data cleaning, organization, and annotation preprocessing. Therefore, next steps include: design the architecture of the Ocean ChatGPT model based on the GPT series model, utilize distributed computing resources for model training, deploy it to large servers or cloud platforms to provide online services, regularly update new knowledge and applications in the marine domain, and collect user feedback data for continuous optimization of the Ocean ChatGPT model.

3. Ocean AI Big Model

The Earth system consists of multiple interrelated spheres such as the atmosphere, ocean, and land, making it highly complex and vast. Simulation and prediction of this system mainly rely on numerical models which are tailored to each sphere and coupled Earth system models that are encompassing all spheres. In recent years, AI big model becomes an important research direction as it has shown remarkable application value and development potential in Earth system science, especially in atmospheric science. However, these big models are mostly data-driven, heavily reliant on the quantity and sources of training data, and generally performing poorly in predicting extreme weather due to sample imbalance. Meanwhile, with the increasing computational resource consumption of AI models, cost reduction poses a significant challenge in their future development.

In the field of oceanography, the greatest challenge in constructing AI big models lies in the lack of reliable training data, particularly four-dimensional observational data covering long time series, high resolution, and various ocean phenomena. Therefore, it is necessary to introduce physical constraints to reduce the dependence on data volume while enhancing model interpretability. In the foreseeable future, AI models will coexist with traditional numerical models complementarily. AI can improve model parameterization, data assimilation, and bias correction schemes within the framework of numerical models, enhancing their computational efficiency. Simultaneously, a blend of AI models and dynamical models can be developed for ensemble forecast systems to improve prediction skills for processes with unclear mechanisms. Finally, establishing ocean and Earth system big models with physical constraints (classical mechanics and information theory) can be achieved through generative AI, which can continuously adjust models and output products according to demand and provide diverse services.

4. Ocean Digital Twin System

The ocean digital twin system is an omnipotent tool for understanding and managing the ocean. Digital twins can efficiently process vast amounts of rapidly incoming unstructured ocean data, cover the potential information resources of big ocean data, and establish multidimensional, standardized ocean information data pools. When combined with new virtual reality and AI technologies, digital twins can bridge the gap from digital representation to visual twins, achieving immersive, highly perceptible, and interactive panoramic visualization of the ocean. Ocean digital twins represent the forefront and hotspot of the integration and improvement of ocean science and information technology.

Ocean digital twins have broad development prospects by providing an important technological foundation for ocean information perception, knowledge discovery, and decision support.

The core of the ocean digital twin system lies in its data foundation and intelligent technology. It requires intelligent, efficient, and refined new perception technologies to acquire more ocean observation data. It also requires to integrate, share, and process various types of data through advanced technologies such as the Internet of Things, blockchain, and data middle platform in order to solidify the data foundation of the ocean digital twin system. In addition, ocean numerical models are developing vigorously towards high resolution and coupling of multiple motion forms. Through advanced data assimilation methods, combined with high-resolution model outputs and various observation data, reliable ocean reanalysis datasets are established, which can not only be used for intelligent model training but also provide support for the digital twin ocean system.

5. Computational Power Optimization and Coordination

The progress and innovation of AI are driven by the continuous evolution and enhancement of computing power. According to publicly available data from ChatGPT, the training process of this model consumed tremendous computing resources, equivalent to 3640 petaflop-days (assuming a calculation of ten quadrillion operations per second, it would take 3640 days). The scarcity and high cost of computing resources have become critical bottlenecks restricting the development of AI. Oceanography research has entered the era of big data, with the global volume of ocean data expected to reach 275 petabytes by 2030, with daily increments reaching the terabyte level.

To meet the development needs of large-scale oceanic models, enhancing oceanic intelligence computing power from multiple dimensions is an urgent priority. Firstly, it is necessary to increase investment in hardware resources for oceanic intelligence computing, establish large-scale oceanic intelligence computing centers and public infrastructure tailored for oceanic applications, and adopt advanced AI chips. This aims to create a technologically advanced, ecologically mature, and sustainable platform for intelligent computing that can be iteratively upgraded to fully support the application and innovation of oceanic AI technology. Secondly, it is necessary to optimize computing power scheduling techniques, enhance scheduling capabilities from system architecture and algorithm optimization, and address issues such as low efficiency and poor stability. This initiative actively responds to our country's strategy of “East Data, West Computing”, aiming to achieve efficient scheduling of computing power across the national network.

III. Conclusion

AI has made tremendous progress in recent years, flourishing not only in the field of computer science but also beginning to shine in various industries. The integration of AI and oceanography will embark on a brand-new journey of exploration, expanding the cognitive boundaries of human perceptions of the oceans and the Earth. The future development of AI in oceanography will far surpass our imagination, generating profound scientific and societal impacts.

AI will propel the advance of oceanography science and technology. Compared with traditional research methods, AI possesses the capability of automatically collecting, efficiently processing, and accurately interpreting oceanic data, thus greatly enhancing research efficiency. The integration of AI with robotics is revolutionizing in the fields of oceanic intelligent perception, intelligent observation platforms, and their collaborative networking systems.

AI will become an important tool for managing and protecting the oceans. Intelligent ocean monitoring, detection, and forecasting systems will provide technological support for addressing increasingly severe issues such as ocean pollution, overfishing, and climate change. They will also offer intelligent and efficient means for optimizing the development of oceanic renewable energy and the sustainable utilization of marine resources, serving for national strategies and socioeconomic development.

The development of AI in oceanography is promising. We need to further refine the theoretical framework and connotation of this cutting-edge interdisciplinary field. We need to develop original algorithms and allocate computing resources tailored to the characteristics of ocean research. Simultaneously, it is crucial to address the potential risks associated with the overuse of AI technology, manage privacy and data security issues properly, and ensure the lawful use of ocean data.

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