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Deep learning for ocean temperature forecasting: a survey

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Abstract

Ocean temperature prediction is significant in climate change research and marine ecosystem management. However, relevant statistical and physical methods focus on assuming relationships between variables and simulating complex physical processes of ocean temperature changes, facing challenges such as high data dependence and insufficient processing of long-term dependencies. This paper comprehensively reviews the development and latest progress of ocean temperature prediction models based on deep learning. We first provide a formulaic definition for ocean temperature prediction and a brief overview of deep learning models widely used in this field. Using data sources and model structures, we systematically divide ocean temperature prediction models into data-driven deep learning models and physically guided deep learning models; and comprehensively explore the relevant literature involved in each method. In addition, we summarize an ocean temperature dataset and sea areas, laying a solid foundation for ocean temperature prediction. Finally, we propose current challenges and future development directions in ocean temperature prediction research based on deep learning. This article aims to analyze existing research, identify research gaps and challenges, provide complete and reliable technical support for climate forecasting, marine disaster prevention, and fishery resource management, and promote the further development of ocean temperature research.

Keywords Ocean temperature prediction, Deep learning, Spatiotemporal data mining, Data-driven, Physical guidance

1 Introduction

In the past few years, researchers have conducted extensive research to predict ocean temperatures to better understand the heat exchange between the ocean and the atmosphere. These studies aim to enhance our understanding of the dynamic changes in the marine environment, thereby providing more accurate predictions and analysis for related fields (Anding and Kauth 1970; Ward 2006; Herbert et al. 2010; McGlone et al. 2010; Scoccimarro et al. 2018). Detecting changes in ocean temperatures has always been a prominent focus in the fields of oceanography and atmospheric science (Corchado 1995). The prediction of ocean temperature covers multiple aspects such as climate research, ecological protection, fisheries management, and disaster prevention. In climate research and prediction, the ocean temperature is an important component of the global climate system and thus has a direct impact on climate change (Salles et al. 2016; Amouamouha and Gholikandi 2018; Gholikandi et al. 2018; Jiang et al. 2018; Kahira et al. 2018; Patil and Deo 2018). Thus, accurately predicting ocean temperatures can help scientists better understand and predict climate change, especially when predicting climate phenomena such as El Niño Southern Oscillation (ENSO) and the La Niña phenomenon, which can cause global weather anomalies and climate change (Nicholls 1984; Gordon 1986; Corchado et al. 2001; Corchado and Aiken

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2002; Roemmich and Gilson 2011; Chaudhary et al. 2023). For the protection of marine ecosystems, predicting ocean temperatures can help forecast coral reef bleaching events, fish migration pathways, and other important ecological changes, thus allowing effective protection measures and maintaining marine biodiversity. Ocean temperatures also affect the distribution and reproduction of fish and other marine organisms. Accurate temperature prediction can help develop scientific fishing plans and ensure the sustainable utilization of fishery resources. Table 1 lists the applications and benefits of accurately predicting ocean temperatures supported by the method in Fig. 1.

Table 1 Applications of ocean temperatures

No.	Application	Reference
1	Climate research and prediction	Chelton and Wentz 2005
2	Marine ecosystem protection	Hindell et al. 2020
3	Fisheries management	Chassot et al. 2011
4	Marine disaster warning	Fang et al. 2017
5	Shipping and ocean engineering	Wang and Wan 2020
6	Scientific research and education	Abraham et al. 2013

Linear regression and statistical methods, such as autoregressive integrated moving average (ARIMA), are widely used in estimating and predicting ocean temperatures by analyzing past data and establishing mathematical models to predict future trends (Karim 2013; Afrifa-Yamoah 2015; Qin et al. 2017; Rosmiati et al. 2021). However, the complex nature of ocean temperature anomalies, and the intrinsic uncertainties of the conditions of sea or ocean systems (Corchado and Fyfe 1999; De Paz et al. 2012), make ocean temperature prediction in space and time using mathematical or statistical models very challenging. Nonetheless, the progressive increase in computing power has led to the development of techniques for investigating ocean systems such as case-based reasoning (CBR) (Du et al. 2004; Mata and Corchado 2009; De Paz et al. 2012), which is based on the solution of similar previous problems. However, this approach is limited when applied to complex issues because of its high dependence on human judgment

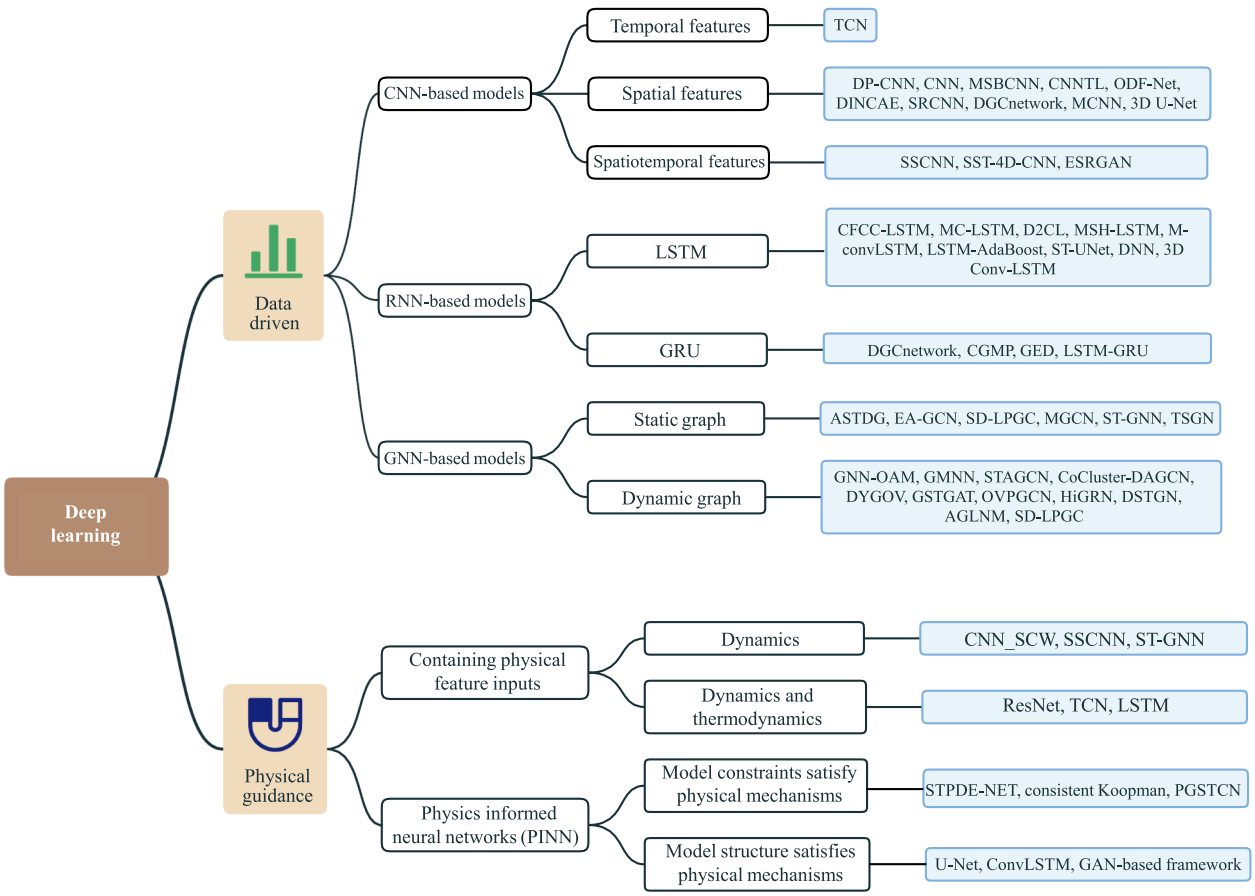


Fig. 1 Taxonomy for ocean temperature prediction

(Herbert et al. 2010). Thus, traditional machine learning methods including logistic regression (LR), and support vector regression (SVR) are proposed to solve these problems (Aguilar-Martinez and Hsieh 2009; Yang et al. 2009; Choi et al. 2010; Nalcaci et al. 2019).

The advancements in computational techniques such as graphical processing units (GPU) make deep machine learning models phenomenal (Mittal and Vetter 2014, 2015; Bridges et al. 2016; Raju and Chiplunkar 2018). According to the significant milestones in deep learning-driven ocean temperature forecasting summarized in Choi et al. (2010), deep-learning models for ocean temperature forecasting have flourished since 2015, and the most popular models after 2020 are recurrent neural networks (RNNs). The advantages of RNNs lie in their good modeling of graph-based problems and ability to capture temporal-spatial dependencies and represent relations in non-Euclidean space.

Related surveys. Deep learning studies have increasingly shown excellent performance in handling complex ocean temperature data and capturing nonlinear relationships, which can handle large-scale datasets. However, current surveys often focus on specific perspectives within a limited range, without a comprehensive investigation and summary of ocean temperature prediction methods based on deep learning (Kennedy 2014; Haghbin et al. 2021; Chaudhary et al. 2023). For example, several studies have delved into ocean temperature predictions for different datasets, sea areas, and depths (Deser et al. 2010; Yasunaka and Hanawa 2011; Kennedy 2014; Merchant et al. 2014). Similarly, for the same sea areas, there have also been studies dedicated to exploring the inherent connections and mutual influences between regions at different time points, and establishing relationships between these characteristics and ocean temperature prediction from a global perspective (Haghbin et al. 2021; Chaudhary et al. 2023). The specific comparison is shown in Table 2.

Our contributions. To address existing literature gaps, this study offers a comprehensive and up-to-date review of the current state of ocean temperature prediction research using deep learning methods. Our contributions are outlined as follows:

(1) **First comprehensive survey**. In recent years, ocean temperature prediction has developed rapidly with the development of deep learning, but so far, there is still a lack of complete and comprehensive research on existing ocean temperature studies. To our knowledge, this is the first in-depth summary and discussion of deep learning-based ocean temperature prediction research that combines physics knowledge.
(2) **Complete and unified classification system**. We propose a complete and unified classification system that divides deep learning-based ocean temperature prediction into two different parts: data-driven deep learning algorithms and physics-guided deep learning algorithms. Each part is further divided into many subcategories, and the specific details of each subcategory are shown in Section 3. This structured classification aims to provide a clear framework for understanding various methods and their applications in ocean temperature prediction research.
(3) **Comprehensive method analysis**. Collect the main literature in relevant fields, including papers, books, and experimental reports, and list all the literature involved in each method, including the research area, dataset, and experimental results. Then, this study comprehensively understands the advantages and disadvantages of various methods, guiding the focus of future model development.
(4) **Looking forward to future directions**. The ocean is a vast ecosystem, with various hydrological elements interdependent and influencing each other.

Table 2 Comparison between our and other related surveys on model-driven (i.e., D, data-driven deep learning; P, physics-guided deep learning), formalization of problem, dataset, area, model classification, spatiotemporal correlation, and forecast day

Survey	Model-driven		Formalization of problem	Dataset	Area	Model classification	Spatiotemporal correlation	Forecast day
	D	P						
Deser et al. 2010	✗	✗	✗	✓	✗	✗	✗	✗
Yasunaka and Hanawa 2011	✗	✗	✗	✓	✗	✗	✗	✗
Merchant et al. 2014	✗	✗	✗	✓	✓	✗	✗	✗
Kennedy 2014	✗	✗	✗	✓	✓	✗	✗	✗
Haghbin et al. 2021	✓	✗	✗	✗	✓	✓	✗	✗
Chaudhary et al. 2023	✓	✗	✗	✓	✓	✓	✗	✓
Our	✓	✓	✓	✓	✓	✓	✓	✓

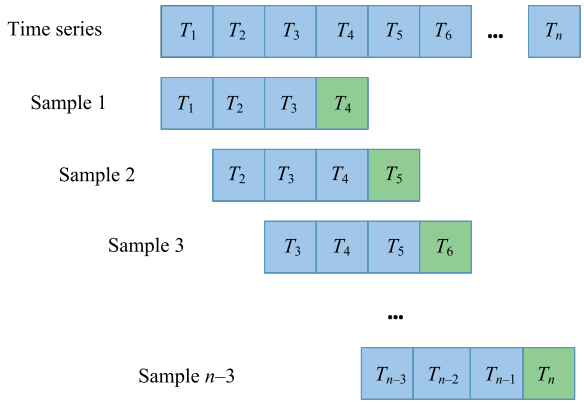


Fig. 2 Sliding window (the step size is 1)

The prediction of a single ocean temperature can only provide limited information, whereas joint prediction can utilize the correlation and dependency between multiple variables to more accurately capture these relationships, thereby improving the overall prediction performance. This is of great significance for scientific research and practical applications.

Paper organization. The rest of this paper is organized as follows: Section 2 defines temporal data and common knowledge of deep learning models. Section 3 provides a specific classification of ocean temperature prediction methods based on deep learning. Sections 4 and 5 provide specific introductions to ocean temperature prediction methods. Section 6 investigates the datasets and experimental areas involved in existing research. Section 7 describes the development prospects and challenges of ocean temperature prediction research. Finally, Section 8 summarizes the entire paper.

2 Preliminary

2.1 Definition and notation

Definition 1 (Ocean temperature time series data) Ocean temperature time series data refer to ocean temperature data measured and recorded within specific time intervals. Given the time series $\mathcal{X} = \{X_{:,0:t}\}$, where $X_{:,t} = \{x_{1:N,t}\}^{\mathrm{T}} \in \mathbb{R}^{N\times 1}$, records d-dimensional data at N locations at time t (Fan et al. 2023).

Definition 2 (Sliding window) As shown in Fig. 2, sliding window technology extracts subsequences by moving a fixed-size window over time series data. Each time the window moves by one step (usually a one-time unit), a series of overlapping or non-overlapping subsequences are generated (Ta et al. 2022; Li et al. 2023a).

Definition 3 (Ocean temperature prediction) For ocean temperature prediction, the problem is described as finding a function to predict future ocean temperature data for τ steps based on historical data from a previous T time points:

$$\boldsymbol{X}_{:,t+1:t+\tau} = \mathcal{F}_\theta(\boldsymbol{X}_{:,t-T+1:t}), \tag{1}$$

where θ represents any learnable parameter in the model.

2.2 Background knowledge of deep learning

In the past decade, with the development of deep learning, an increased number of ocean temperature prediction models based on deep learning have been proposed, and the prediction accuracies have been further improved while expanding their temporal and spatial scales of prediction.

CNN. Convolutional neural networks (CNNs) can extract spatiotemporal information from ocean temperature, given their convolutional layer structure. Ocean temperature data have a strong spatiotemporal correlation, and the structure of CNN models can effectively extract and capture spatiotemporal features (Zhang et al. 2019; Chen et al. 2021; Yan et al. 2021). Therefore, CNN has shown great potential in ocean temperature prediction research. In real-world scenarios, CNNs' convolutional kernels are often used to extract feature space, and transformer's self-attention mechanism is used to capture long spatiotemporal feature sequences (Yan et al. 2022). A general CNN ocean temperature prediction model is shown in Fig. 3. The convolutional layer can extract the spatiotemporal features of sea surface temperature (SST) data, whereas the pooling layer preserves the important features extracted from the convolutional layer, reducing unnecessary feature space (Shin et al. 2016; Alzubaidi et al. 2021; Bhatt et al. 2021).

RNN. RNN is a network model designed to handle time series problems. Ocean temperature data usually have obvious time correlation and sequence dependence, and current ocean temperatures may be affected by the ocean temperatures of the previous few moments. RNN can effectively capture and utilize this sequence dependency, remember previous information through hidden states, and use this information in predictions (Fan et al. 2017; Li et al. 2018; Pal et al. 2021). The general structure of the RNN model is shown in Fig. 4. Long short-term memory (LSTM) and gate recurrent unit (GRU) are variants of RNN and are two commonly used time series prediction models (Fu et al. 2016; de Melo et al. 2019; Yang et al. 2020). They have unique door control units that control which information can be transmitted to the next stage.

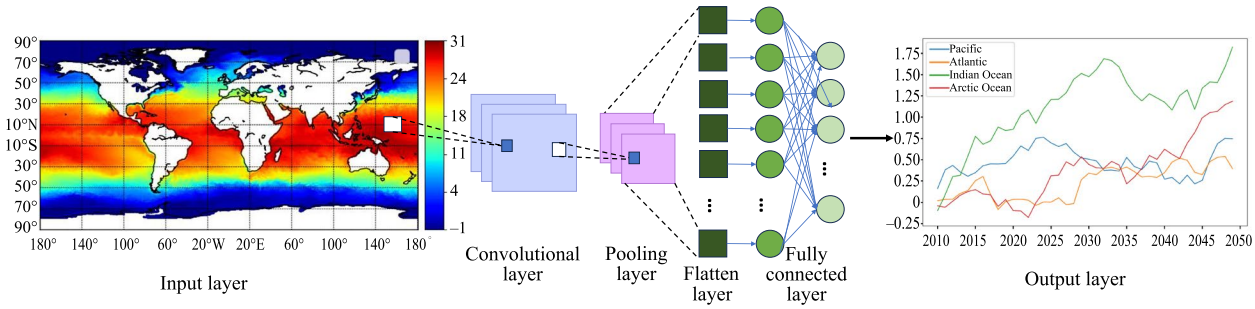


Fig. 3 General structure of the CNN model

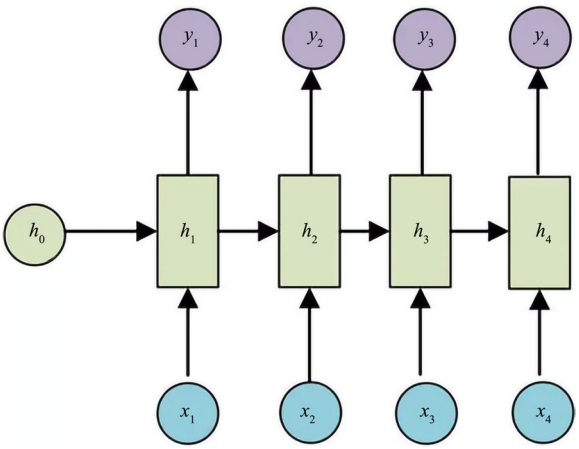


Fig. 4 General structure of the RNN model

GNN. In recent years, graph neural network (GNN) methods have received increased attention in the field of spatiotemporal data mining (Hu et al. 2020). GNN can effectively capture spatial correlations between different sea areas by introducing graph structures into neural networks (Roy et al. 2021; Zhou et al. 2021). The structure of a general GNN ocean temperature prediction model is shown in Fig. 5. To effectively extract spatial correlations between ocean temperature data, define a graph $\mathcal{G}_t = (\mathcal{V}, \mathcal{E}_t)$, where $\mathcal{V}$ represents the set of nodes corresponding to N positions, $\mathcal{E}$ denotes the edges connecting these nodes. The problem of ocean temperature prediction is further formulated as:

$$\boldsymbol{X}_{:,t+1:t+\tau} = \mathcal{F}_\theta(\boldsymbol{X}_{:,t-T+1:t}; \mathcal{G}_t). \quad (2)$$

3 Overview and categorization

After a comprehensive and extensive investigation, the classification of existing ocean temperature prediction methods is shown in Fig. 1. According to the data foundation and application methods of ocean temperature, deep learning methods can be divided into data-driven deep learning methods and physically guided deep learning methods. Data-driven deep learning methods mainly rely on a large amount of historical data to train models. Meanwhile, the physics-guided deep learning methods combine physical models and deep learning techniques, with physical principles serving as constraints or prior information to improve the accuracy and interpretability of the models.

(1) **Data-driven deep learning**. Data-driven ocean temperature prediction includes CNN, RNN, and GNN. The CNN-based ocean temperature prediction model is further divided into three subcategories based on the extracted spatiotemporal information. RNN-based deep learning models are divided into LSTM models and GRU models according to their different variants. Meanwhile, GNN-based deep learning models use different types of graph structures for representation extraction, further subdivided into dynamic graph structures and static graph structures. Each subcategory will research relevant literature, covering aspects such as datasets, research areas, predicted days, and model accuracy.

(2) **Physics-guided deep learning**. The physics-guided ocean temperature prediction method is divided into deep learning models with physical features as input and physics-informed neural networks (PINNs). Each subcategory is also described in terms of datasets, research areas, predicted days, and model accuracy.

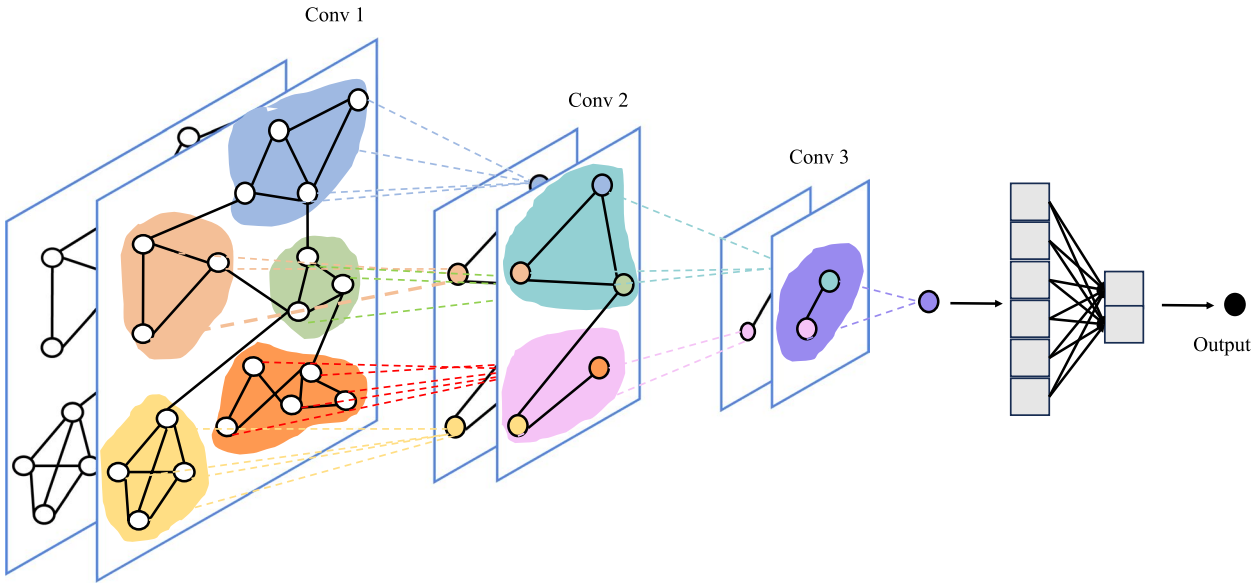


Fig. 5 General structure of the GNN model

4 Data-driven deep learning

4.1 CNN-based models

Ocean temperature change is a complex process with high spatiotemporal correlation. By capturing this spatiotemporal dependency, we can predict the ocean temperature of a region more accurately.

Temporal. Ocean temperature has trend and seasonal characteristics. Global warming leads to a gradual increase in ocean temperature, which can be captured through temporal feature extraction. Meanwhile, extracting seasonal features helps the model identify and predict annual periodic ocean temperature changes, helping them better understand and predict future ocean temperatures.

Spatial. Ocean temperature has a clear spatial correlation. This means that adjacent ocean temperatures typically exhibit similar patterns of change. By extracting spatial features, this spatial correlation can be captured, improving the accuracy of prediction models. Meanwhile, different regions in the ocean, such as nearshore, distant ocean, equator, and polar regions, exhibit varying patterns of ocean temperature variation. Extracting these geographical features helps the model identify and predict ocean temperature changes in different areas. Extracting features at various spatial scales (such as local regions and the entire sea area) can help the model consider local and global ocean temperature variation patterns.

Early works began with extracting feature information, but later researchers realized the importance of spatiotemporal information in the field of ocean temperature prediction and began to use various methods to process spatiotemporal information in ocean temperature time series data. For instance, Sun et al. (2022) propose a temporal convolutional network (TCN) to extract temporal features from ocean temperature data. By stacking multiple layers of convolution, features are extracted layer by layer and global information is aggregated to capture patterns on a temporal scale. Displaying a predicted root mean square error (RMSE) of 0.5℃ on a real ocean temperature dataset. Mao et al. (2023) propose a dual path convolutional neural network (DP-CNN) that utilizes the known spatial information of sea surface temperature (SST), sea surface salinity (SSS), and sea surface height (SSH) to supplement the subsurface (ST) and solve the problem of missing data. The predicted RMSE in the South China Sea (SCS) is 0.31℃. Feng et al. (2022) propose inputting SST and heat content (HT) into CNN for sea surface temperature prediction, and the results showed that CNN can predict sea surface temperature six months in advance. To further extract the trend of ocean temperature changes under multi-scale features, Mu et al. (2020) propose a multi-scale Bayesian convolution network (MSBCNN) to extract internal structural information of ocean temperature, and the predicted results show that MSBCNN outperforms the other traditional approaches and state-of-the-art models. Based on the extraction of spatiotemporal features, more research began to focus on the long-term trends of sea surface temperature changes. An integrated deep gated recurrent unit and convolutional neural network (DGCnetwork) model (Yu et al. 2020) is proposed, which focuses on

deep long-term dependencies under ocean temperature patterns. The RMSEs predicted in the East China Sea (ECS) and the Yellow Sea are 0.67℃ and 0.56℃. In addition, extracting the three-dimensional features of ocean temperature data can establish a wide-angle feature prediction model in a comprehensive and three-dimensional manner. Therefore, Xie et al. (2024) propose a 3D U-Net structure for predicting ocean temperature in the SCS using multi-source data. The results show that the RMSE for predicting sea surface temperature is 0.69℃. In addition to using models to extract spatiotemporal information on ocean temperature, incorporating positional information into the input features of the model can also provide more accurate spatial correlations for the model. Thus, Zhang et al. (2024b) propose a novel spatiotemporal siamese CNN (SSCNN), which not only considers the differences in temperature characteristics of different sea areas, but also captures information features from longitude and latitude directions. The predicted RMSE in the Indian Ocean is 0.47℃. In current research, there is relatively little prediction of temperature changes below the sea surface, Zuo et al. (2022) propose a stereo spatial and temporal 4-D convolution (SST-4D-CNN) model that captures sea temperature (ST) changes in seawater and underlying seawater. The experimental results show that the prediction accuracy of horizontal and profile is above 98.02%. Izumi et al. (2022) propose an enhanced super-resolution generative adversarial network (ESRGAN) that perceives ocean temperature changes by learning pixel similarity between images. ESRGAN is more capable of characterizing the complex distribution of ocean currents compared with CNN. In addition to the methods discussed above, a summary of more methods is shown in Table 3.

4.2 RNN-based models

Ocean temperature data are essentially time series data, and RNN can effectively capture the dynamic characteristics and variation patterns of time series data through their cyclic structure.

LSTM. The variations in ocean temperatures are influenced by various factors, including seasonal changes, climate patterns, and ocean currents. These factors may span long periods. LSTM can capture and store long-term dependencies through its memory unit, which helps predict future ocean temperature changes more accurately. Meanwhile, predicting long-span ocean temperature data can easily lead to gradient vanishing and exploding problems. LSTM can alleviate such problems using gating mechanisms, ensuring more stable and reliable training.

Table 3 Overview of CNN-based models

	Source	Model	Area	Dimension	Data	Input	Lead day	Result
Temporal	Sun et al. 2022	TCN	Indian Ocean	2D	OISST	SST, wind speed, etc.	30	RMSE = 0.50℃
Spatial	Mao et al. 2023	DP-CNN	SCS	3D	CMEMS	SST, SSH, SSS	30	RMSE = 0.31℃
	Feng et al. 2022	CNN	Indian Ocean	2D	NCEP	SST, HT	30	-
	Mu et al. 2020	MSBCNN	5°N–5°S 160°E–150°W	2D	NCEP	SST	30	$CC_{0.9} > 95\%$
	Miao et al. 2023b	CNNTL	SCS	2D	CMEMS	SST	30	RMSE = 0.31℃
	Wang et al. 2023	ODF-Net	Global	2D	Argo	SST	-	RMSE = 0.74℃
	Barth et al. 2020	DINCAE	WCC	2D	AVHRR	SST, SSH, SSS	-	RMSE = 1.16℃
	Ducournau et al. 2016	SRCNN	-	2D	OISST	SST	-	-
	Yu et al. 2020	DGCnetwork	ECS Yellow Sea	2D	OISST	SST	30	$RMSE_{ECS}$ = 0.67℃ $RMSE_{Yellow}$ = 0.56℃
	Miao et al. 2023a	MCNN	SCS	2D	CMEMS, ERA5	SST	7	RMSE = 0.45℃
	Han et al. 2019	CNN	Pacific	3D	ARGO	SST, SSH, SSS	30	RMSE = 0.37℃
	Xie et al. 2024	3D U-Net	SCS	2D	OISST	SST, wind speed, etc.	30	RMSE = 0.69℃
Spatiotemporal	Zhang et al. 2024b	SSCNN	Indian Ocean	2D	AMSR-E	SST, wind speed, etc.	30	RMSE = 0.47℃
	Zuo et al. 2022	SST-4D-CNN	99°E–150°E 10°S–52°N	3D	-	ST	5	RMSE = 0.19℃
	Izumi et al. 2022	ESRGAN	Pacific	2D	OISST	SST	-	RMSE = 0.92℃
	Zhang et al. 2024a	3D-Geoformer	Pacific	3D	GODAS	ST	600	-

GRU. Similar to LSTM, GRU can capture and store long-term dependencies, but its structure is simpler with only two gates: the update gate and reset gate, making it more computationally efficient in training and prediction. The efficiency of GRU is an important advantage for large-scale ocean temperature datasets.

After CNN, researchers came up with RNN to find a more suitable model for processing temporal data. Based on RNN, several variants are obtained: LSTM and GRU. Yang et al. (2017) propose a combined FC-LSTM and CNN, which combines temporal and spatial information on sea surface temperature. The results show a predicted RMSE of 1.07℃ in the Bohai Sea. Meanwhile, Lin and Zhong (2021) propose a multichannel LSTM (MC-LSTM) model, which decomposes sea surface temperature sequences into sequences with different meanings and establishes connections with sea surface temperature. The final predicted RMSE in the Yellow Sea is 0.36℃. In addition to ocean temperature data, hydrological and environmental data can also play a promoting role in ocean temperature prediction models. Such as Hou et al. (2021) propose a novel dense dilated convolutional LSTM (D2CL) model, which extracts features from sea surface temperature data using multiple different feature extractors. The results show that the predicted RMSE in the ECS is 0.66℃. Pan et al. (2024) propose an effective attention model (EAM) that utilizes attention mechanisms on extracted features to avoid redundant feature information. The RMSE of the predicted results after using the attention mechanism is 0.66℃. In addition to feature extraction based on fixed prediction steps, Liu et al. (2019) propose a multi-head hierarchical LSTM (MSH-LSTM) that can alleviate the error accumulation problem caused by multi-step prediction. The RMSE of the final prediction result is 1.28℃. Similar to CNN models, RNN models have relatively limited research on ocean temperature prediction at different depths. Based on this situation, Zhang et al. (2020a) propose a multi-layer convolutional LSTM (M-convLSTM) model that can extract vertical temperature changes over the sea surface and below 2000 m. The prediction accuracy can also reach a high level of 0.20℃. To integrate multi-dimensional spatiotemporal influences, Xie et al. (2021) propose a convolutional gated recurrent unit (GRU) with a multi-layer perceptron (CGMP) to predict Bohai SST. Convolutional layers can capture spatial correlations between adjacent positions, compensating for the shortcomings of methods based on temporal information without considering spatial information. A detailed summary of RNN-based deep learning models is shown in Table 4.

4.3 GNN-based models

The graph structure can naturally represent adjacent and connecting relationships between different geographical locations. Each node can represent a specific position, and edges represent the relationship between these positions. It allows using different node and edge features to flexibly represent different types of relationships and dependencies, enabling the model to understand and predict ocean temperature changes comprehensively.

Static graph structure. The static graph structure uses fixed nodes and edges to represent the relationship between geographical locations and positions, which can effectively capture the spatial dependencies and features between different sea area positions (Samsi et al. 2017).

Dynamic graph structure. The dynamic graph structure can update the nodes and edges of a graph over time, representing the characteristic relationships in the sea area at different times (Goyal et al. 2020; Manessi et al. 2020). It can reflect the changes in ocean temperature over time from a global perspective.

Ou et al. (2024) propose a GNN with optimized attention mechanisms (GNN-OAMs), which can dynamically capture the spatiotemporal relationships between sea surface temperatures by combining multiple adjacency matrices. The RMSE of the predicted results is 0.41℃. Liang et al. (2023) propose a graph memory neural network (GMNN) that utilizes a graph encoder to extract features from the graph structure. The RMSE of the ocean prediction results is 0.23℃. Because of the ability of dynamic graph structures to dynamically adjust the information of nodes and edges, dynamic graphs have rapidly developed in the field of data mining. In this regard, the dynamic graph for ocean variable forecasting (DYGOV) model is proposed, which considers the interrelationships between different weather phenomena in the ocean and extracts their spatiotemporal relationships to predict sea surface temperature (Wang et al. 2024a). The RMSE of the sea surface temperature prediction is 0.96℃. Moreover, based on the dynamic graph structure, some researchers have proposed to divide graph structures into different clusters to better aggregate information, so Yang et al. (2023) propose a hiGraph recurrent network (HiGRN), which utilizes a hierarchical clustering generator to extract information from different layers and introduces multi-level attention to fuse local and global information. The RMSE of the global sea surface temperature is 0.4℃.

4.4 Brief summary

From Tables 3, 4, and 5, we can draw the following conclusions:

Table 4 Overview of RNN-based models

	Source	Model	Area	Dimension	Data	Input	Lead day	Result
LSTM	Yang et al. 2017	CFCC-LSTM	Bohai Sea	2D	OISST	SST	30	RMSE = 1.07℃
	Lin and Zhong 2021	MC-LSTM	Yellow Sea	2D	IAP	SST	16	RMSE = 0.36℃
	Xiao et al. 2019b	LSTM	ECS	2D	OISST	SST	10	RMSE = 0.75℃
	Hou et al. 2021	D2CL	ECS	2D	OISST	SST	30	RMSE = 0.66℃
	Patil and Iiyama 2022	LSTM	Tohoku region	2D	JCOPE2	Ocean current, wind speed, etc.	30	RMSE = 0.49℃
	Choi et al. 2023	LSTM	Korean Peninsula	2D	ERA5	SST	7	RMSE = 0.74℃
	Broni-Bedaiko 2019	LSTM	30°S–30°N 120°E–60°W	2D	NCEP	SST	365	RMSE = 0.90℃
	Cao et al. 2023	LSTM	5 study locations	2D	AHI	SST	10	RMSE = 1.77℃
	Liu et al. 2019	MSH-LSTM	Pacific	2D	NMME	SST	270	RMSE = 1.28℃
	He et al. 2020	LSTM	-	2D	-	SST	14	RMSE = 0.52℃
	Tresnawati et al. 2024	LSTM	Indonesian Sea	2D	NASA	SST, wind speed, etc.	30	MAE = 0.45℃
	Hou et al. 2022	MIMO	5°N–5°S 120°W–170°W	2D	OISST	SST	30	RMSE = 0.76℃
	Zhang et al. 2020a	M-convLSTM	Pacific	3D	ARGO	ST	30	RMSE = 0.20℃
	Wei et al. 2020	LSTM	Seas of China	2D	CMEMS	SST	365	RMSE = 0.66℃
	Jia et al. 2022	LSTM	Pacific	2D	OSTIA	SST	365	RMSE = 0.06℃
	Xiao et al. 2019a	LSTM-AdaBoost	ECS	2D	OISST	SST	10	RMSE = 0.66℃
	Zhang et al. 2017	LSTM	Bohai Sea	2D	OISST	SST	30	RMSE = 0.39℃
	Ren et al. 2024	ST-UNet	SCS Bohai Sea	2D	OISST	SST	30	MAE_{SCS} = 0.32℃ MAE_{Bohai} = 0.50℃
	Jahanbakht et al. 2021	DNN	Bohai Sea	2D	OISST	SST	30	MSE = 0.09℃
	Wei and Guan 2022	3DConv-LSTM	China Seas	2D	OSTIA	SST	30	RMSE = 0.30℃
	Pan et al. 2024	EAM	Global	2D	OISST	SST	365	RMSE = 0.21℃
	Yue et al. 2024	SA-PredRNN	Global	3D	Argo	ST	365	RMSE = 0.36℃
GRU	Yu et al. 2020	DGCnetwork	ECS Yellow Sea	2D	OISST	SST	30	$RMSE_{ESC}$ = 0.67℃ $RMSE_{Yellow}$ = 0.56℃
	Xie et al. 2021	CGMP	Bohai Sea	2D	OISST	SST	30	-
	Kartal 2023	GRU	Mediterranean Sea	2D	MODIS	SST	30	RMSE = 0.49℃
	Xie et al. 2019	GED	SCS	2D	OISST	SST	30	RMSE = 0.58℃
	Zhang et al. 2020b	GRU	Bohai Sea	2D	OISST	SST	30	RMSE = 0.89℃
	Jiang et al. 2021	LSTM-GRU	Global	2D	ARGO	SST	-	RMSE = 1.67℃

(1) For CNN-based ocean temperature prediction research, it can be concluded that extracting spatial features to learn the interactions between ocean temperatures is the most common method. Compared to temporal and spatial feature extraction, spatiotemporal feature joint extraction has a greater advantage in accuracy. This indicates that ocean temperature prediction not only depends on the trend of temporal changes, but is also closely related to the temperature distribution and its space changes. Especially the SST-4D-CNN model proposed by Zuo et al. (2022) has the best RMSE accuracy at 0.19℃. Compared with models such as CNN and 3D U-Net, SST-4D-CNN, given its unique 4D convolutional structure, not only considers spatiotemporal correlations but also takes into account the impact of thermocline changes at different depths on sea surface temperature, resulting in superior predictive performance. In addition, although the ESRGAN model also considers spatiotemporal correlation, it is difficult to explore deep spatiotemporal information due to its simple combination of convolution and activation functions, resulting in poor prediction accuracy.

(2) RNN-based deep learning models are the most widely used in the field of ocean temperature pre-

Table 5 Overview of GNN-based models

	Source	Model	Area	Dimension	Data	Input	Lead day	Result
Static graph	Pan et al. 2023	ASTDG	10.75°N–19.25°N 112°E–117.25°E	3D	CMEMS	ST	30	RMSE = 0.51℃
	Peng et al. 2023	EA-GCN	ECS Indian Ocean	2D	OISST	SST	60	$RMSE_{ECS}$ = 0.95℃ $RMSE_{India}$ = 0.48℃
	Li et al. 2024	SD-LPGC	China Seas	2D	-	SST	12	RMSE = 0.87℃
	Zhang et al. 2021	MGCN	ECS Bohai Sea	2D	OISST	SST	30	$RMSE_{ECS}$ = 0.63℃ $RMSE_{Bohai}$ = 0.49℃
	Kim et al. 2023	ST-GNN	16 locations	2D	OISST	SST, wind speed, etc.	7	RMSE = 1.01℃
	Sun et al. 2021	TSGN	0°–60°N 100°E–180°E	2D	-	SST, lat, lon, etc.	7	RMSE = 0.63℃
Dynamic graph	Ou et al. 2024	GNN-OAM	148°E–149°E 29°N–30°N	2D	CORTA	SST	5	RMSE = 0.41℃
	Liang et al. 2023	GMNN	0°–60°N 100°E–180°E	2D	OISST	SST	7	RMSE = 0.23℃
	Chen et al. 2023a	STAGCN	ECS	2D	OISST	SST	30	RMSE = 0.96℃
	Chen et al. 2024	CoCluster-DAGCN	Pacific	2D	ARGO	SST	-	RMSE = 0.28℃
	Wang et al. 2024a	DYGOV	Indian Ocean	3D	-	ST	12	RMSE = 0.41℃
	Gao et al. 2023	GSTGAT	SCS	2D	OISST	SST	30	MAE = 0.33℃
	Ye et al. 2023	OVPGCN	Bohai Sea	2D	ERA5	SST	6	RMSE = 1.02℃
	Yang et al. 2023	HiGRN	Global	2D	OISST	SST	12	RMSE = 0.40℃
	Nan et al. 2024	DSTGN	98.875°S–98.875°N 0.125°E–359.875°E	3D	CMEMS	ST	7	RMSE = 0.28℃
	Wang et al. 2022	AGLNM	SCS	2D	OISST	SST	7	MAE = 0.31℃
	Li et al. 2023b	SD-LPGC	Bohai Bay SCS	2D	-	SST	12	$RMSE_{Bohai}$ = 1.08℃ $RMSE_{SCS}$ = 0.68℃

diction. Among the variants of RNN, the LSTM model is used more frequently than GRU, and the prediction accuracy based on the LSTM model is generally better than GRU. This is attributed to the gating mechanism of LSTM. Compared with the GRU model, LSTM has three gating units, and each unit has an independent unit state, which allows LSTM to capture more spatiotemporal information. In addition, it is worth mentioning that the DNN model not only uses SST, but also uses air temperature assistance to train sea surface temperature. Two deep learning frameworks extract feature information of ocean temperature and air temperature respectively, stack them together to jointly optimize the prediction model and obtain better results.

(3) For GNN-based ocean temperature prediction models, the use of dynamic graph structures for ocean prediction results in higher overall accuracy. Compared with static graphs, dynamic graph structures can dynamically adjust the connectivity and weights between different regions, more accurately reflecting the spatial heterogeneity of ocean temperatures. In addition, DSTGN combines static and dynamic graphs, and integrates spatiotemporal convolution into the same framework. By integrating the respective advantages of the above modules, unknown dependency relationships are explored under different ocean temperature patterns, and better results are achieved.

5 Physics guided deep learning

5.1 Neural networks containing physical feature inputs

Physical parameters, such as temperature, wind speed, humidity, and air pressure, are usually closely related to ocean temperature. Multivariate time series data, including physical parameters, help capture these complex relationships and guide ocean temperature prediction.

Dynamics. Dynamic parameters, mainly including wind speed, flow velocity, and pressure, can capture dynamic processes in the ocean and affect the spatiotemporal changes of ocean temperatures. For example, strong

winds can increase turbulence on the sea surface, promote vertical mixing of seawater, and affect the distribution of sea surface temperature. The surface flow velocity controls the horizontal transport of heat on the sea surface, significantly affecting the sea surface temperature.

Thermodynamics. Thermodynamic parameters mainly include radiative heat flux, and different forms of heat flux together determine the heat transfer between the ocean and the atmosphere, directly affecting ocean temperatures. Latent heat and sensible heat reflect the heat exchange caused by evaporation, condensation, and temperature differences between the ocean and the atmosphere, which affects the temperature changes of the sea surface.

Miao et al. (2023a) use dynamics-based sea surface wind speed and velocity to predict sea surface temperature, whereas CNN models extract the relationships between different parameters and use the physical changes between different parameters to guide the process of sea surface temperature prediction. Kim et al. (2023) use wind speed to assist in the prediction process of sea surface temperature, and utilize the powerful representation ability of GNNs to extract the physical changes involved in the relationship between sea surface temperature and wind speed. Zhang et al. (2024b) use CNN models to extract long sequence features from wind speed and multi-hydrological data. Long-period features can be influenced by wind speed, mapping the intrinsic connections between different parameters. Chen et al. (2023b) use multiple dynamic and thermodynamic parameters to assist in predicting ocean temperature. Similar to dynamics, thermodynamics is also an important influencing factor in ocean temperature prediction. By using dynamics and thermodynamics to guide ocean temperature prediction, it is possible to capture long-term (6-month) ocean temperature changes.

5.2 Embedded physics-informed neural network

PINN is a method of deeply coupling physical knowledge with deep learning models, applying deep learning models to practical problems involving physical changes, improving model performance, and compensating for the shortcomings of poor interpretability in deep learning models (Krishnapriyan et al. 2021; Cuomo et al. 2022). PINN can not only explicitly embed physical laws in the model, but also transform physical laws into model constraints.

Model structure that satisfies physical mechanisms. Explicitly embedding physical laws into models ensures that the model output conforms to physical principles. During the training process, it can be ensured that the model learns under the guidance of a certain physical law.

Model constraints that satisfy physical mechanisms. In the training process of deep learning models, a physical regularization term is introduced to make the model converge to the physical constraint conditions during repeated iterations. This not only constrains the prediction results of the model but also limits the prediction range of the model to prevent it from outputting unreasonable results.

Yuan et al. (2023) use the mixed layer heat budget equation to provide physical guidance for the temperature prediction process. Combining physical information from different depths and using the heat budget equation as a constraint to improve ocean temperature prediction performance. In addition to combining the process of heat change, the principles of dynamics also significantly impact ocean temperature changes, Koopman is one of such tools used to explain nonlinear dynamics. In this respect, Rice et al. (2020) propose a method combining Koopman and convolution to extract dynamic information from ocean temperatures, and guide the model with Koopman constraints. Compared with the baseline method, the Koopman-based ocean temperature prediction method has high accuracy. Meanwhile, Wu et al. (2023) propose a layered ocean temperature physics-guided model, where heat transfer occurs between surface and bottom temperatures, resulting in a non-linear relationship between ocean temperatures at different depths. The use of this stratification phenomenon significantly improves the accuracy of ocean temperature prediction. Ocean currents continuously input heat from the waters near the equator into the polar regions, playing an extremely important role in regulating global ocean temperatures. Therefore, Wang et al. (2024b) propose using a convection simulation module to simulate the influence of ocean currents on sea surface temperature. This method uses the sea surface temperature from previous moments and ocean currents to guide the prediction process of sea surface temperature at the next moment. The results show that the proposed method improves the accuracy of sea surface temperature prediction by 1% to 5% and increases the interpretability of the model.

5.3 Brief summary

From Tables 6 and 7, we can draw the following conclusions:

(1) High accuracy in ocean temperature prediction can be achieved using dynamic and thermodynamic parameters as inputs for ocean prediction models. Dynamic parameters involve the motion processes of the ocean and atmosphere, whereas thermodynamic parameters involve energy exchange and phase transition processes, which play a key role

Table 6 Overview of neural networks containing physical feature input

	Source	Model	Area	Dimension	Data	Input	Lead day	Result
Dynamics	Miao et al. 2023a	CNN_SCW	SCS	2D	CMEMS ECMWF	SSTA Wind speed, current velocity	7	RMSE = 0.33℃
	Zhang et al. 2024b	SSCNN	India Ocean	2D	CCMP, AMSR-E SMOS, IPRC	SST Wind speed, etc.	30	RMSE = 0.47℃
	Kim et al. 2023	ST-GNN	16 locations	2D	OISST ERA5	SST Wind speed, etc.	7	RMSE = 1.01℃
Dynamics + thermodynamics	Chen et al. 2023b	ResNet	110°E–290°E 60°S–60°N	2D	OISST NCEP, GODAS	SST, SSH, LH, SSS Wind speed, heat, currents	180	RMSE = 0.58℃
	Sun et al. 2022	TCN	Indian Ocean	2D	OISST	SST, wind speed, etc.	30	RMSE = 0.50℃
	Patil and Iiyama 2022	LSTM	Tohoku region	2D	ERA5 JCOPE2	Ocean current Wind speed, etc.	30	RMSE = 0.49℃
	Tresnawati et al. 2024	LSTM	Indonesian Sea	2D	NASA ERA5, NCEP	SST Wind speed, etc.	30	RMSE = 0.45℃

Table 7 Overview of PINNs

	Source	Model	Area	Dimension	Data	Input	Lead day	Result
Model constraints satisfy physical mechanisms	Yuan et al. 2023	STPDE-NET	-	2D	OISST CMEMS, ERA5	SST Ocean current, etc.	10	RMSE = 0.91℃
	Rice et al. 2020	Consistent Koopman	Gulf of Mexico	2D	OISST	SST	180	MAE = 0.63℃
	Wu et al. 2023	PGSTCN	SCS	3D	-	ST	10	RMSE = 0.45℃
Model structure satisfies physical mechanisms	Wang et al. 2024b	U-Net	20°N–33°N 133°E–209°E	2D	CMEMS	SST	6	SMAPE = 0.42℃
	Meng et al. 2023	ConvLSTM	3.99°N–24.78°N 98.4°E–124.4°E	2D	GHRSST	SST	10	RMSE = 0.37℃
	Meng et al. 2021	GAN-based framework	SCS	3D	OISST HYCOM	ST	-	RMSE = 1.29℃

in ocean temperature changes. For example, the CNN_SCW model uses wind speed and ocean current velocity as input variables for its prediction network, effectively reflecting the influence of external physical parameters on ocean temperature changes. In this way, we can capture deep temperature change patterns and better reflect the interaction between ocean temperature and other variables.

(2) PINN is a deep coupling of physical knowledge based on deep learning models, allowing the model to follow physical constraints during the iterative optimization process. This method uses physical information to guide the optimal solution of deep learning models. Among them, the generative adversarial network (GAN)-based framework uses a combination of a GAN and an encoder to capture physical knowledge in the input data, enabling the model training process to be conducted under the constraints of physical information and increasing the interpretability of the model.

(3) In theory, compared with models that use physical parameters as inputs, PINN should have higher prediction accuracy by embedding physical knowledge into the model due to its deep coupling with physical knowledge. However, most existing models learn physical constraints by extracting the relationships between physical variables and ocean temperatures. In addition, methods such as STPDE-NET and PGSTCN use physical constraints as loss functions to guide the training process of the model, which can only provide physical feedback to the model and

Table 8 Details of the datasets

Dataset	Spatial resolution	Temporal resolution	Time
OISST	0.25° × 0.25°	Daily/weekly/monthly	1981
Argo	-	Daily	2010
MODIS	1 km	Daily/weekly/monthly	2002
NCEP	2.5° × 2.5°	Daily/monthly	1948
GHRSST	0.25° × 0.25°	Daily	2002
ERA5	0.25° × 0.25°	Hourly	1940

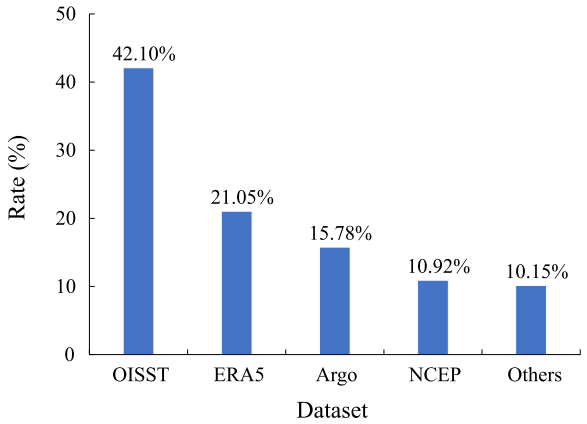


Fig. 6 Dataset usage frequency

do not truly learn specific physical patterns, resulting in prediction results that do not match expectations. However, it is believed that with more PINN methods, expected research prospects and value will be demonstrated.

6 Dataset and experimental area

Infrared and microwave radiometers carried on remote sensing satellites can measure the thermal radiation on the ocean surface and convert it into temperature data. After investigating nearly 100 ocean temperature studies, it is found that they use the following datasets: the National Oceanic and Atmospheric Administration's Optimum Interpolation Sea Surface Temperature (OISST) (Reynolds et al. 2002), Argo datasets (Wong et al. 2020), Moderate Resolution Imaging Spectroradiometer (MODIS) (Kilpatrick et al. 2015), National Centers for Environmental Prediction (NCEP) (Kalnay et al. 2018), Group for High-Resolution Surface Temperature (GHRSST) (Chin et al. 2017) and European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA5) (Hersbach et al. 2018), etc. The detailed information on these datasets is shown in Table 8. Then, we analyze the frequency of dataset usage and the distribution of experimental sea areas, as shown in Figs. 6 and 7. According to the statistical results, it is not difficult to see that OISST has become the most commonly used dataset for ocean temperature prediction due to its high resolution and wide time coverage. The South China Sea has a significant impact on monsoons (Wang et al. 2009), and the Pacific is a high-incidence area for ENSO and the La Niña phenomenon (Glynn et al. 2017). Thus these two regions have received widespread attention (Meyers et al. 2007; McGregor and Ebi 2018).

7 Challenges and directions

7.1 Current challenges

Given the above research and discussion, we elaborate on the current challenges and future development directions

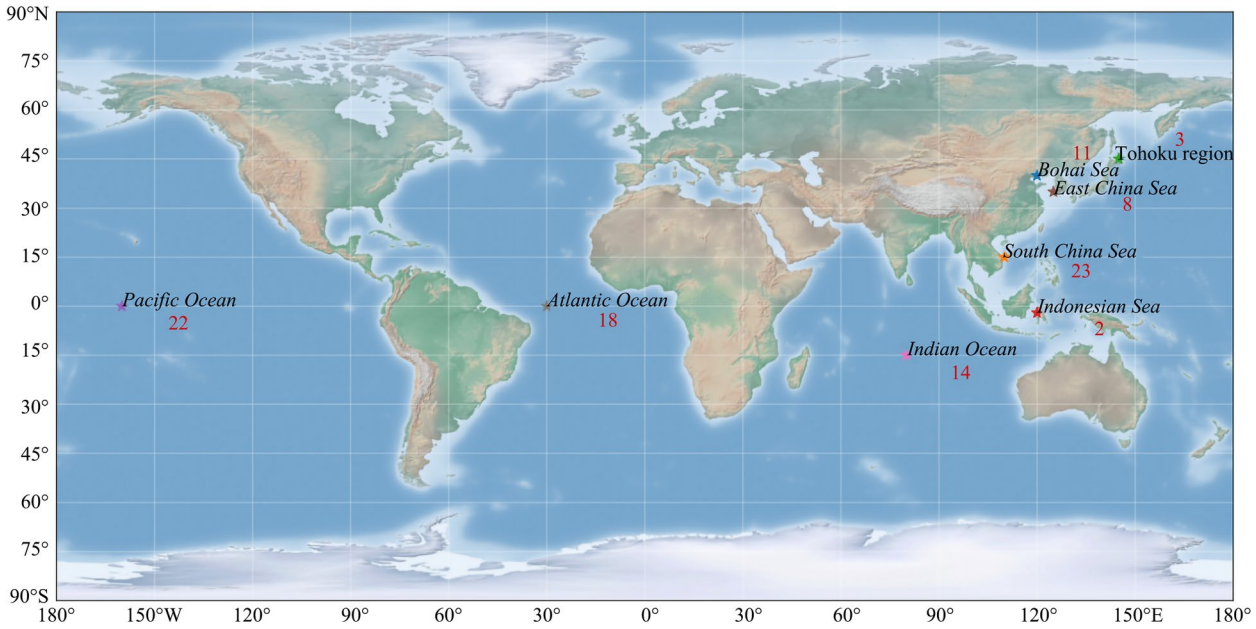


Fig. 7 Distribution of experimental sea area. (The red numbers represent the times of the area has been studied)

in terms of data, models, and algorithms. The current challenge is described in Fig. 8.

Data. (i) Standardized management of ocean temperature data. Current data sources are diverse, and the spatial and temporal distribution of data collection is uneven, which hinders the unified processing and application of ocean temperature data. (ii) Data quality and accuracy. Because of complex marine environments, many values are missing in ocean temperature data. Adverse weather conditions also lead to deviations in observation results (Dash et al. 2010). (iii) Long-term data maintenance. Long-term continuous observations are crucial for global climate change, but maintaining long-term global data poses financial challenges.

Models. (i) Comprehensive model design. The current development of RNN prediction models based on time series is relatively prosperous, but only a few GNN-related models are most suitable for modeling spatiotemporal information. (ii) Large marine ecosystem (LME) models. This highlights the lack of unified modeling for multiple hydrological information, collaborative development of ocean big data mining and prediction work.

Algorithms. (i) Spatiotemporal feature noise. Current research mostly captures spatiotemporal correlations through convolution or graph structures, but convolution operations or graph structure learning processes can easily lead to excessive dimensionality, resulting in the learning of many noisy features and suppressing the periodic changes of spatiotemporal correlations. (ii) Poor interpretability. Current algorithms are mostly result-oriented, which means that the quality of an algorithm is judged solely based on the accuracy of the results, and cannot be explained by geographical environment or oceanographic principles. Ocean temperature is a long-term process, and its periodic changes are highly correlated with the marine ecosystem and influenced by multiple variables in the ocean. Thus, further integrating oceanographic principles into deep models for interpretable training will be a major challenge. (iii) Insufficient learning of graph structures. In the fields of recommendation systems and trajectory representation, using graph structures to represent the correlation dependencies between data has achieved great success. However, in the field of ocean spatiotemporal prediction, this survey indicates that using RNN for spatiotemporal prediction still dominates, the introduction of graph structures only obtains global static correlations, and deeper regional correlations or hierarchical correlations between different variables are

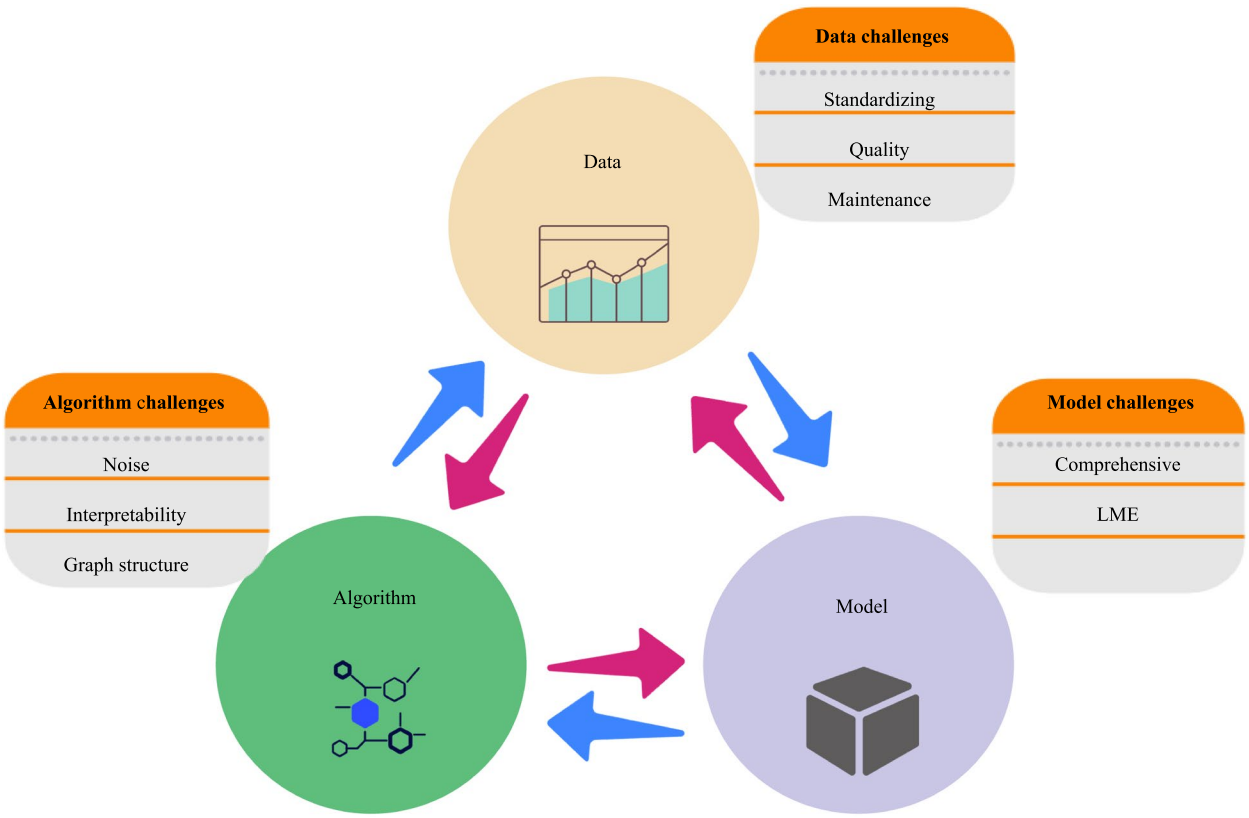


Fig. 8 Current challenges

often ignored, resulting in insufficient learning of graph structures. Thus, applying graph structure algorithms from other fields to the ocean domain is currently an important task.

7.2 Future directions

Based on the current research status and challenges, the future development direction of ocean temperature prediction is summarized as follows:

Standardization and completeness of data. In ocean temperature prediction scenarios, various ocean temperature data are widely used due to their respective characteristics. However, due to differences in spatiotemporal resolution, coverage areas, and seawater depths, it is impossible to horizontally compare model performances under different datasets. We believe that standardizing various ocean temperature datasets will greatly reduce the time and cost of data preprocessing, and facilitate further applications.

Ocean prediction large models. With the rise of ChatGPT, large models have become one of the important trends in the development of the computer field today. The ocean is a complex ecosystem that includes various biological and physical environments. As an important component of the ocean system, ocean temperature is influenced by factors such as ocean currents and the heat absorption and release of seawater. In the future, other hydrological and environmental data can be considered, combined with various physical changes occurring in the ocean system, to incorporate the involved physical principles and features into the model, improve the interpretability of the model, and ultimately integrate it into large-scale language models in the field of ocean data mining.

Multivariate fusion algorithm. Multiple hydrological elements are interdependent and have inseparable spatiotemporal consistency. The GNN-based ocean temperature prediction model can use a graph structure to represent the spatiotemporal characteristics of various ocean elements, and consider using a hierarchical graph structure to extract the relationships between different elements. When underwater ocean temperature data are missing, the missing temperature can be interpolated by mining the relationship between other hydrological elements and temperature to conduct subsequent tasks better. At present, big data mining is developing toward the representation of multidimensional, multilayered, and heterogeneous graph structures, providing new opportunities for the joint prediction of multiple factors. This can help develop a universal multilayer heterogeneous graph framework to improve the performance of ocean temperature prediction comprehensively and even promote further development in the field of ocean data mining.

8 Conclusions

In this survey, we systematically explore the current research status of ocean temperature prediction based on deep learning. This study provides a clear and comprehensive perspective for researchers by investigating existing methods, data, and sea areas, providing new insights for the development of deep learning-based ocean temperature prediction, and pointing out the direction for the next step of ocean temperature research. At the same time, the existing problems are summarized and a development blueprint is outlined, further promoting discussions on ocean temperature prediction research.

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Authors' contributions
Xingyu Zhao searched for literature and wrote the manuscript. Yanwei Yu conceived the idea for this project and provided critical revisions throughout all stages of manuscript preparation. Jianpeng Qi and Lei Zhou guided the manuscript framework and literature analysis.

Availability of data and materials
The OISST dataset is available at https://psl.noaa.gov/ (accessed on August 10, 2024). The ERA5 dataset is available at https://cds.climate.copernicus.eu/ (accessed on August 10, 2024). The Argo dataset is available at https://argo.ucsd.edu/ (accessed on August 10, 2024). The NCEP dataset is available at https://psl.noaa.gov/ (accessed on August 10, 2024). Other datasets can be found in the references.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no conflict of interest.

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