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ORIGINAL PAPER

COMPARATIVE ANALYSIS OF DIFFERENT DEEP LEARNING ALGORITHMS FOR THE PREDICTION OF MARINE ENVIRONMENTAL PARAMETERS BASED ON CMEMS PRODUCTS

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ABSTRACT

Marine environmental parameters as seawater temperature, salinity and sea surface height are crucial for understanding ocean dynamics and their impact on global climate systems. Inversion and prediction of marine environmental parameters with satellite altimetry (e.g. Copernicus Marine Environment Monitoring Service) is a powerful approach to enhance our understanding of ocean dynamics. Deep learning models (e.g. LSTM, ANN, CNN) are helpful in predicting marine environmental parameters. However, existing single model prediction methods are difficult to make accurate predictions in the time-varying marine environment time series due to specific neural network architectures and training methods. It remains to be verified whether hybrid models based on LSTM have good performance and effectiveness in marine environment modeling and prediction. In this study, we propose an enhanced hybrid model which combines signal to noise ratio and variational mode decomposition with long short-term memory (SNR-VMD-LSTM) on marine environmental parameters prediction based on Copernicus Marine Environment Monitoring Service (CMEMS) product. To verify the performance of the proposed prediction method, we conducted a comparative analysis on seafloor temperature, seawater temperature, salinity, and sea surface height marine environmental parameters series derived from CMEMS products with five grid sites along the west coast of the United States. Firstly, SNR is used to determine the *K* parameters of VMD. Secondly, each decomposed intrinsic mode function (IMF) component is utilized to construct a new time series, serving as a feature input to the LSTM model for marine environmental parameters prediction. To evaluate the predictive accuracy of the SNR-VMD-LSTM model, different prediction models were evaluated based on the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Compared with the VMD-LSTM model, SNR-VMD-LSTM can quickly determine the value of parameter *K* and R^2 is closer to 1, and improve the efficiency of prediction. Compared with LSTM, the experimental results of SNR-VMD-LSTM shows that the RMSE accuracy of the four different datasets is increased from an average of 60.0 % to 91.4 %, and the MAE accuracy is increased from an average of 40.0 % to 91.8 %. The hybrid model prediction results have high accuracy and exhibit strong correlation with the original time series, which can better predict and monitor changes in the marine environment. Therefore, our method can be applied to the prediction of long-term time series of environmental ocean parameters.

1. INTRODUCTION

Satellite altimetry is a crucial technology for measuring various marine environmental parameters, such as sea surface height (He et al., 2022; Shaw et al., 1999; Tierney et al., 2000), ocean circulation (Fu et al., 1995; Tierney et al., 2000), wind speed (Chelton et al., 1985), and the seawater temperature (Segschneider et al., 2000; Medina-Lopez et al., 2019) and salinity (Dinnat et al., 2019; Ridgway et al., 2010) characteristics of ocean waters. Currently, several organizations provide marine environment parameters based on satellite altimetry, such as the GLOBAL_MULTIYEAR_ PHY_001_030 products from Copernicus Marine Environment Monitoring Service (CMEMS, Huang et al., 2024). In recent decades, marine environmental monitoring has been a hot research area, and many researchers have been seeking effective methods to predict and monitor marine environmental changes (Ditria et al., 2022; Wilson et al., 2002; Richardson et al., 2006). Marine environmental monitoring usually involves acquiring a large amount of data and conducting extensive data processing (Zhang et al., 2021; Kremezi and Karathanassi, 2020), including multiple aspects of ocean temperature, salinity, marine organisms, and marine geographic information (Hafeez et al., 2018; Pan, 2003; Chang and Bai, 2018). Traditional monitoring methods mainly rely on a limited network of observation stations and sensors, which leads to inhomogeneity in the spatial and temporal data.

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Therefore, enhancing marine environmental monitoring requires more automated methods, high-resolution and global data (Mahrad et al., 2020; Brewington, 2014).

Marine environmental forecasting is of great significance for the protection of marine rights and interests, the development of marine economies, and the prevention and mitigation of marine disasters (Agarwala, 2021; Ma et al., 2023). Various scholars have applied advanced technologies such as deep learning, neural networks, and large-scale data mining to process data (Zhou, 2020) and have proposed physical models, statistical models, and deep learning models for marine environment prediction to better understand and forecast the dynamic processes involved in marine environments (Sun and Scanlon, 2019; Temitope Yekeen and Balogun, 2020). Moreover, the improved data quality and accuracy of data-driven models (Ghamisi et al., 2019) enables high-precision predictions of extreme weather events, seasonal climate change, and marine ecosystems (Yekeen and Balogun, 2020). However, marine systems worldwide are changing rapidly against the background of global climate change, which is introducing more challenges to marine environmental forecasting. For instance, traditional prediction methods often involve numerous theoretical assumptions and uncertainty associated with the parameterization process, as well as difficulties related to accuracy and timeliness, especially when dealing with large-scale computations (Reichstein et al., 2019).

Deep learning is widely used in the prediction of marine environments time series, employing various neural network architectures and training methods (Wen et al. 2020). Neural network methods are commonly used to predict changes in sea level. For example, Makarynskyy et al. (2004) applied artificial neural networks (ANNs) to perform multi-span predictions using sea level measurement data collected from a tidal station in Australia. Wavelet-Artificial Intelligence approaches have been effectively integrated to enhance sea level variation prediction, as shown by Alshouny et al. (2022). LeCun et al. (2015) stated that Long Short-Term Memory (LSTM) includes deep feedforward networks, regularization, optimization algorithms, convolutional networks, sequence modeling, and practical methods, while Goodfellow et al. (2016) introduced a wide range of topics in deep learning, Balogun and Adebisi (2021) used ARIMA, SVR (Support Vector Regression), and LSTM models to predict changes in the sea level along the coastline of the western Malaysian Peninsula. LSTM is recognized for its ability to learn long-term dependencies (Hochreiter and Schmidhuber, 1997), and it has been successfully applied in this study for marine environmental time-series prediction it has thus been demonstrated that utilizing neural networks is feasible for forecasting changing sea levels. Furthermore, to improve the prediction accuracy, numerous scholars have conducted hybrid model modeling. Song et al. (2022) utilized a hybrid model combining empirical mode decomposition (EMD), wavelet transform (WT), and Elman neural network (ENN) methods to predict changes in the sea level over time. Wang et al. (2021) employed a Gated Recurrent Unit (GRU) to predict wind-speed time series following the application of CEEMD and wavelet packet decomposition (WPD). These studies, among others, have verified that hybrid models demonstrate good performance for predicting time-series data in natural environments. Variational mode decomposition (VMD) is a fully non-recursive adaptive method for complex signal decomposition that exhibits a strong performance, particularly in handling nonlinear and nonstationary signals (Dragomiretskiy and Zosso, 2013; Lv et al., 2022). Considering the advantages of the VMD method in the analysis of complex, nonlinear, multi-scale, and nonstationary data, and the fact that the algorithm shows good anti-noise performance, some scholars have explored combining VMD and neural network models: Tao et al. (2023) used a mixed model that combined VMD with LSTM to predict water quality; Wang et al. (2020) used particle swarm optimization (IPSO) to optimize the VMD-LSTM model parameters. Roche and Sun (2024) used SWOT data to evaluate the effects of LSTM, Auto-LSTM, and Metropolis Manning algorithms on the flood prediction of river flow levels. Chen et al. (2023) incorporated the EEMD method to enhance the VMD-LSTM model and advanced the quadratic decomposition of the residual sequence in the VMD, thus improving the accuracy of predicting changes in sea levels over time. It has been established that the aforementioned method exhibits robust performance and effectiveness in time-series modeling and prediction. Similar to the use of deep learning models in long-term trend estimation of sea level data by combining tide gauge and altimetry data, as presented by Erkoç and Doğan (2024), this study applies deep learning techniques to marine environmental parameter prediction.

However, within the VMD method, two critical parameters—namely the number of mode decompositions (K) and the quadratic penalty factor (α) must be predetermined. Improper parameter configurations may result in either the over-decomposition or under-decomposition of signals, significantly impairing the effectiveness of the decomposition process (Mirjalili et al., 2014). If it is difficult to determine the optimal parameters for the VMD model, it may adversely impact the prediction accuracy of the LSTM model, particularly in dealing with complex nonlinear and irregular time-series data.

To enhance the VMD-LSTM model, we propose utilizing the signal-to-noise ratio (SNR) as a metric to assess the quality of VMD (Mei et al., 2021; Ding et al., 2021). As well as optimizing the parameters of VMD, we develop a novel deep learning model termed SNR-VMD-LSTM. In this model, the SNR is used to determine the optimal value of K for VMD.

Table 1 Information of the analyzed Grid Station based on CMEMS product.

Grid Station	ID	Longitude (◦)	Latitude (◦)	Time Span (years)
SAN FRANCISCO	0010	-122.465	37.807	1993-2020
LOS ANGELES	0245	-118.272	33.72	1993-2020
LA JOLLA (SCRIPPS PIER)	0256	-117.257	32.867	1993-2020
CRESCENT CITY	0378	-124.182	41.745	1993-2020
NEAH BAY	0385	-124.612	48.367	1993-2020

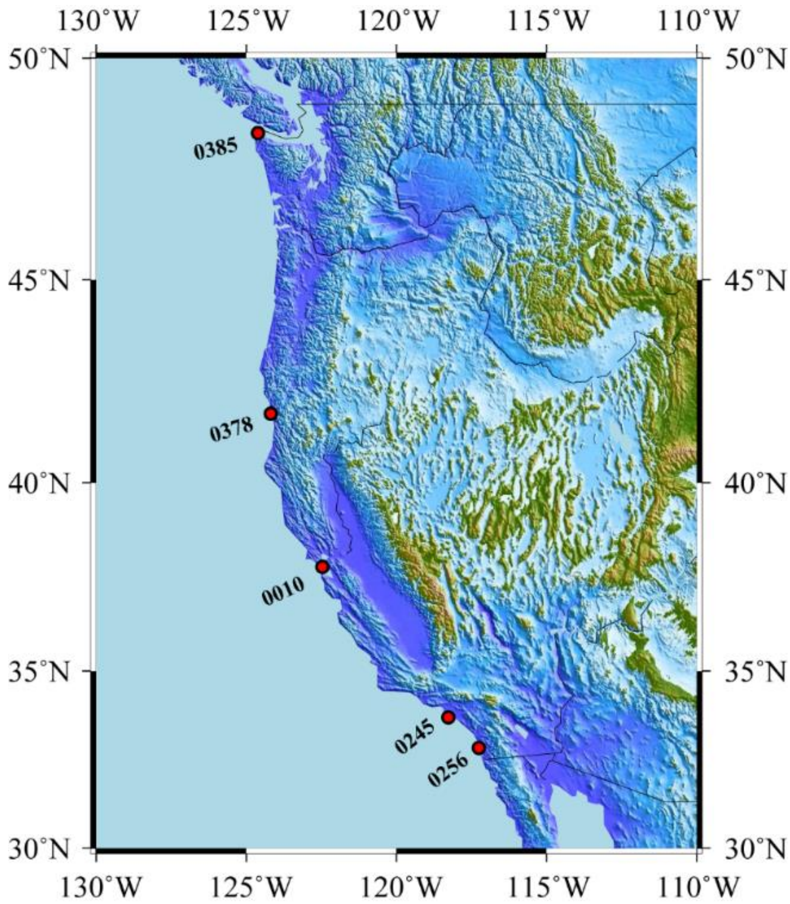


Fig. 1 Spatial distribution of the analyzed sites.

Subsequently, each model component's IMF resulting from the decomposition is input into the LSTM model as the input feature for training. Then, predictions are made after the hyperparameters of the LSTM model are adjusted to their optimal values. Our SNR-VMD-LSTM model not only retains the prediction accuracy of the original VMD-LSTM model in each IMF, but also optimizes the *K* value and improves the time-series prediction effectiveness.

Thus, in this study, we compared and analyzed various deep learning models and enhanced deep learning hybrid prediction models, which were proposed by comparing ocean environmental parameters such as seabed temperature, seawater temperature, salinity, and sea surface height.

2. DATA AND METHODS

2.1. *MARINE ENVIRONMENTAL PARAMETERS FROM CMEMS PRODUCTS*

In this work, we utilize the latest reprocessed daily products "GLOBAL_MULTIYEAR_PHY_001_030" (with access of https://doi.org/10.48670/moi-00021) from CMEMS with period from 1993 to 2020 (Copernicus Marine Environment Monitoring Service, 2023). Specifically, we performed a comparative analysis of marine environmental parameters on seafloor temperature, seawater temperature, salinity, and sea surface height derived from CMEMS products with 5 grid stations along the west coast of the United States (Detail site information see in Figure 1 and Table 1).

2.2. *SNR-VMD-LSTM MODEL*

Step 1: Optimizing the parameters of VMD using the SNR

VMD is a completely non-recursive adaptive complex signal decomposition method with good performance in decomposing nonlinear and nonstationary signals (Dragomiretskiy et al., 2013). The VMD algorithm can decompose complex signals into a series of bandwidth-limited frequency modulation and amplitude modulation signals, namely the intrinsic mode function (IMF), by setting parameters such as the mode number, penalty parameter, and rising step size. The VMD process is essentially a process of constructing and solving a variational problem, and this constructed constrained variational problem can be expressed as follows（Nazari and Sakhaei, 2020）:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial t \left[(\delta(t) + \frac{j}{\pi}) u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \quad s.t. \sum_k u_k = f \tag{1}$$

In this equation, t is time, f is the original signal, u_k is the modal function, ω_k is the actual center frequency of each mode, $e^{-j\omega_k^t}$ is the estimated center frequency of each analytical signal, $\|\cdot\|_2$ is the L_2 norm, $s.t.$ represents the constraint condition, and $\sum_k u_k$ is the sum of all modal numbers.

To obtain its optimal solution, Lagrangian multipliers and quadratic penalty factors are introduced to transform the constrained variational problem into an unconstrained variational problem. Therefore, the augmented Lagrangian expression is obtained as follows (Humphrey et al., 1996; Xu et al., 2021):

$$L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_k \left\| \partial t \left[(\delta(t) + \frac{j}{\pi t}) u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle \tag{2}$$

By using the alternating-direction multiplier algorithm and iteratively updating u_k^{n+1}, ω_k^{n+1}, λ^{n+1}, the saddle point of Equation (2) is obtained, which is the optimal solution of Equation (1).

For the number of modes K and penalty factors α that have the greatest impact on the VMD process, improper settings can have a serious impact on the decomposition results. The remaining parameters are generally set to default values. When K is set to a value that is too small or too large, it will cause the signal to be under-decomposed or over-decomposed, respectively, resulting in mode aliasing.

VMD allows for the autonomous selection of the number of mode components obtained during decomposition. This means that when using VMD for data decomposition, it is crucial to choose the appropriate number of mode components, referred to as K, to achieve high-quality decomposition results.

This study used the signal-to-noise ratio (SNR) as a quality measure for VMD to determine the optimal K value for the decomposition of sea-level time series in VMD. Multiple experiments have shown that the selection of the K value should be within the range of 4 to 8, and when K is 8, the decomposition of each individual time series is optimal (Mei et al., 2021).

$$\mathrm{SNR} = 10\, lg \frac{\sum_{i=1}^{N} m^2(i)}{\sum_{i=1}^{N} [m(i) - n(i)]^2} \tag{3}$$

where $m(i)$ represents the original signal, and $n(i)$ represents the reconstructed signal. The optimal range for the penalty factor of VMD is between 1.5 and 2 times the size of the decomposed data (Ding et al., 2021). After experimental verification, this study set penalty factor α of VMD to 15000 as the optimal value.

Step 2: VMD Decomposition

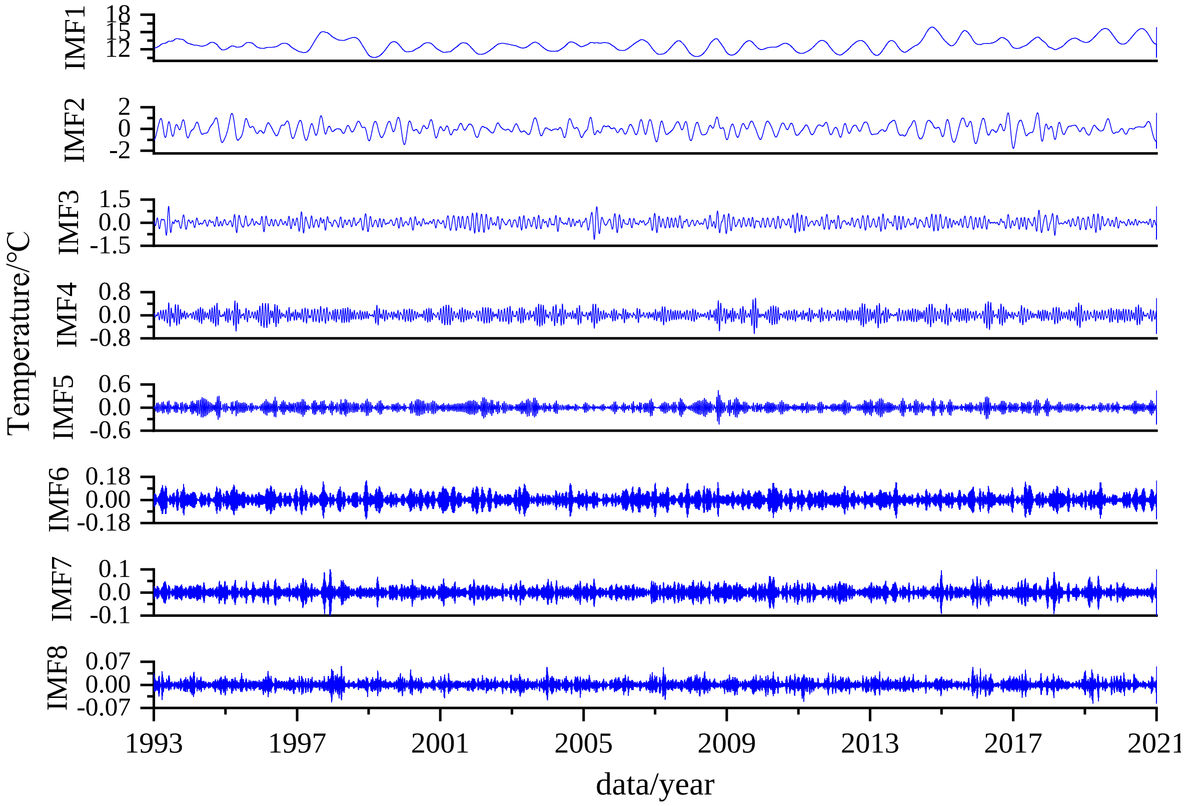
Because of the relatively small range of grid stations covered in this study, the frequency and amplitude of fluctuations in the seabed temperature, seawater temperature, salinity, and sea level sequences are very similar. The optimal K values for different sites are shown in Table 2, and the VMD of the seabed temperature, seawater temperature, salinity, and sea surface height are shown in Figure 2.

Step 3: Principle of the LSTM model

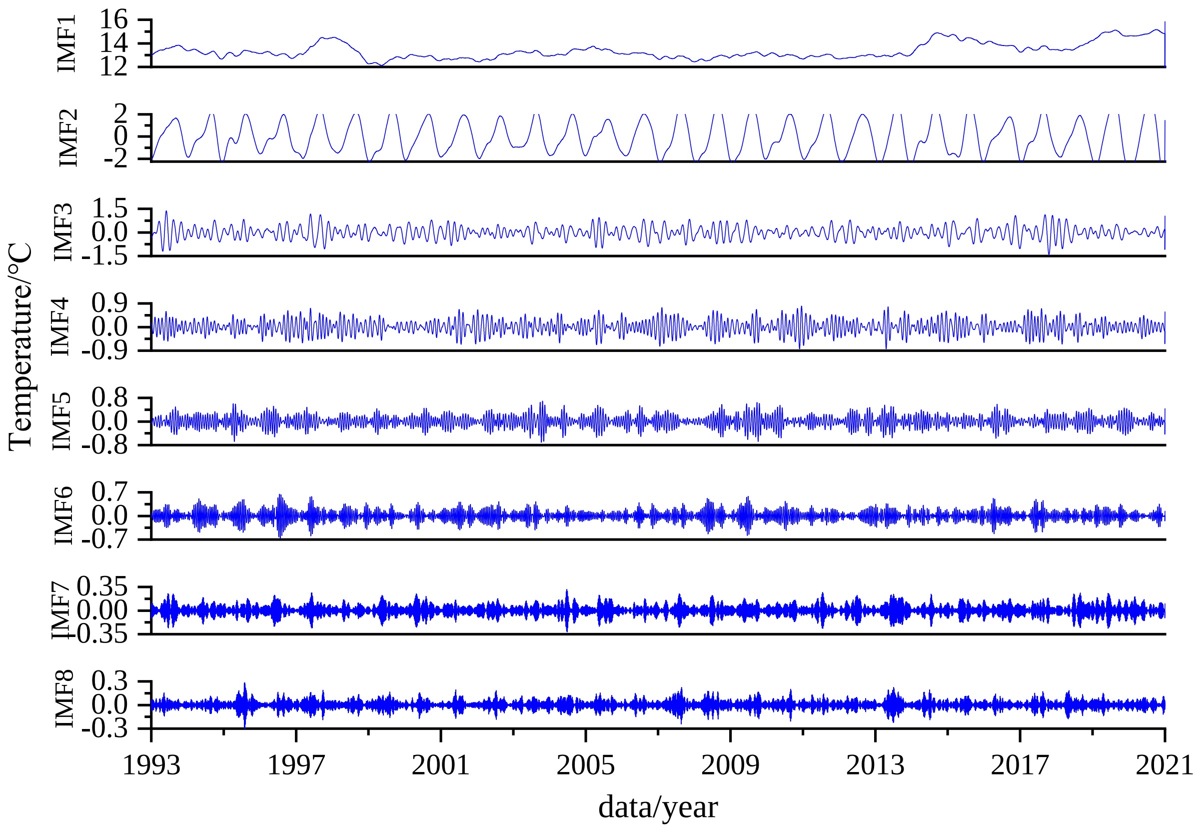
LSTM addresses the drawback of recurrent neural networks (RNNs) being unable to recall data from distant locations (Gers et al., 2000; Graves, 2012; Hochreiter and Schmidhuber et al., 1997). The LSTM network structure is called a cell, which includes an input layer, a hidden layer, and an output layer. Each hidden layer controls data storage and access through input gates, forgotten gates, and output gates (Xu et al., 2022; Yan et al., 2023). The LSTM network

Table 2 Selection of optimal *K* values for different sites.

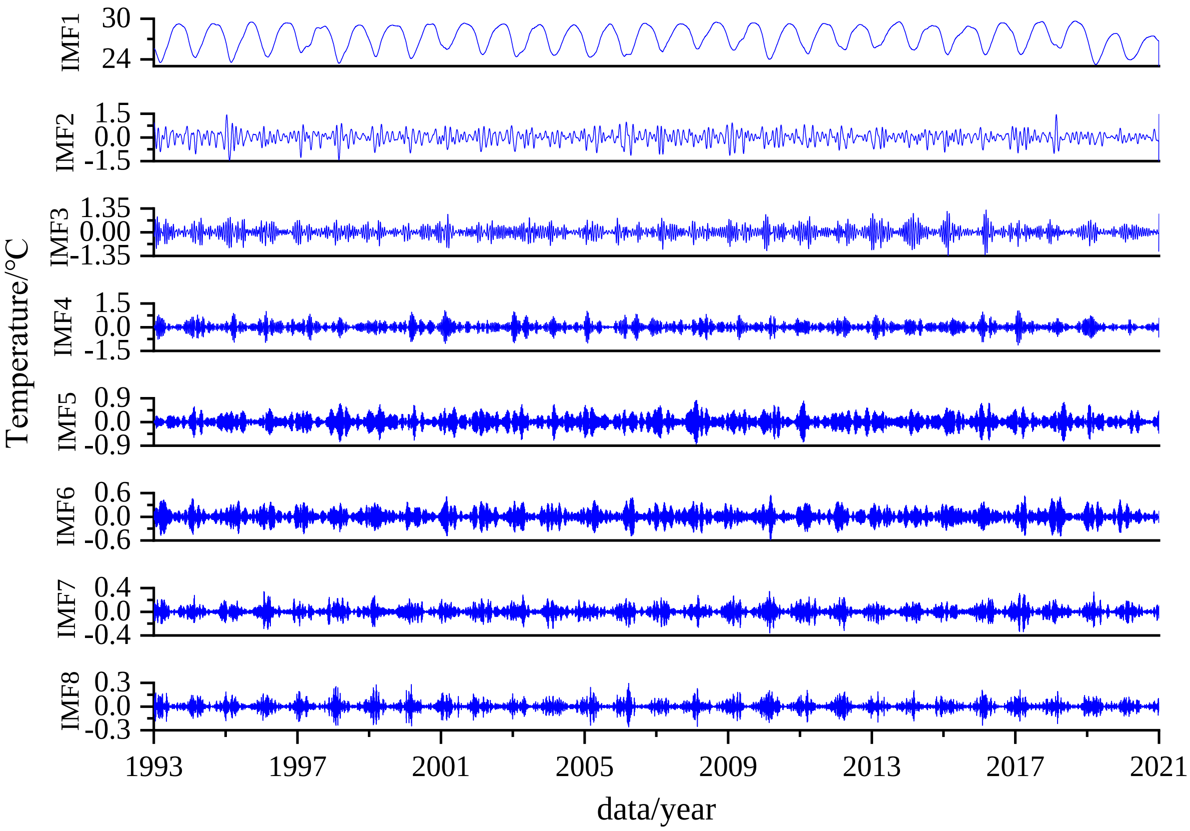
ID	Seabed Temperature	Sseawater Temperature	Salinity	Sea Level Height
	K	*K*	*K*	*K*
0010	8	8	8	6
0245	8	8	4	8
0256	8	8	8	8
0378	8	8	7	8
0385	8	8	8	5



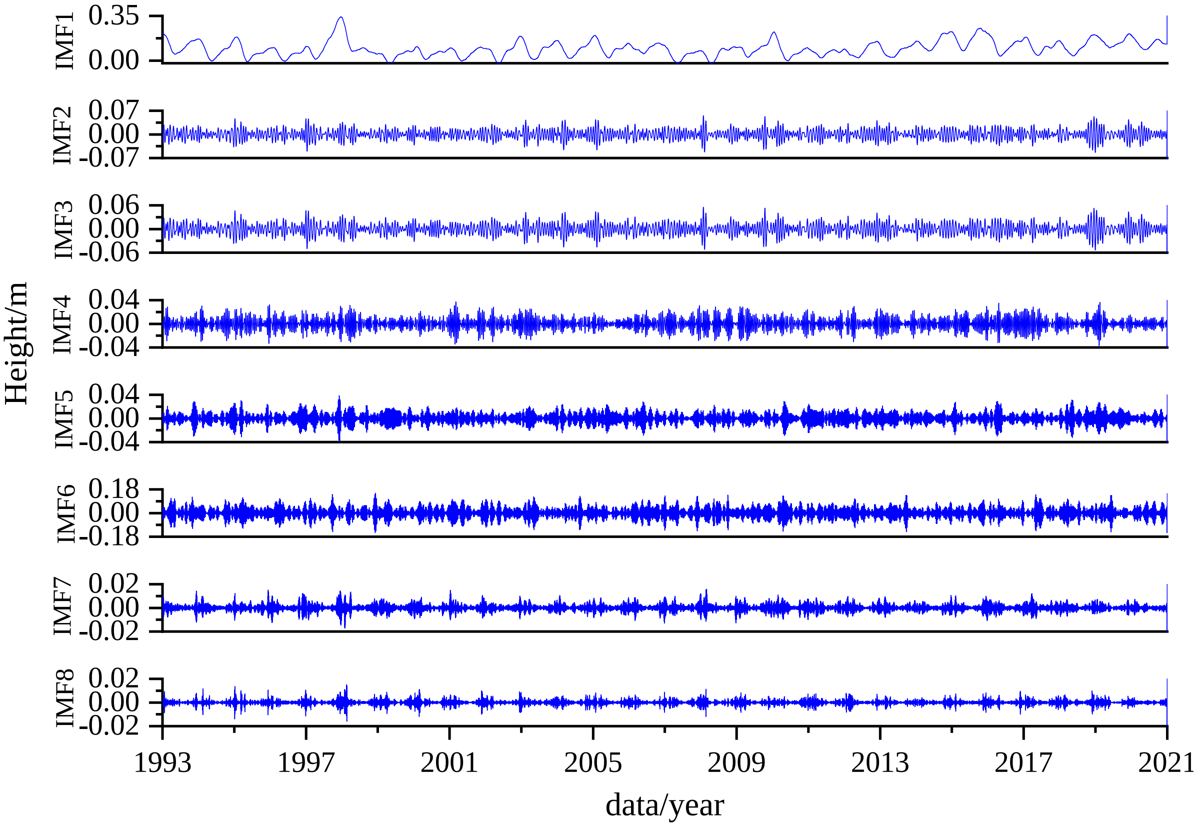
(a) seabed temperature



(b) seawater temperature



(c) salinity



(d) sea surface height

Fig. 2 VMD decomposition of seabed temperature (a), seawater temperature (b), salinity (c), and sea surface height (d).

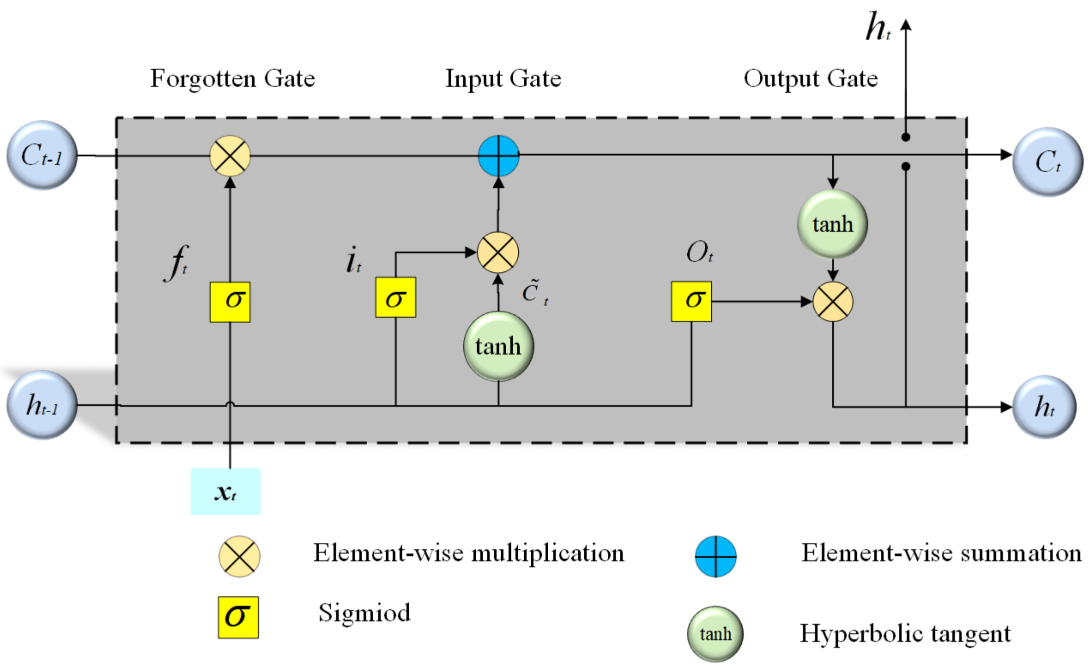


Fig. 3 Basic structure of LSTM.

module is shown in Figure 3, and the calculation mathematical steps are as follows (Xu et al. 2022; Choi et al., 2023):

Forgotten Gate f_t:

$$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f) \tag{4}$$

where $\boldsymbol{h_{t-1}}$ is the previous cell output, σ is the activation function, $\boldsymbol{x_t}$ is the current cell input, W_f is the weight, and b_f represents the threshold.

Input Gate i_t :

$$\boldsymbol{i_t = sigmoid(W_i[h_{t-1}, x_t] + b_i)}$$
$$\tilde{C}_t = tanh(W_C[h_{t-1}, x_t] + b_C)$$
$$\boldsymbol{C_t = i_t \times \tilde{C}_t + f_t \times C_{t-1}} \tag{5}$$

where $\tilde{C}_t$ is the candidate vector, $\boldsymbol{C_t}$ is the current unit state, and $\boldsymbol{C_{t-1}}$ is the previous unit state.

Output gate O_t :

$$O_t = sigmoid(W_o[h_{t-1}, x_t] + b_o)$$
$$h_t = O_t \times tanh(C_t) \tag{6}$$

The output layer result is obtained by multiplying the cell state through the tanh layer with the sigmoid layer result, in which $\boldsymbol{O_t}$ and $\boldsymbol{h_t}$ are the current cell output (Sagheer and Kotb, 2019).

Step 4: Evaluation of results

This study used RMSE (root mean square error), MAE (mean absolute error), and R^2 (coefficient of determination) values to evaluate the accuracy of prediction models. These mathematical principles were calculated as follows (Ozer, 1985; Belonenko et al., 2021):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(y_i - \hat{y}_i)| \tag{8}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{9}$$

where y_i is the actual data value, $\hat{y}_i$is the predicted result from each model, *n* is the number of station, and $\bar{y}$is the mean of the actual values. The smaller the RMSE and MAE values, the higher the prediction accuracy of the model. On the contrary, larger RMSE and MAE values indicate that the prediction accuracy of the model is relatively low. The R^2 values exist within the range of [0,1], wherein the closer the R^2 values are to 1, the better the prediction model's performance.

In summary, the SNR-VMD-LSTM model is designed to achieve rapid and accurate decomposition by optimizing the key parameter *K* of VMD using the correlation coefficient method. For the IMF components decomposed through VMD, the residual value is very small and can be directly removed. Then, the IMF decomposition values are separately predicted using LSTM to obtain the prediction results. A flowchart of the SNR-VMD-LSTM model is shown in Figure 4.

2.3. VMD-ANN MODEL

ANN is a computational model inspired by biological neural networks, consisting of a large number of simple processing units interconnected to solve complex computational problems by simulating the workings of neurons in the human brain. We compared SNR-VMD-LSTM and performed ANN

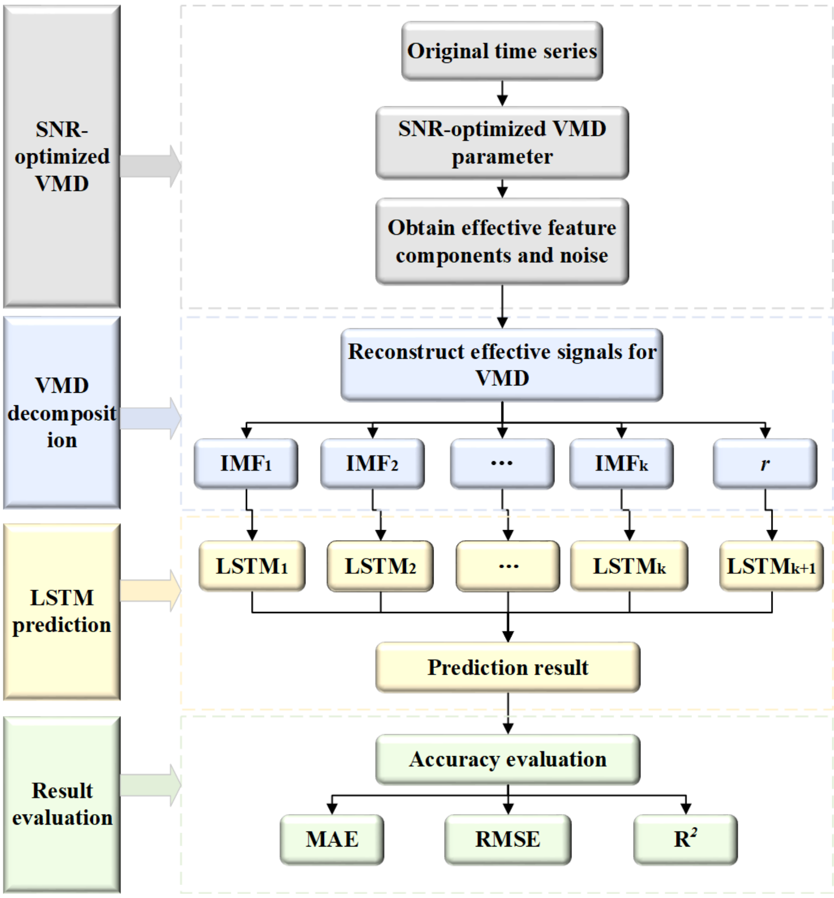


Fig. 4 SNR-VMD-LSTM flowchart.

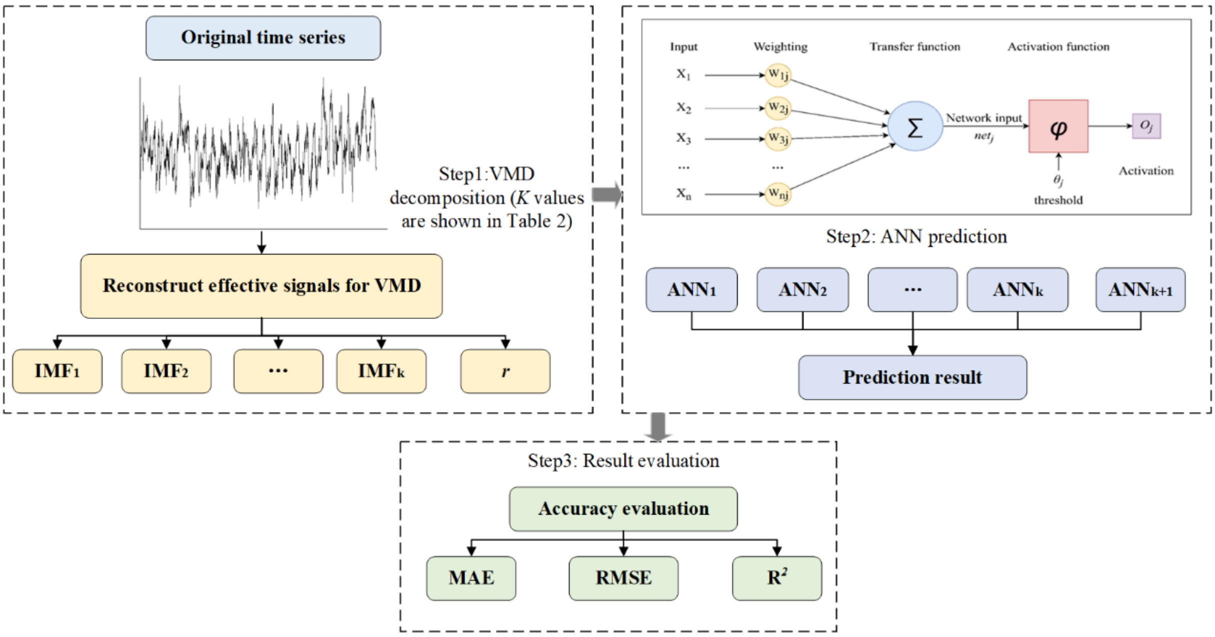


Fig. 5 VMD-ANN flowchart.

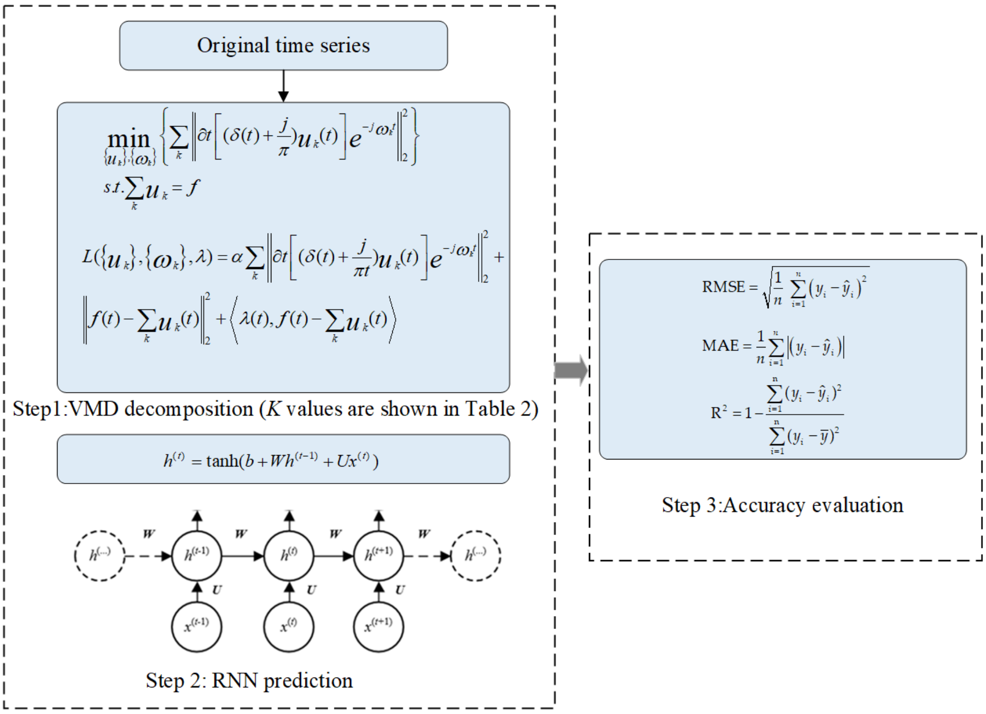


Fig. 6 VMD-RNN flowchart.

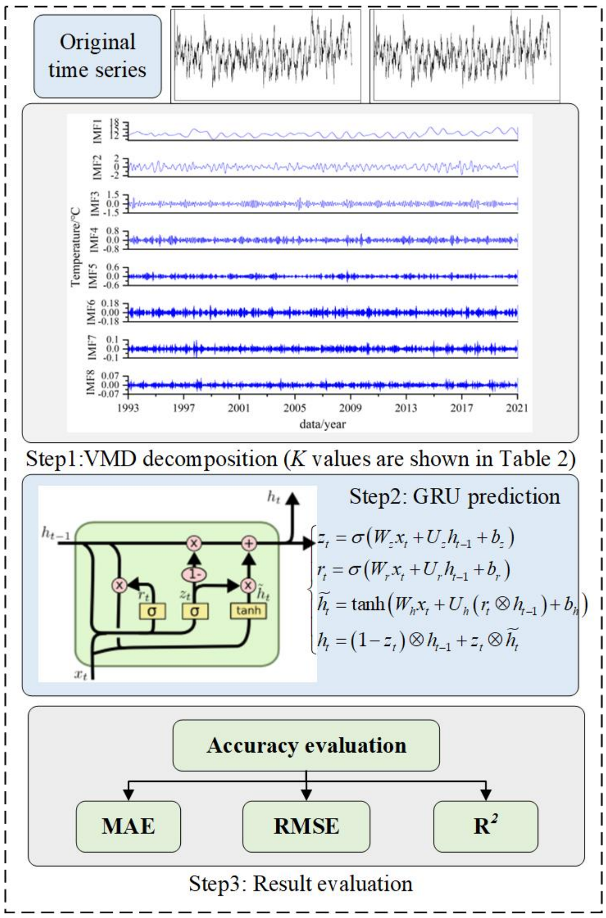


Fig. 7 VMD-GRU flowchart.

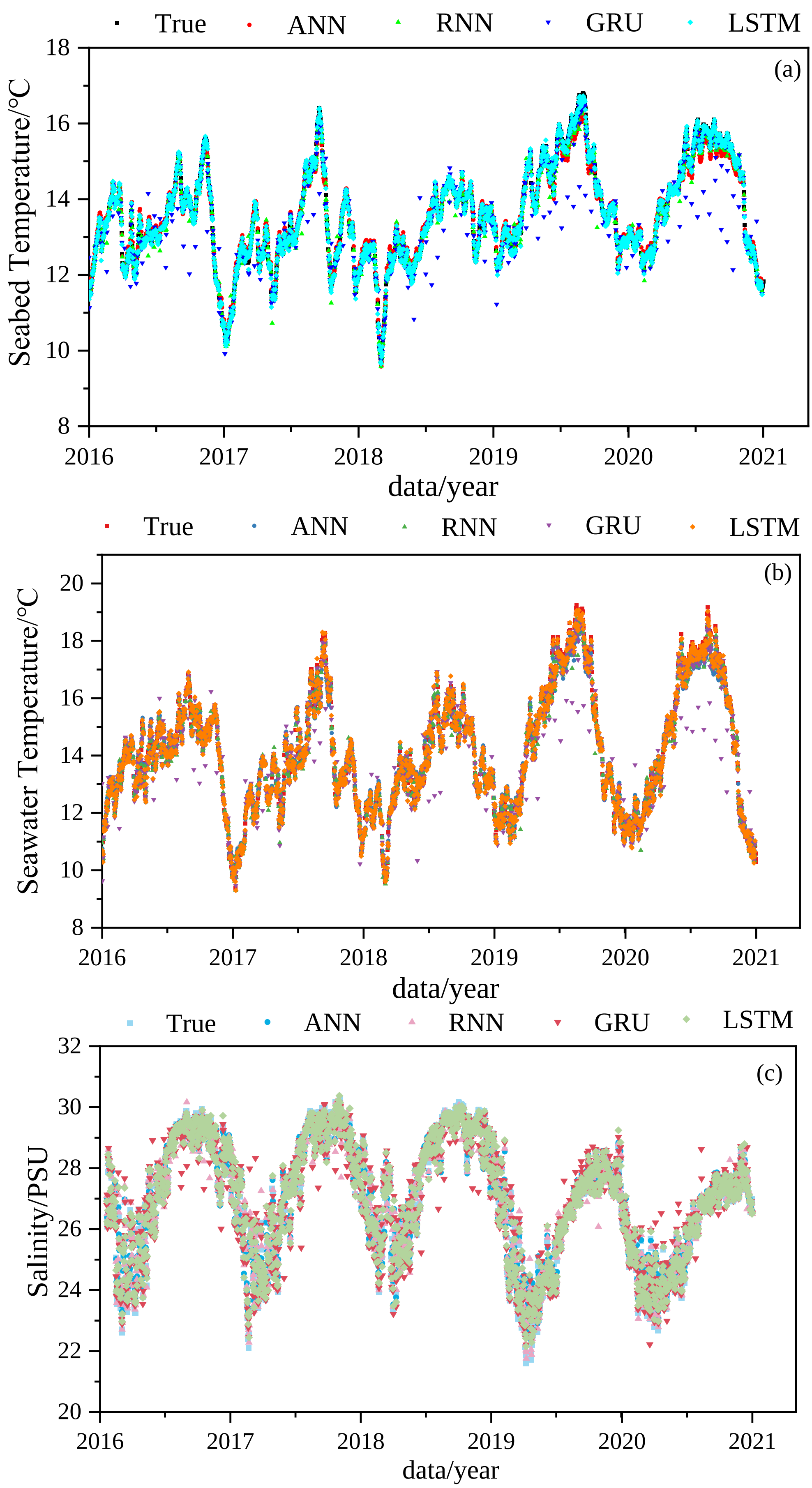
prediction on the environmental ocean parameter sequence of this study after VMD decomposition. Seo et al. (2018) used VMD for multi-scale time series decomposition and constructed VMD-ANN and ELM models for short-term demand forecasting. Zhou et al. (2024) combined recurrent neural networks with variational mode decomposition and multifractal to predict rainfall time series. Their research has demonstrated that VMD-ANN has been widely applied in the field of hydrology. Figure 5 shows the VMD-ANN flowchart.

2.4. VMD-RNN MODEL

The basic principle of RNN prediction model is based on its cyclic layer structure, where each cyclic layer has a weight matrix for processing time series data. Jiang et al. (2020) used VMD to decompose time series into multidimensional subsequences, in order to reveal the potential hidden information of the original time series and improve the prediction accuracy of time series. A Stacked Recurrent Neural Network (SRNN) model was constructed to predict subsequences, demonstrating the successful prediction of VMD-SRNN in time series. More detailed information about RNN can be obtained in Sherstinsky (2020). Figure 6 shows the flowchart of VMD-RNN.

2.5. VMD-GRU MODEL

The core of the GRU model lies in its gating mechanism, which mainly includes two gates: update gate and reset gate. Zhao et al. (2023) proposed the VMD-LSTM/GRU model, which combines the advantages of LSTM model, GRU model, and VMD technology, to predict nonstationary and irregular


True
ANN
RNN
GRU
LSTM
(a)
Seabed Temperature/°C
data/year
(b)
Seawater Temperature/°C
data/year
(c)
Salinity/PSU
data/year

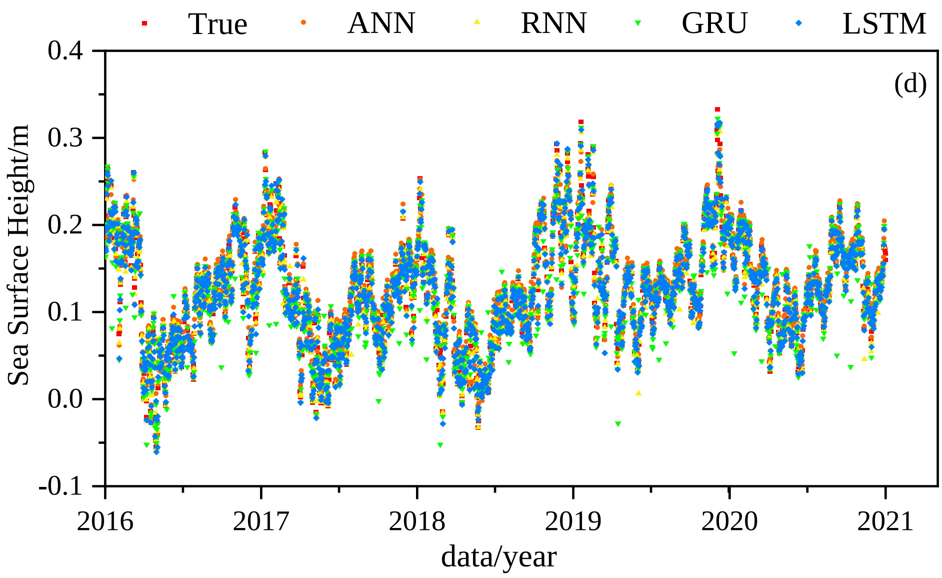


Fig. 8 Prediction result curve. (a), (b), (c), (d) are the results curves of predicting seabed temperature, seawater temperature, salinity, and sea surface height using a single model (taking 0010 station as an example for altitude).

waves on the east coast of China, demonstrating the application of VMD-GRU and VMD-LSTM in the ocean. More detailed information about GRU can be obtained in Dey and Salem (2017) and Fu et al. (2016). Figure 7 shows the flowchart of VMD-GRU.

To verify the effectiveness and predictive performance of the SNR-VMD-LSTM model proposed in this study, the GRU model was selected and compared with the ANN and RNN models, the LSTM single model, and the combination models VMD-ANN, VMD-RNN, and VMD-GRU.

To better comprehensively evaluate the predictive performance of each model, and according to the established dataset division requirements for deep learning prediction models (Li et al., 2023), we made adjustment to the dataset by dividing it based on 8:1:1. To ensure the effectiveness of comparisons between the studied prediction methods, the same parameter settings were used across all models. The sites selected for this study provided us with long-term time series data (spanning 28 years), so each model was trained on data from 1993.0 to 2012.9. The validation dataset, used to adjust the model hyperparameters and prevent overfitting, encompassed data from 2012.9 to 2015.9. The test set used for evaluating the performance of the models ranged from 2015.9 to 2020.9. Each model had 50 iterations, and the hyperparameter learning rate that controlled the parameter update step was set to 0.001. Each input layer and output layer had a dimension of 1, and each hidden layer had a dimension of 256. The length of each sliding data window was 12, and the batch size of the one-time input in the time series data was 16.

3. RESULTS AND DISCUSSION

3.1. ANALYSIS OF THE PREDICTIONS OF SINGULAR DEEP LEARNING MODELS

Taking the seabed temperature, seawater temperature, salinity, and sea surface height data from the 5 grid stations as examples, the results of using different standalone prediction models in different directions are shown in Figure 8.

Upon observing the prediction results achieved with the singular models, it can be seen that the RNN and ANN model results in Figure 8 (a) curve downward, the GRU model results have a large deviation, and the LSTM model predictions correlate relatively well with the original time series. Similarly, compared with the original time series, the prediction curves of the GRU model in Figures 8 (b), (c), and (d) are all offset in a downward direction, indicating that this model's predicted values are too small and have a large degree of error. Compared with the original sequence, the ANN and RNN prediction results are shifted upward, which suggests that these predicted values are too large. The LSTM model's predictions match the original sequence more closely, and the curve of these predicted results is stable. To further analyze their performance, we evaluated these singular prediction models using different parameters and data from different sites based on the *RMSE*, *MAE*, and R^2 values. The results of this evaluation are shown in Table 3.

3.2. EVALUATION OF SINGULAR MODEL PREDICTION RESULTS

For this section, we comprehensively evaluated and compared the predictive performance of four different models: ANN, RNN, GRU, and LSTM. Three different sequences of seabed temperature,

Table 3 Evaluation of single model prediction results for different parameters of the selected site.

ID	Model	Seabed Temperature RMSE (℃)	Seabed Temperature MAE (℃)	Seabed Temperature R^2	Seawater Temperature RMSE (℃)	Seawater Temperature MAE (℃)	Seawater Temperature R^2	Salinity RMSE (PSU)	Salinity MAE (PSU)	Salinity R^2	Sea Surface Height RMSE (mm)	Sea Surface Height MAE (mm)	Sea Surface Height R^2
0010	ANN	0.192	0.147	0.979	0.283	0.225	0.982	0.423	0.314	0.952	17.004	12.417	0.919
	RNN	0.151	0.106	0.971	0.273	0.240	0.974	0.446	0.324	0.951	17.750	13.019	0.933
	GRU	0.307	0.133	0.946	0.439	0.246	0.955	0.527	0.355	0.926	23.154	14.925	0.851
	LSTM	**0.197**	**0.099**	**0.996**	**0.245**	**0.195**	**0.985**	**0.384**	**0.276**	**0.961**	**15.868**	**11.486**	**0.930**
0245	ANN	0.238	0.202	0.929	0.422	0.318	0.976	0.023	0.013	0.982	10.737	8.464	0.953
	RNN	0.122	0.078	0.972	0.424	0.316	0.964	0.025	0.013	0.981	11.485	8.486	0.952
	GRU	0.218	0.103	0.940	0.552	0.319	0.947	0.053	0.024	0.906	15.628	8.883	0.899
	LSTM	**0.070**	**0.042**	**0.994**	**0.396**	**0.298**	**0.988**	**0.022**	**0.011**	**0.985**	**9.366**	**6.796**	**0.931**
0256	ANN	0.153	0.116	0.979	0.482	0.305	0.985	0.096	0.071	0.902	16.923	14.257	0.887
	RNN	0.098	0.061	0.951	0.413	0.322	0.977	0.069	0.045	0.905	9.957	7.458	0.890
	GRU	0.242	0.107	0.920	0.465	0.324	0.960	0.098	0.056	0.898	15.666	9.214	0.902
	LSTM	**0.081**	**0.057**	**0.991**	**0.404**	**0.294**	**0.989**	**0.065**	**0.041**	**0.954**	**7.252**	**5.596**	**0.979**
0378	ANN	0.137	0.111	0.983	0.244	0.165	0.965	0.068	0.046	0.986	20.986	15.729	0.931
	RNN	0.140	0.097	0.961	0.276	0.189	0.956	0.076	0.049	0.984	22.964	17.210	0.933
	GRU	0.225	0.111	0.955	0.365	0.221	0.924	0.129	0.066	0.950	27.370	18.902	0.883
	LSTM	**0.082**	**0.058**	**0.994**	**0.236**	**0.156**	**0.968**	**0.058**	**0.035**	**0.990**	**20.695**	**15.274**	**0.933**
0385	ANN	0.067	0.044	0.985	0.233	0.174	0.992	0.388	0.284	0.971	24.319	17.929	0.922
	RNN	0.070	0.045	0.991	0.242	0.172	0.981	0.409	0.270	0.970	25.579	19.204	0.934
	GRU	0.138	0.063	0.938	0.411	0.212	0.975	0.551	0.307	0.942	29.578	20.654	0.885
	LSTM	**0.048**	**0.0283**	**0.992**	**0.179**	**0.131**	**0.995**	**0.305**	**0.206**	**0.982**	**23.655**	**17.302**	**0.926**

seawater temperature, salinity, and sea surface height data were used for this evaluation. The objective was to identify the model that performs best in forecasting time series in order to establish a reliable foundation for constructing the subsequent hybrid models. Table 3 presents the precise evaluation metrics for the predictions generated by each model for different sites.

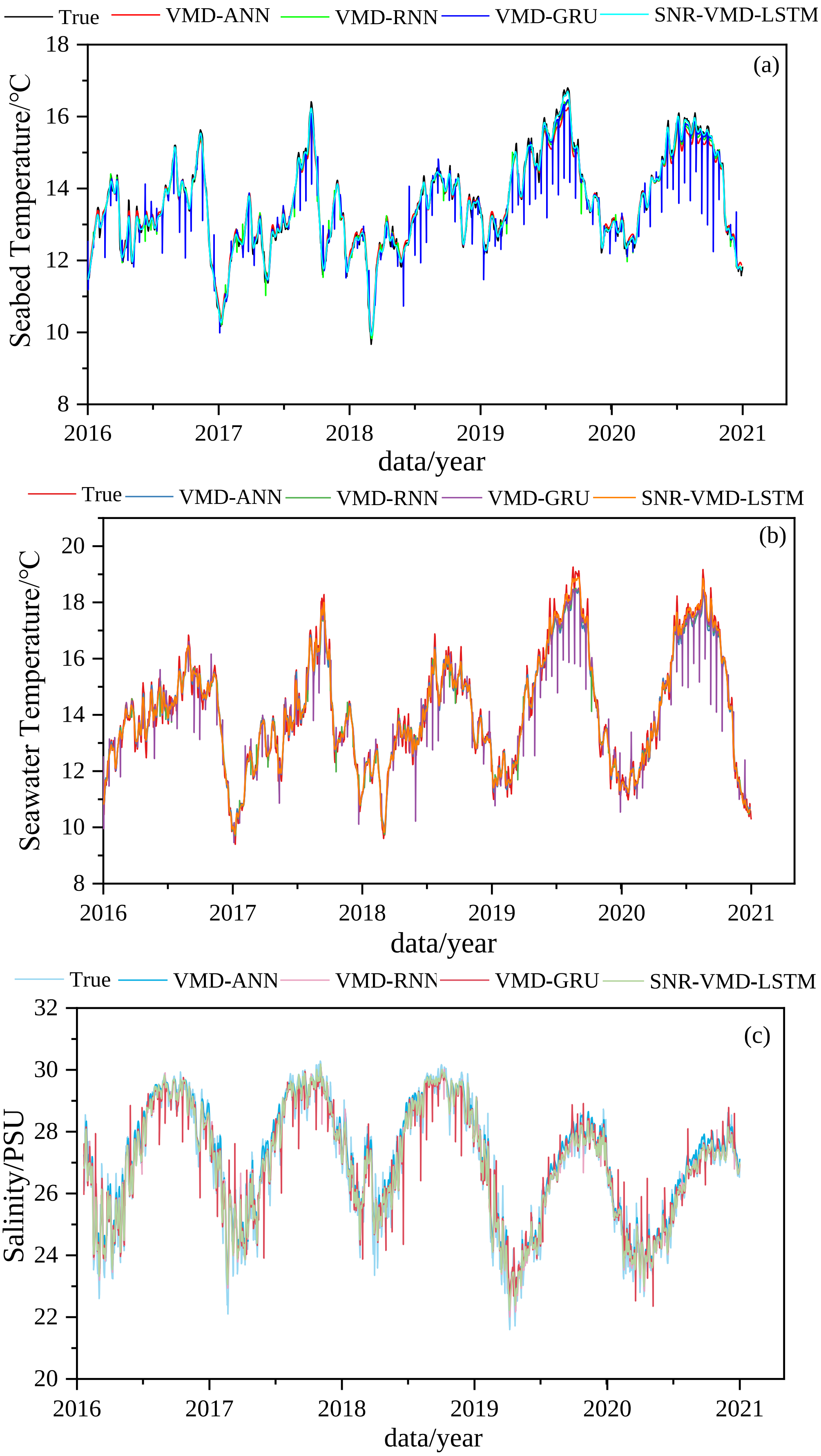
For the time-series datasets on seabed temperature, seawater temperature, salinity, and sea surface height, the GRU model showed the worst predictive performance, with a maximum RMSE of 0.55 mm and a maximum MAE of 0.36 mm across different sites. In contrast, the LSTM model performed the best, with a maximum RMSE of 0.38 mm, a maximum MAE of 0.26 mm, and a maximum R^2 value of 0.99 for the different stations. The overall ranking of the models in terms of their performance is as follows: LSTM>RNN>ANN>GRU. However, although this demonstrates LSTM's superiority, as a single model, it fails to fully extract the features of the data during the training process, resulting in relatively high RMSE and MAE values. This phenomenon highlights the challenge that a single model faces in accurately capturing all fluctuations and trends in time series data, especially in complex time-series prediction tasks. Therefore, in our subsequent hybrid model construction work, it was necessary to integrate the characteristics of the VMD method to further improve the prediction accuracy of the model.

3.3. COMPARATIVE ANALYSIS OF THE PREDICTIVE QUALITY OF COMBINATION MODELS

The use of a single ANN, RNN, GRU, or LSTM model can affect the accuracy of predictions and may lead to biased prediction results. VMD can decompose complex displacement sequences and then train them through LSTM to reconstruct each sequence and achieve higher accuracy. To further improve the prediction accuracy of LSTM, and to verify the effectiveness and reliability of the SNR-VMD-LSTM model, we used the SNR optimized VMD component dataset as feature values and input them into ANN, RNN, GRU, and LSTM models to construct composite models, namely VMD-ANN, VMD-RNN, and VMD-GRU, respectively.

The approach taken in this study involved using the SNR to determine the optimal K value for VMD, which is an optimization of the K value of the VMD-LSTM method. The experimental results show that the predictive performance of SNR-VMD-LSTM and VMD-LSTM is consistent within the thousandth percentile. Therefore, using different datasets from different sites, we compared and evaluated the quality of the predictive results achieved with the VMD-ANN, VMD-RNN, and VMD-GRU combined models and the SNR-VMD-LSTM model after optimizing the K value. Taking the 0010 station as an example, Figures 9 (a), (b), (c), and (d) depict the seabed temperature, seawater temperature, salinity, and sea surface height prediction curves, respectively, for each of these different combination models, with "True" representing the original time series of the different datasets.

As shown in Figure 6, the SNR-VMD-LSTM model demonstrated a good fitting performance in relation to the original sequence. Although other combination models-maintained consistency with the original sequence in terms of volatility trends, there is a certain gap in the accuracy of their predictions compared to our SNR-VMD-LSTM model. (a) The VMD-GRU model, depicted in Figures (b), (c), and


True
VMD-ANN
VMD-RNN
VMD-GRU
SNR-VMD-LSTM
(a)
Seabed Temperature/°C
data/year
(b)
Seawater Temperature/°C
(c)
Salinity/PSU
2016
2017
2018
2019
2020
2021

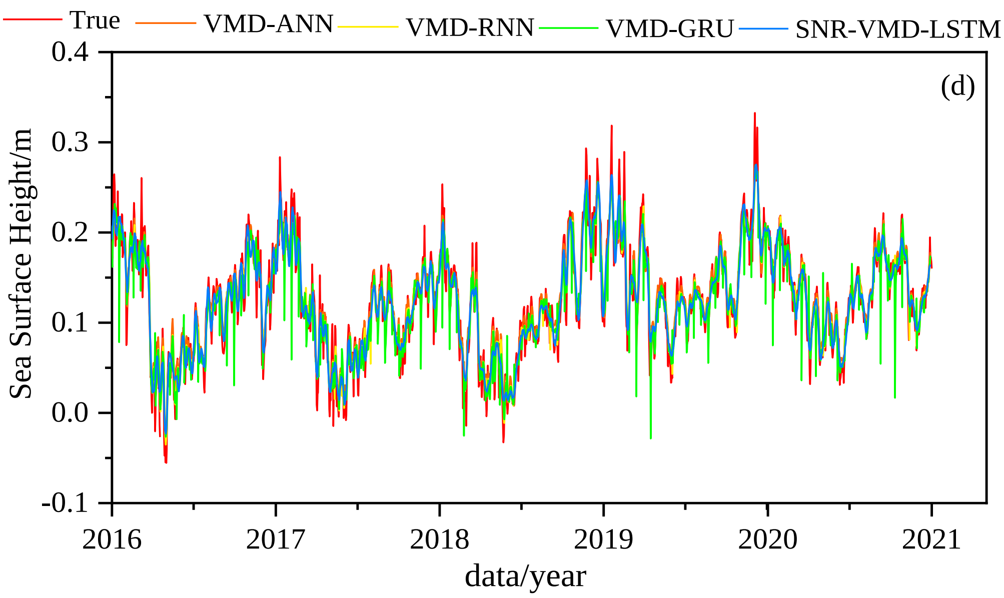


Fig. 9 Prediction result curve. (a), (b), (c), (d) are the results curves of predicting seabed temperature, seawater temperature, salinity, and sea surface height using combining model.

Table 4 Evaluation of multi model prediction results for submarine temperature and seawater temperature.

ID	Model	Seabed Temperature RMSE (℃)	MAE (℃)	R^2	Seawater Temperature RMSE (℃)	MAE (℃)	R^2
0010	VMD-ANN	0.159	0.113	0.987	0.266	0.215	0.993
	VMD-RNN	0.124	0.083	0.979	0.200	0.193	0.994
	VMD-GRU	0.296	0.132	0.945	0.367	0.196	0.968
	SNR-VMD-LSTM	**0.096**	**0.073**	**0.995**	**0.242**	**0.187**	**0.987**
0245	VMD-ANN	0.194	0.172	0.954	0.401	0.301	0.991
	VMD-RNN	0.093	0.064	0.994	0.406	0.352	0.989
	VMD-GRU	0.194	0.088	0.946	0.445	0.299	0.986
	SNR-VMD-LSTM	**0.063**	**0.047**	**0.997**	**0.387**	**0.288**	**0.994**
0256	VMD-ANN	0.112	0.093	0.987	0.422	0.291	0.990
	VMD-RNN	0.082	0.052	0.994	0.411	0.274	0.991
	VMD-GRU	0.233	0.104	0.945	0.401	0.301	0.969
	SNR-VMD-LSTM	**0.049**	**0.034**	**0.997**	**0.386**	**0.270**	**0.973**
0378	VMD-ANN	0.059	0.044	0.997	0.102	0.085	0.993
	VMD-RNN	0.106	0.069	0.996	0.144	0.103	0.992
	VMD-GRU	0.207	0.082	0.999	0.256	0.107	0.956
	SNR-VMD-LSTM	**0.059**	**0.043**	**0.995**	**0.163**	**0.111**	**0.985**
0385	VMD-ANN	0.045	0.033	0.993	0.131	0.102	0.997
	VMD-RNN	0.050	0.032	0.994	0.165	0.105	0.995
	VMD-GRU	0.138	0.050	0.944	0.353	0.145	0.982
	SNR-VMD-LSTM	**0.038**	**0.027**	**0.995**	**0.130**	**0.097**	**0.998**

(d), had the worst predictive performance, and the curve of its predictions (d) is obviously shifted downwards compared to the original sequence, while the predicted curves of VMD-ANN and VMD-GRU are shifted upwards. From these overall prediction results, the models can be ranked as follows: SNR-VMD-LSTM>VMD-RNN>VMD-ANN>VMD-GRU. The predictions of the SNR-VMD-LSTM model are very close to the original data, especially regarding the amplitude of fluctuations. This emphasizes the predictive advantage of this hybrid model in combination with the VMD method, resulting in better overall results and a higher-quality predictive performance.

3.4. *QUALITY EVALUATION OF COMPOSITE MODEL RESULTS*

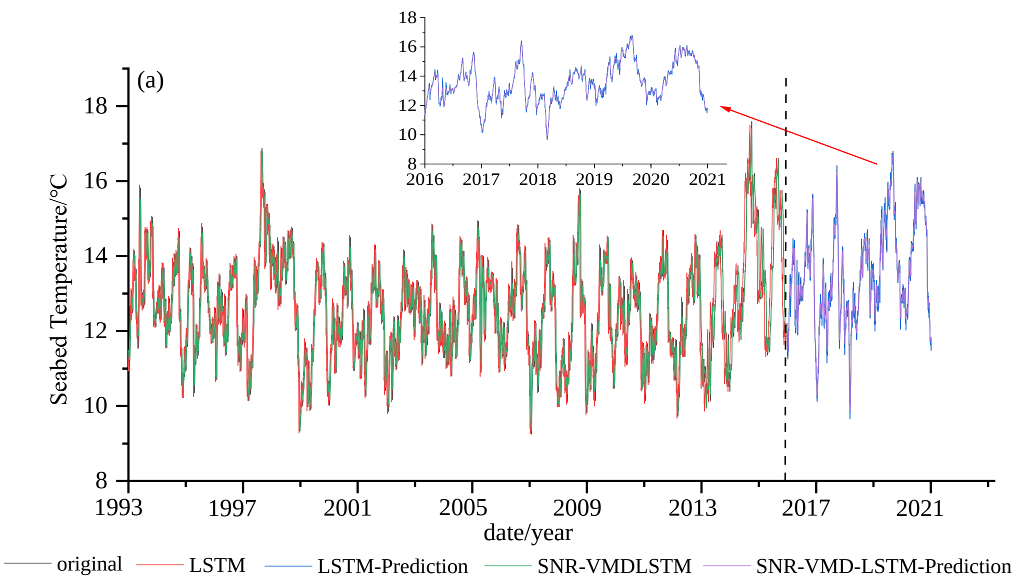
Based on the above discussion, i.e., the prediction performance ranking of the combination model: SNR-VMD-LSTM>VMD-RNN>VMD-

Table 5 Evaluation of prediction results of salinity and sea surface height models.

ID	Model	Salinity RMSE (PSU)	Salinity MAE (PSU)	Salinity R^2	Sea Surface Height RMSE (mm)	Sea Surface Height MAE (mm)	Sea Surface Height R^2
0010	VMD-ANN	0.298	0.241	0.974	11.789	11.764	0.979
	VMD-RNN	0.221	0.223	0.961	11.822	11.609	0.983
	VMD-GRU	0.367	0.192	0.962	15.841	11.827	0.915
	SNR-VMD-LSTM	**0.259**	**0.186**	**0.982**	**11.755**	**8.549**	**0.962**
0245	VMD-ANN	0.019	0.011	0.996	6.236	5.194	0.983
	VMD-RNN	0.016	0.010	0.996	6.157	4.395	0.970
	VMD-GRU	0.047	0.019	0.922	13.559	6.212	0.917
	SNR-VMD-LSTM	**0.018**	**0.009**	**0.989**	**5.369**	**4.117**	**0.988**
0256	VMD-ANN	0.049	0.038	0.969	8.778	7.435	0.967
	VMD-RNN	0.041	0.0286	0.973	6.761	4.679	0.971
	VMD-GRU	0.079	0.041	0.922	12.977	6.242	0.927
	SNR-VMD-LSTM	**0.038**	**0.026**	**0.985**	**5.470**	**4.260**	**0.988**
0378	VMD-ANN	0.031	0.023	0.991	14.700	10.549	0.991
	VMD-RNN	0.050	0.032	0.990	14.389	10.782	0.979
	VMD-GRU	0.107	0.045	0.965	17.162	10.981	0.944
	SNR-VMD-LSTM	**0.043**	**0.028**	**0.994**	**14.230**	**10.511**	**0.968**
0385	VMD-ANN	0.212	0.169	0.991	18.920	13.720	0.946
	VMD-RNN	0.236	0.161	0.987	18.911	13.816	0.949
	VMD-GRU	0.433	0.191	0.962	21.159	13.982	0.946
	SNR-VMD-LSTM	**0.207**	**0.145**	**0.992**	**18.597**	**13.653**	**0.955**

ANN>VMD-GRU, we evaluated the prediction results of the four combination models, as shown in Table 4 and Table 5, which depict the multi-model prediction results for the seabed and seawater temperature and the prediction results for the salinity and sea surface height, respectively.

The RMSE and MAE value of the SNR-VMD-LSTM model for each station in Table 4 and Table 5 were significantly decreased. Under different parameters, this model's maximum and minimum RMSE values were 0.02 mm and 0.01 mm, respectively, and its maximum and minimum MAE values were 0.02 mm and 0.01 mm, respectively. The maximum RMSE values for the VMD-GRU, VMD-ANN, and VMD-RNN models were 0.45 mm, 0.30 mm, and 0.22 mm, respectively. The predictive performance of SNR-VMD-LSTM for the sea surface height was good, with the results being almost consistent with the original sequence, and the R^2 value of this composite model was closer to 1. Moreover, the SNR-VMD-LSTM model's prediction accuracy for the RMSE and MAE was 0.01 mm~0.02 mm, which proves that the SNR-VMD-LSTM model is capable of a better prediction performance than the combined models of VMD-RNN, VMD-ANN, and VMD-GRU. This verifies the conclusion that SNR-VMD-LSTM>VMD-RNN>VMD-ANN>VMD-GRU.



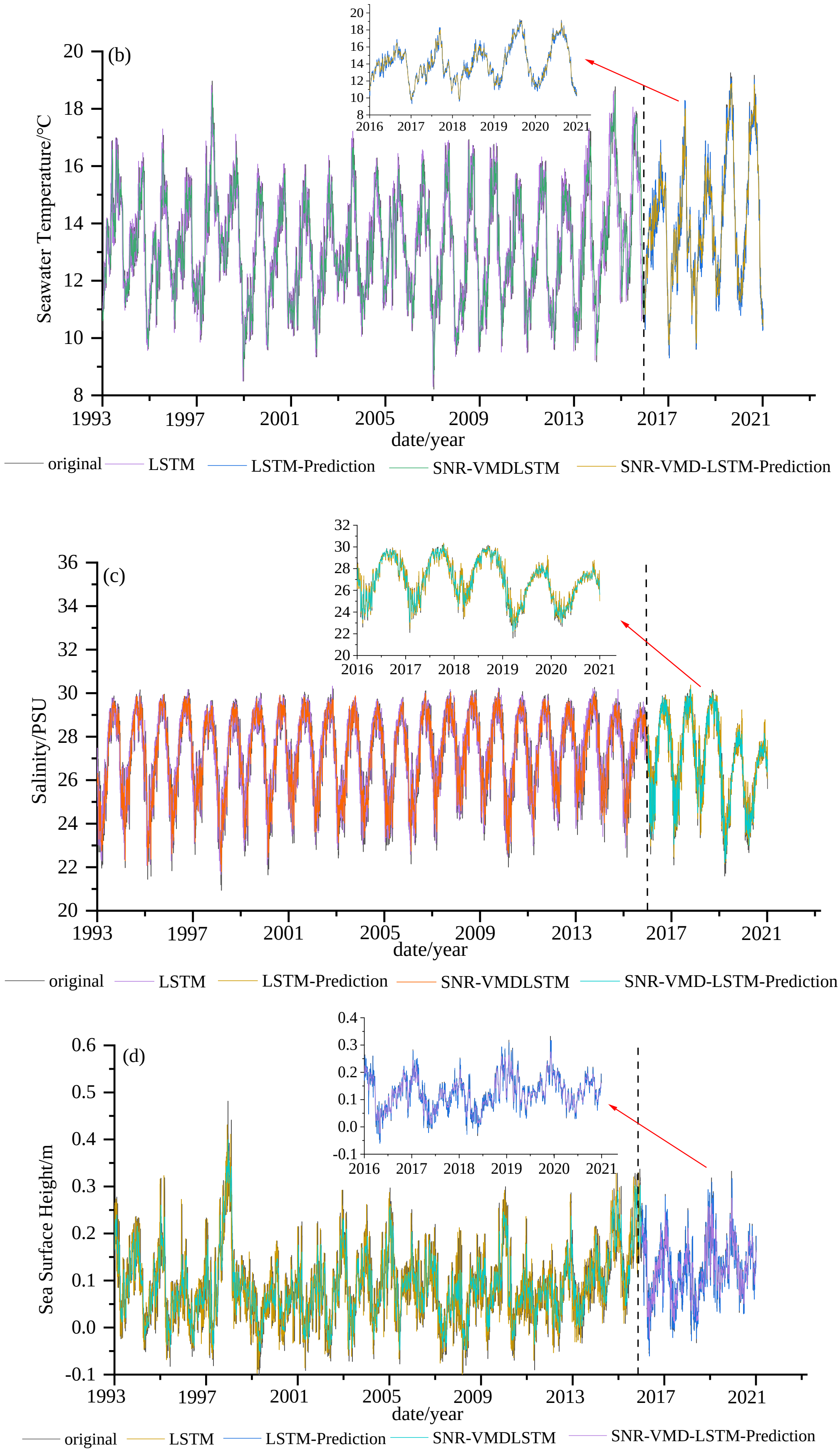


Fig. 10 The prediction curves of LSTM and SNR-VMD-LSTM model. (a), (b), (c), and (d) represent the results curves of predicting sea temperature, seawater temperature, salinity, and sea surface height.

3.5. COMPARISON BETWEEN SNR-VMD-LSTM AND LSTM MODELS

To gain a more accurate understanding of the enhancements achieved with the SNR-VMD-LSTM model compared to the LSTM model on different time-series datasets, we carefully studied the RMSE, MAE, and R^2 of the two methods for predicting sea temperature, sea water temperature, salinity, and sea level time-series data collected from five different sites.

Compared with the LSTM model, the decomposition and reconstruction of the SNR-VMD-LSTM model can better fit the original sequence and provide more reliable prediction results. Taking the 0010 station as an example, we compared and analyzed the predictions generated by the LSTM and SNR-VMD-LSTM models. Figure 10 shows the curves of these prediction results, Figure 11 shows a comparison of their RMSE and MAE results under different parameters, and Figure 12 shows the changes in their R^2 values under different parameters.

According to the LSTM and SNR-VMD-LSTM model prediction curves in Figure 10, they consistently exhibited similar performance in predicting the accuracy of different parameters. However, compared to the SNR-VMD-LSTM model, the LSTM model exhibited some fluctuations in evaluation metrics across different time-series predictions. This means that the stability and accuracy of the LSTM model in predicting different time series are not as good as the robustness and accuracy of the SNR-VMD-LSTM model. In Figure 11, the RMSE and MAE values of the SNR-VMD-LSTM model are both smaller than those of the LSTM model. In Figure 12, the R^2 value of the SNR-VMD-LSTM model is almost close to 1, but the R^2 value of the LSTM model differs significantly. The combined model's results demonstrate a better fit regarding the R^2 value curve compared to the original sequence.

Compared with the single prediction models, the SNR-VMD-LSTM prediction model gave more accurate results after decomposition and reconstruction of the original sequence, proving the effectiveness of the SNR-VMD-LSTM model in predicting time-series data and its good dynamic characteristics. However, the SNR-VMD-LSTM prediction model has certain limitations, such as the complex structure of LSTM leading to an increase in computational complexity and a large number of parameters, which can easily cause overfitting during training. Therefore, it is necessary to set regularization parameters reasonably to avoid overfitting. This method is very suitable for sequential data, but not for spatial data, and to avoid gradients becoming too large and disrupting the stability of the learning process.

4. CONCLUSIONS

Deep learning is often used for monitoring marine environments to better understand and predict the dynamic processes within these environments (Hao et al., 2023; Usharani, 2023). In this study, we propose a hybrid model to improve the accuracy of marine environmental parameters prediction based on CMEMS products. We used an SNR-optimized VMD method to construct this new prediction model. To verify the accuracy of different deep learning methods in predicting the time series of marine environmental parameters, we compared the prediction results of several singular prediction models, namely ANN, RNN, GRU, and LSTM models, and found that curve of the LSTM predictions was close to the original time-series curve. Thus, to predict long-term environmental ocean parameters, we improved the VMD-LSTM prediction model and constructed our new SNR-VMD-LSTM model. Our conclusions were as follows:

1. After optimizing VMD through utilizing the SNR, the new SNR-VMD process effectively weakens the influence of modal aliasing and endpoint effects, and the signal characteristics are dynamic and can accurately obtain the key parameter K for VMD.
2. In single-model prediction, the experimental results show that LSTM>RNN>ANN>GRU. After VMD, SNR-VMD-LSTM>VMD-RNN>VMD-ANN>VMD-GRU, verifying the good performance of the SNR-VMD-LSTM prediction model.
3. Compared with the LSTM prediction model, the results revealed that the SNR-VMD-LSTM model had the highest prediction accuracy for the marine environment dataset, with average RMSE, MAE values of 0.018 mm, 0.011 mm, and maintained the average R2 value within the range of 0.97 to 1. This proves that our SNR-VMD-LSTM prediction model demonstrates a higher level of accuracy in predicting results after decomposition and reconstruction of the original sequence and verifies the effectiveness and feasibility of the SNR-VMD-LSTM model's prediction.

SNR-VMD-LSTM is a data drive time series prediction algorithm, it's scalability and generalization still need further investigated, especially how to establish a general deep learning framework for geodetical time series need further exploration and we plan to build prediction models for ocean environments based on big data and artificial intelligence—including data on the sea level (Liu et al., 2020; Song et al., 2021), seawater temperature (Ozbek, 2024; Chen et al., 2024), ocean sound field (Virovlyansky, 2017), and waves and winds (Alvise et al., 2017) and investigate bias correction for model prediction results in the future (Borja et al., 2016). This will provide efficient and reliable support for the forecasting and prediction of marine environmental parameters.

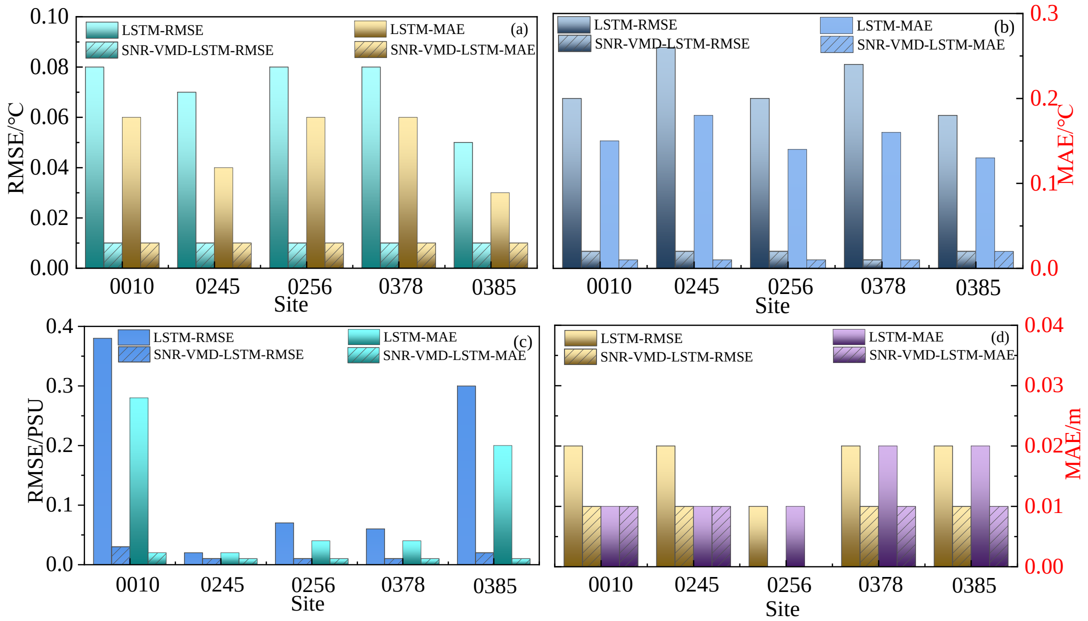


Fig. 11 The comparison of RMSE and MAE results under different parameters. (a) (b), (c), and (d) represent the RMSE and MAE result curves of seawater temperature, seawater temperature, salinity, and sea surface height.

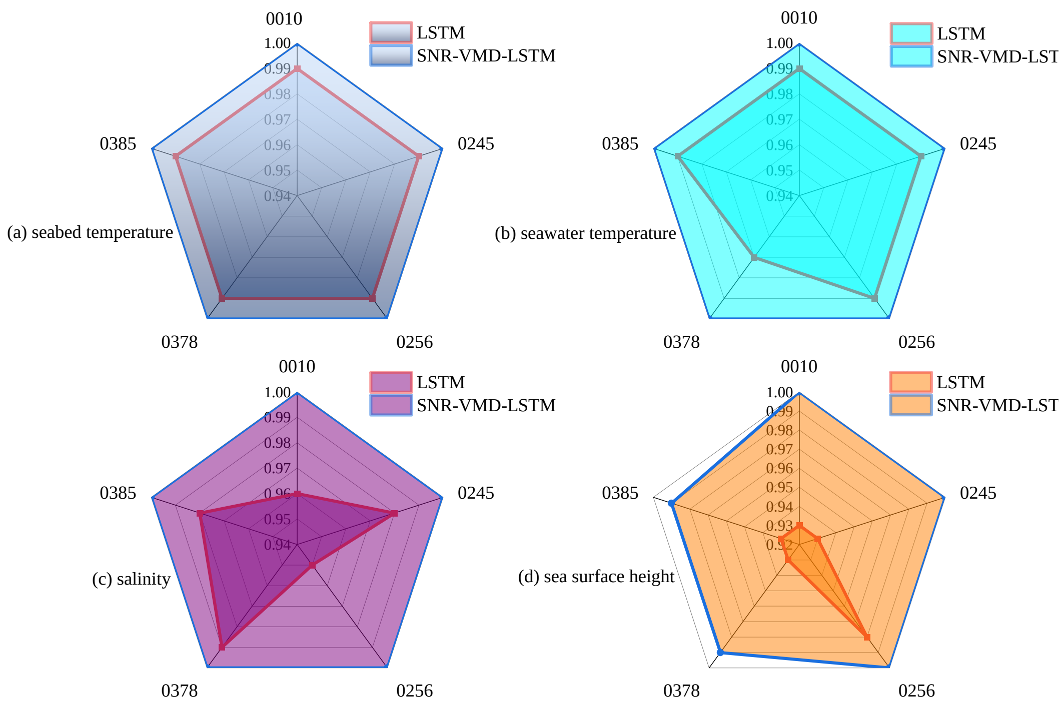


Fig. 12 The changes in R^2 values under different parameters. (a) (b), (c), and (d) represent the R^2 result curves of seawater temperature, seawater temperature, salinity, and sea surface height.

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