Significant wave height prediction model based on LSTM cell spatiotemporal network

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Abstract. Marine operations, engineering activities, and transportation are highly influenced by sea waves, and accurately predicting the 2D wave field is crucial for ensuring safe and efficient project execution and avoiding the sea wave disaster. While existing deep learning applications for wave height prediction primarily focus on single-point forecasts, it's important to note that single-point data may not capture the overall regional trends effectively. Therefore, this paper establishes two spatiotemporal network models based on LSTM cells for Lianyungang Port and compares their performance. The results demonstrate that PredRNN, with its newly designed spatiotemporal memory cell which is able to deliver memory states through layers and laysers on current node and can learn the short-term non-linear variation, outperforms ConvLSTM, especially when dealing with unbalanced input samples. With the forecasting leading time increasing from 6h to 12h the correlation coefficient of PreRNN is over 0.9, ConvLSTM decreases to 0.849. Under the lower accuracy of input samples condition, PredRNN also performs better. In summary, PredRNN is less affected by the quality of input samples, which has engineering value in significant wave forecasting for marine operations.

Keywords: significant wave height prediction; deep learning; spatiotemporal network; PredRNN.

1 Introduction

Waves in sea areas exhibit strong nonlinear characteristics and greatly influence ocean engineering, offshore operations, and maritime transportation. Especially for dredging construction areas, it can accurately and promptly predict wave height fluctuations in a relatively short time, which is a crucial basis for operators to take safe and efficient actions in time, such as issuing emergency warnings for large waves, providing environmental guidance for construction, and forming a long-term prediction model. Therefore, short-term wave height prediction emerges as a vital issue in the field of marine science.

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Traditional wave forecasting is often implemented through numerical simulation, using computer models to simulate the physical processes of wave propagation and calculate the characteristic parameters of the waves. However, this approach requires significant computational resources and lengthy computation time, making it more suitable for large-scale ocean wave simulations. Additionally, in real marine operations, obtaining forecasted wave heights using numerical models requires operators with a certain level of model knowledge. As a result, numerical models have various limitations in practical use cases.

With the rapid development of AI technology, its excellent feature extraction and information representation capabilities have led to widespread applications. Gradually, it has demonstrated its advantages in wave prediction, primarily focusing on single-point prediction. For instance, Deo et al. initially employed artificial neural networks (ANN) or autoregressive (AR) to predict point waves in time series[1, 2]. Subsequently, researchers like Mandal and Prabaharan[3] and Srinivasan et al.[4] argued that recurrent neural networks (RNN) outperformed traditional methods in time series problems. In recent years, the deformed long short-term memory (LSTM) variant of RNN has gained prominence in wave prediction. Hochreiter and Schmidhuber[5] first introduced this network, which selectively remembers long-term information through a series of gates. This feature proves highly useful for rapidly changing wave prediction over time. Numerous scholars have demonstrated that this network is superior to traditional models in wave prediction[6-9]. However, it is worth noting that deep learning applications in wave prediction have predominantly focused on single-point prediction. This limitation contrasts with numerical models, as real-world scenarios and requirements involve two-dimensional and spatially correlated wave patterns. Single-point features alone cannot capture spatial correlation, so they cannot represent regional features for analysis. As a result, in recent years, there has been a shift towards using spatio-temporal networks for regional wave prediction[10, 11]. This paper uses two spatio-temporal network models based on LSTM cells to study the short-term prediction of wave fields in the sea area near Lianyungang. The two models are the ConvLSTM algorithm proposed by Shi et al.[12] and the PredRNN algorithm proposed by Wang et al.[13]. ConvLSTM replaces the traditional fully connected layer with a convolutional layer, making it possible to input two-dimensional matrix data. Compared with the LSTM model, this model, with excellent spatio-temporal characteristics, can address the issue of spatial information loss and improve the accuracy of two-dimensional prediction. In contrast, the PredRNN algorithm seeks to overcome a drawback of ConvLSTM, where storage units between layers are independent, leading to the neglect of upper-level memory by lower-level memory in subsequent time steps. Thus, this algorithm modifies a new spatio-temporal unit (ST-LSTM) to transfer memory states vertically and horizontally.

2 Research area and methodology

2.1 Research areas and data sources

This study focuses on the sea area near Lianyungang, spanning from 122° to 124°E longitude and 30° to 33°N latitude. The data relies on the WW3 reanalysis dataset of the National Oceanic and Atmospheric Administration (NOAA) in the United States. According to the simulation requirements, we mainly select significant wave height and wind field elements (including wind direction and 10-meter wind speed), covering the time range from January 1, 2017, to December 31, 2020, with a temporal resolution of 1 h and a spatial resolution of 0.5° × 0.5°. Many scholars have verified this dataset's appropriateness, showing favorable consistency with the observed values [14]. In the model established in this paper, the input consists of the preceding n hours, and the output comprises the subsequent n hours, with the n selected as 6 h and 12 h, respectively. Among them, the data from 2017 to 2019 serve as training data, while the data in 2020 are used for predictions. To ensure the accuracy and quality of the model, all data are linearly interpolated to 0.05° × 0.05° based on the original spatial resolution.

2.2 Research methodology

2.2.1 ConvLSTM. ConvLSTM evolves from the LSTM network, which is often utilized for two-dimensional prediction. Classical LSTM network controls the information transmission between units through the input gate, output gate, and forgetting gate, realizing the prediction of time series data. However, suppose it is applied to two-dimensional data. In that case, it needs to expand the data to fully connected layer, which consumes substantial computing resources and makes it challenging to capture the spatial correlation and characteristics of the two-dimensional spatial field. Therefore, Shi et al. [12] proposed to replace FC-LSTM with a convolutional layer, that is, to replace matrix multiplication with a convolution operation, whose specific expression in a unit is:

$$i_t = \sigma(W_{xi} * x_t + W_{hi} * h_{t-1} + W_{ci} \circ c_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma\left(W_{xf} * x_t + W_{hf} * h_{t-1} + W_{cf} \circ c_{t-1} + b_f\right) \tag{2}$$

$$c_t = f_t \circ c_{t-1} + t_t \circ \tanh(W_{xc} * x_t + W_{hc} * h_{t-1} + b_c) \tag{3}$$

$$o_t = \sigma(W_{xo} * x_t + W_{ho} * h_{t-1} + W_{co} \circ c_t + b_o) \tag{4}$$

$$h_t = o_t \circ \tanh(c_t) \tag{5}$$

where i_t represents the input gate; f_t represents the forget gate; o_t represents the output gate; c_t represents the current moment state; c_{t-1} represents the previous moment state; h_t represents the final output; W represents the weight coefficient of a given gate; b represents the bias coefficient of a given gate; ∘ represents the Hadamard product; σ represents the sigmoid function; * denotes convolution operation.

The convolution operation is highly effective at capturing the spatial characteristics of data, while LSTM excels at tracking changes in data over time. Consequently, ConvLSTM, which combines these two techniques, is well-suited for describing the spatial-temporal characteristics of variables.

2.2.2 PredRNN. Although the ConvLSTM network can decode the spatial structure, the memory units of each layer are independent and only pass between the time domains of the same layer. In other words, they solely update in the time domain. In this case, the bottom layer will entirely disregard the contents remembered by the upper layer in the previous time step. Therefore, Wang et al. [13] proposed a new ST-LSTM cell for PredRNN, which can transfer memory states in both vertical and horizontal directions, as expressed as follows:

$$g_t = \tanh\left(W_{xg} * x_t + W_{hg} * H_{t-1}^l + b_g\right) \tag{6}$$

$$i_t = \sigma(W_{xi} * x_t + W_{hi} * H_{t-1}^l + b_i) \tag{7}$$

$$f_t = \sigma\left(W_{xf} * x_t + W_{hf} * H_{t-1}^l + b_f\right) \tag{8}$$

$$C_t^l = f_t \circ C_{t-1}^l + i_t \circ g_t \tag{9}$$

$$g_t{}' = \tanh\left(W_{xg}{}' * x_t + W_{mg} * M_t^{l-1} + b_g{}'\right) \tag{10}$$

$$i_t{}' = \sigma(W_{xi}{}' * x_t + W_{mi} * M_t^{l-1} + b_i{}') \tag{11}$$

$$f_t{}' = \sigma\left(W_{xf}{}' * x_t + W_{mf} * M_t^{l-1} + b_f{}'\right) \tag{12}$$

$$M_t^l = f_t{}' \circ M_t^{l-1} + i_t{}' \circ g_t{}' \tag{13}$$

$$o_t = \sigma(W_{xo} * x_t + W_{ho} * H_{t-1}^l + W_{co} * C_t^l + W_{mo} * M_t^l + b_o) \tag{14}$$

$$H_t^l = o_t \circ \tanh(W_{1\times1} * [C_t^l, M_t^l]) \tag{15}$$

In the formula, there are two memory units: C_t^l represents the time memory unit transferred from the previous time step to the current time step in the traditional LSTM cell, while M_t^l is a spatio-temporal memory unit, which is passed vertically from the previous layer to the current node at the same time step. In particular, the memory state received for the bottom layer units is transmitted by the top layer units of the previous time step, creating a zigzag pattern in their memory state transmission, as illustrated in Figure 1. The above is achieved by constructing another set of gate structures for M_t^l in the ST-LSTM cell while preserving the original C_t^l gate structure. Then, the two kinds of memories are spliced together, seamlessly integrating them through a shared output gate. This process effectively stimulates shape changes and motion trajectories within spatio-temporal sequences.

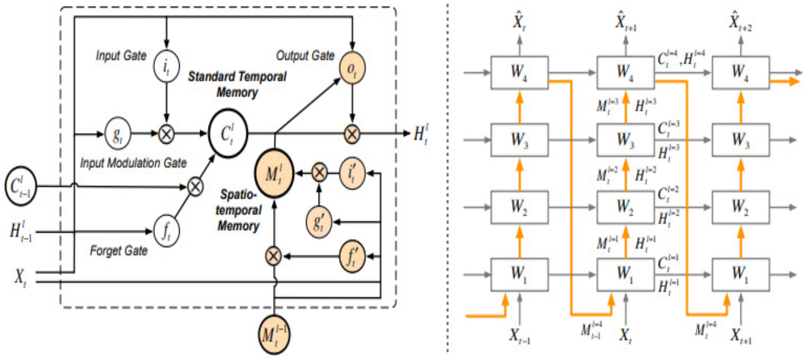
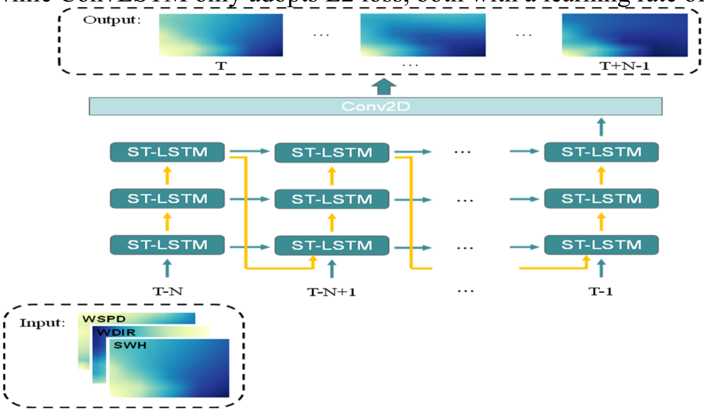


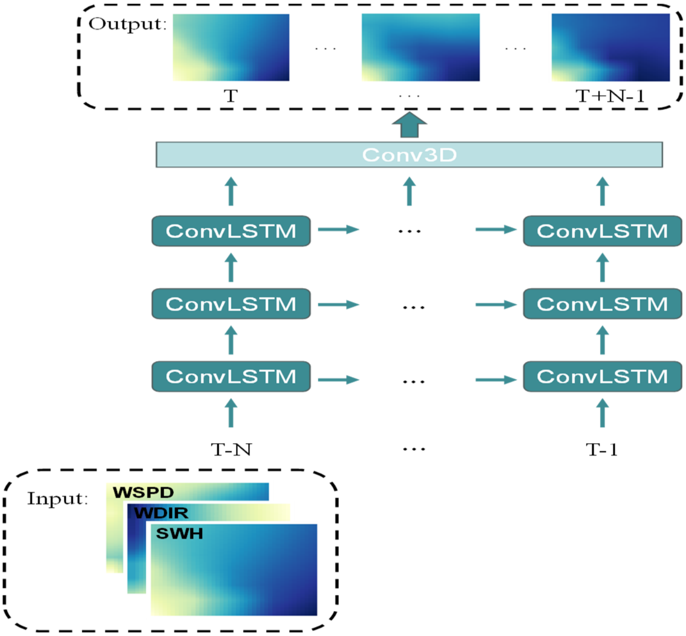
Fig. 1. ST-LSTM Cell Structure and PredRNN Spatio-temporal Memory Flow (quoted from Wang et al. (2017)

2.3 Prediction model framework and parameter setting

This study establishes two wave prediction models based on the ConvLSTM network and PredRNN network, with their frameworks shown in Figure 2. The significant wave height, wind direction, and 10-meter wind speed of the first n continuous time steps are taken as inputs to predict the wave height of the later n time steps. The network structure of the PredRNN spatio-temporal wave prediction model consists of three PredRNN layers, followed by an additional Conv2d layer serving as the output to obtain the prediction results of significant wave height in the future n hours. The ConvLSTM spatio-temporal wave prediction model obtains the prediction results of wave height in the next n hours through three ConvLSTM layers and one Conv3d output layer. We do not add a pooling or up-sampling layer in the convolution process. Still, we use a filling setting to make the feature graph generated by the intermediate process consistent in size. PredRNN model employs L1 + L2 loss as its loss function, while ConvLSTM only adopts L2 loss, both with a learning rate of 0.0001.



(a)PredRNN Wave Height Prediction Model Frame-work Diagram



(b)ConvLSTM Wave Height Prediction Model Framework Diagram

Fig. 2. Model Framework Diagrams

2.4 Evaluation methods

This study takes the root mean square error (RMSE) and mean absolute error (MAE) as indicators to evaluate the model prediction error. RMSE can depict the dispersion between the model prediction data and the reanalysis data, while MAE can measure the actual situation and error ratio. Their expressions are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_p - H_m)^2} \tag{16}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|H_p - H_m\right| \tag{17}$$

where n is the total amount of time series; H_p represents the wave height predicted by the model; H_m represents the wave height of the reanalysis data of the WW3. The model also selects the correlation coefficient (CC) to express the correlation between the predicted data and the reanalysis data, and its expression is as follows:

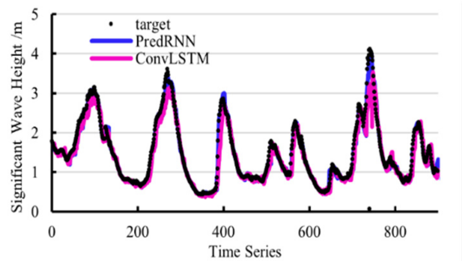
$$CC = \frac{\frac{1}{n}\sum_{i=1}^{n}((H_p - \overline{H_p})(H_m - \overline{H_m}))}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_p - \overline{H_p})^2} \cdot \sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_m - \overline{H_m})^2}} \tag{18}$$

Where $\overline{H_p}$ represents the average wave height predicted by the model and $\overline{H_m}$ represents the average wave height of the reanalysis data of the WW3.

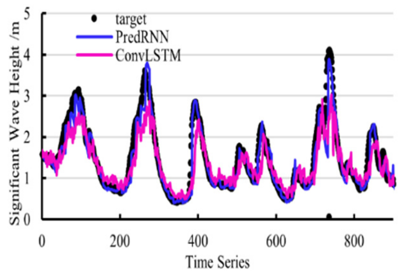
3 Research results

3.1 Comparison of model prediction results

This section presents the results of applying spatio-temporal network prediction models to waves. As shown in Figure 3, both models exhibit excellent overall trends in predicting data and can accurately predict the positions of wave peaks and troughs. Comparatively, ConvLSTM has an unavoidable time delay, which becomes more noticeable when the prediction time series increases to 12 h forward. In contrast, PredRNN demonstrates minimal time delay in both 6-hour and 12-hour forward predictions, delivering excellent predicting performance. Regarding the accuracy of numerical predictions at wave peaks and troughs, PredRNN performs quite accurately in both 6-hour and 12-hour forward predictions. ConvLSTM, on the other hand, exhibits a bias in predicting wave heights at peak positions, resulting in lower predicted values. This bias is especially prominent as the predicting series lengthens or the actual wave height increases. The reason behind this is that the whole year data are selected to train the two models, in which the data with wave height surpassing 3 m (corresponding to the 5-level sea state) merely accounts for 8% of the whole year data. This data imbalance often results in a lack of learning from the larger wave height samples during training. Obviously, ConvLSTM is more sensitive to this data imbalance problem, leading to its suboptimal performance in predicting larger wave heights. In contrast, PredRNN effectively overcomes this issue during prediction, making it an ideal spatio-temporal wave prediction model.



(a)Prediction Results of the 6-hour Forward Model



(b)Prediction Results of the 12-hour Forward Model

Fig. 3. Model Prediction of the wave height (shown at the center point)

To further evaluate the prediction ability of the two models, we calculated the MAE (its spatial distribution is shown in Figure 4), RMSE, and CC between the prediction results of the two models and the reanalysis data, respectively, as shown in Table 1. The MAE diagram elucidates that in the 6-hour forward prediction, both models exhibit relatively small MAE, and the spatial distribution is pretty uniform. The values in the grid are all within 0.15 m, even with the MAE of the PredRNN model of only 0.055 m. When the prediction step increases to 12 h forward, the MAE values of the two models grow. In this conjuncture, ConvLSTM displays more significant errors, particularly in an area where errors are notably more prominent in the upper triangular region. This phenomenon arises because wave heights in the sea area inherently exhibit higher values in the upper triangular region. Combined with ConvLSTM's higher errors in predicting larger wave heights, this becomes more pronounced as the prediction step increases, as observed in Figure 4. The PredRNN model obviously improves this problem, showing a more balanced distribution of errors in wave height. Meanwhile, Table 1 reveals the RMSE and CC values for both models. The RMSE values for both models rise with the increase of time steps, with ConvLSTM exhibiting higher RMSE values, indicating a higher presence of outliers in its predictions. In terms of CC values, PredRNN consistently maintains CC values above 0.9, whether in 6-hour or 12-hour forward prediction. In contrast, ConvLSTM's CC values decrease to 0.849 in the 12-hour forward prediction, indicating that PredRNN is a more suitable spatio-temporal prediction model.

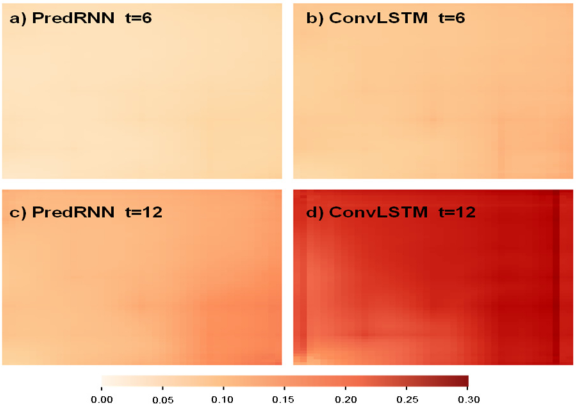


Fig. 4. MAE Spatial Distribution of PredRNN (a, c) and ConvLSTM (b, d) predictions: a), b) 6 h; c), d) 12 h

Table 1. Evaluation parameters of model prediction performance

	MAE(m)		RMSE(m)		CC	
	6h	12h	6h	12h	6h	12h
PredRNN	0.055	0.120	0.134	0.237	0.976	0.924
ConvLSTM	0.096	0.228	0.179	0.326	0.956	0.849

3.2 Application of the models in improving prediction accuracy

From the previous section, the two models have favorable results in the 6-hour forward prediction, with their CC above 0.95. Therefore, we further propose applying the models to predictions while striving for increased precision. This section selects the Delft3d finite volume flow model to establish the wave numerical model for the selected sea area. The wave data generated by the simulation are shown in Figure 5. This numerical model, established with some roughness, exhibits more significant errors and lower accuracy. The numerical simulation data are used as the input data of the two spatio-temporal network models established in this paper (continuous data for the first 6 h), and the reanalysis data of WW3 is still employed as the output (the later 6 hours).

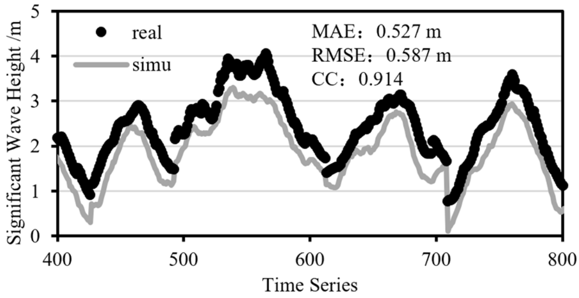


Fig. 5. Numerical Simulation Prediction Results (shown at the center point)

Figure 6 demonstrates that the predicted values of the two models are significantly higher than those of the numerical model while forecasting forward. Notably, the PredRNN model stands out with better performance, delivering not only more accurate numerical values at wave peaks and troughs but also smoother prediction curves. Although ConvLSTM also demonstrates improved prediction accuracy, the prediction curve exhibits noticeable spikes, and with lower prediction values, its performance at the peak position is slightly worse than that of the PredRNN model.

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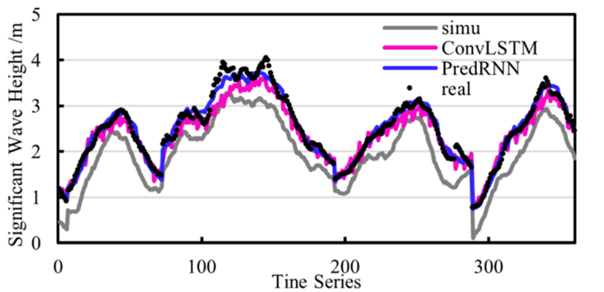

Fig. 6. Comparison of Model Prediction Results

Furthermore, the evaluation parameters are calculated to evaluate the prediction effect of the two models. As depicted in Figure 7, both models exhibit MAE and RMSE values that skew towards the higher end on the right side of the predicted sea area, accompanied by gridlines. Comparatively, the PredRNN model displays smaller error values, while the ConvLSTM model shows more significant errors with more distinct gridlines. The presence of these gridlines may be attributed to the input numerical simulation data with a grid resolution of 0.5° × 0.5°, resulting in suboptimal transitions at grid intersections. The reason for the larger error values on the right side of the predicted marine area could stem from the fact that the study area, near Lianyungang, experiences predominantly east-to-west winds throughout the year, that is, from right to left. Since this region's waves are primarily wind-driven, it is conceivable that the input data may not adequately account for wave generation beyond the attention area to the right (eastern side).

As presented in Table 2, both models show improvements in accuracy compared to numerical simulation predictions, with a significant CC enhancement. The correlation of the prediction data obtained by the PredRNN model is increased from the original 0.914 of the numerical simulation results to 0.938, and the CC of the ConvLSTM model is increased to 0.929. MAE and RMSE values are significantly reduced, particularly for the PredRNN model, which reduces them by 72.3% and 56.9%, respectively. This reduction not only enhances overall accuracy but also decreases the number of outliers. Therefore, it can be considered that the two models effectively enhance precision while predicting, among which PredRNN exhibits superior predictive capabilities and is less affected by data quality limitations.

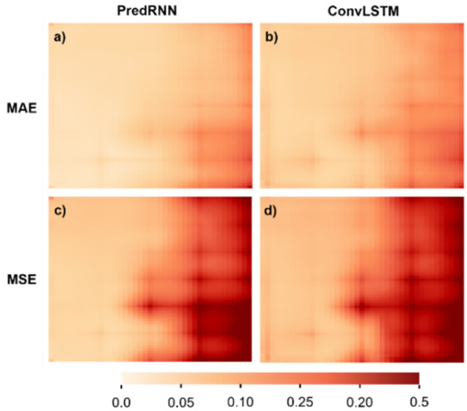

Fig. 7. Spatial Distribution of MAE (a, b) and RMSE (c, d) of PredRNN (a, c) and ConvLSTM (b, d) predictions

Table 2. Evaluation parameters of model prediction performance in improving accuracy

	MAE (m)	RMSE (m)	CC
PredRNN	0.146	0.252	0.938
ConvLSTM	0.183	0.284	0.929
Simu	0.527	0.585	0.914

The research mentions that the model input exerts a certain influence on the prediction effect, so it is necessary to discuss the impact of the combination of input data in the model on the prediction effect. The real-world waves are affected by many factors, including tides, currents, rainfall, etc. However, considering the model's light weight, the consumption of calculation and storage resources, and the predominant influence of wind-driven waves in our study area [15], we focus on three key input parameters: 10-meter wind speed, wind direction, and wave height. The results of ablation tests are shown in Table 3. When the two wind field factors are removed, the influence on the model is almost the same, and the MAE and RMSE of the model are reduced by 0.015 m and 0.013 m, respectively, which suggests that the addition of wind field factors in the study area brings adequate information support to the model. However, the historically significant wave height remains the dominant factor. Its inclusion effectively lowers the model's MAE and RMSE by approximately 0.109 m and 0.105 m, respectively, roughly more than eight times the impact of wind field elements.

Table 3. Ablation test of PredRNN model input parameters

Experiment ID	Removed factor	MAE (m)	RMSE (m)	CC
PredRNN	Nothing	0.055	0.134	0.976
R-wind direction	Wind Direction	0.070	0.147	0.969
R-wind velocity	Wind velocity	0.069	0.147	0.969
R-SWH	SWH	0.164	0.239	0.922

Overall, for wind-driven wave regions, including wind field information as input can enhance the model's predictive performance, but significant wave height remains the dominant factor. The ablation test in this paper alone cannot well interpret the significance of wind field elements in wave prediction models. Future research should further select non-wind-driven sea areas or swell data for comparison to better verify the significance of wind field elements.

Based on this study, we applied the established network to the real dredging operation process. By utilizing the historical wave height data as input, we predicted the wave heights for the next 12 hours. The model let operators accurately know the time of wave height exceeds 2 meters, which gives the time for dredging vessel relocating to a safety zone. Moreover, operators added that the model is user-friendly because it can give the expected results without professional personnel.

4 Conclusions

This paper establishes two spatio-temporal network models for modeling and predicting the reanalysis data (WW3) of the sea area near Lianyungang. The models employ significant wave height, wind direction, and 10-meter wind speed as inputs to predict the spatial distribution of waves. According to the above prediction results, compared to the ConvLSTM model, the PredRNN model maintains the correlation above 0.9 in both 6-hour and 12-hour forward predictions and displays insensitivity to the imbalance of training data, thus accurately predicting larger wave heights (corresponding to Sea State 5, greater than 3 m). Both models show remarkable effects in improving the accuracy of wave height prediction. Nonetheless, the ConvLSTM model exhibits noticeable spikes in its prediction curve; meanwhile, the PredRNN model has a smoother curve and improves the CC of wave height from 0.914 (numerical simulation) to 0.938 after prediction. Additionally, it reduced MAE and RMSE values by 72.3% and 56.9%, respectively. These findings collectively indicate that the PredRNN model is less constrained by input data quality limitations and is a relatively ideal spatio-temporal model for predicting significant wave height.

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