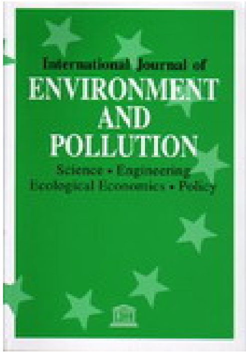


International Journal of Environment and Pollution

ISSN online: 1741-5101 - ISSN print: 0957-4352
https://www.inderscience.com/ijep

New algorithm for numerical simulation of beach evolution under extreme weather and neural network optimisation prediction model

Songzhe Li, Hongqian Zhang

DOI: 10.1504/IJEP.2025.10073562

Article History:

Received:	11 February 2025
Last revised:	23 May 2025
Accepted:	05 June 2025
Published online:	05 January 2026

New algorithm for numerical simulation of beach evolution under extreme weather and neural network optimisation prediction model

Songzhe Li and Hongqian Zhang*

Key Laboratory of Engineering Sediment,
Tianjin Research Institute for Water Transport Engineering,
Ministry of Transport,
Tianjin, 300456, China
Email: songzhe.li@foxmail.com
Email: zhanghongqian2024@163.com
*Corresponding author

Abstract: This study proposes a novel beach evolution prediction algorithm integrating convolutional neural networks and numerical simulation to enhance accuracy under extreme weather. An improved deep-water flow model, based on the Navier-Stokes and sand-water mixing equations, captures hydrodynamic changes influenced by wind, waves, tides, and currents. Meteorological and oceanic data are preprocessed using local weighted regression and interpolation methods to ensure quality. A neural network model dynamically predicts beach evolution, with k-fold cross-validation ensuring stability across extreme weather scenarios. Results show high accuracy, with mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE) all below 0.4 and prediction errors under 12%.

Keywords: extreme weather; beach evolution; numerical simulation; neural network; prediction analysis.

Reference to this paper should be made as follows: Li, S. and Zhang, H. (2025) 'New algorithm for numerical simulation of beach evolution under extreme weather and neural network optimisation prediction model', *Int. J. Environment and Pollution*, Vol. 75, No. 4, pp.280–299.

Biographical notes: Songzhe Li received his Bachelor's degree and Master degree from Hohai University, China, and received Doctor's degree from Tianjin University, China. Now, he works in Tianjin Research Institute for Water Transport Engineering, Ministry of Transport. His research interest includes sediment movement and beach morphological evolution in estuaries and coasts.

Hongqian Zhang received the Bachelor's degree and Master degree from Hohai University, China, and received Doctor's degree from Tianjin University, China. Now, he works in Tianjin Research Institute for Water Transport Engineering, Ministry of Transport. His research interest includes hydrodynamic characteristics of wave boundary layer and waterway regulation engineering.

1 Introduction

Beach evolution is a complex process affected by many factors, especially under extreme weather conditions; its evolution characteristics are more significant and have higher uncertainty. Extreme weather factors such as storm surges, heavy rains, strong winds, and changes in ocean temperature often drastically impact beach morphology (Wiberg et al., 2020). Beach evolution is affected by meteorological factors and is closely related to various phenomena in oceanography. Oceanography provides a theoretical basis for understanding the role of tides, currents, waves, and other factors in beach morphology (Khatmullina and Chubarenko, 2019; Limber et al., 2018). The impact of beach evolution on ecological, environmental protection, disaster prevention and mitigation, and coastal engineering construction is profound. Therefore, understanding and predicting the dynamic evolution of beaches has important theoretical and practical value (Farrell et al., 2021; Zhang et al., 2020). With the increasing intensification of climate change, the frequency and intensity of extreme weather events have increased significantly, and the impact on beaches has become more complex and severe (Dodet et al., 2019; de Schipper et al., 2021). Traditional beach evolution numerical simulation methods often have the problem of insufficient simulation accuracy in such a complex and changing environment, especially for the response to emergencies such as storm surges, typhoons and heavy rainfall, and the accuracy and applicability of model prediction results are limited (De Lisle, 2019; Davidson-Arnott et al., 2018). Therefore, developing high-precision numerical simulation models that can adapt to extreme weather conditions is imperative. New methods are urgently needed to overcome the limitations of existing technologies (Cooper et al., 2020; Armenio et al., 2019).

In order to solve the deficiencies in traditional methods and existing research, this paper proposes a numerical simulation algorithm for beach evolution, focusing on the simulation of the dynamic evolution of beaches under extreme weather conditions and combining neural networks for predictive analysis. When designing, the algorithm fully considers the suddenness and complexity of extreme weather events. The numerical simulation results can be closer to the dynamic evolution process under the real beach environment through the fine modelling and data processing of dynamic factors such as meteorology and tides. At the same time, to improve the accuracy and adaptability of the prediction, this paper applies a neural network model, using its advantages in complex pattern recognition and nonlinear data fitting to assist in predicting the beach evolution process. By learning the implicit laws in historical meteorological and topographic data, the neural network can further optimise the prediction results based on the model output and compensate for the shortcomings of traditional numerical models in complex environments. The research results provide a scientific basis for beach protection and restoration, disaster prevention and mitigation, coastal zone management and engineering design. Through the combination of innovative numerical simulation algorithms and neural network models, this paper aims to promote the progress of beach evolution research and provide strong technical support for responding to increasingly frequent extreme weather events.

2 Related work

In recent years, researchers have attempted to improve the accuracy of beach evolution simulation through a series of improvement schemes (Apostolopoulos and Nikolakopoulos, 2021; Álvarez Antolínez et al., 2019). For example, numerical simulation methods based on grid models simulate the combined effects of factors such as wind, waves, and tides, which, to a certain extent, improves the model's ability to depict the dynamic changes of the beach (Peng et al., 2021; Anderson et al., 2018). Vitousek et al. (2017) proposed a coastline change model, which simulated the beach evolution process in a refined step-by-step manner and achieved relatively good results. However, such traditional models usually simplify boundary conditions and ignore certain dynamic factors when applied, making it difficult to adapt to sudden environmental changes caused by extreme weather (Panda, 2023; Liu et al., 2022). In addition, these methods usually assume that climate conditions are stable and show apparent deviations when dealing with nonlinear extreme events (Papadimitriou et al., 2022; Faraggiana et al., 2022). Although some studies have applied more complex models and attempted to improve simulation accuracy by considering multiple factors, the effectiveness of the models is still limited when dealing with situations where climate conditions change dramatically (Weber de Melo et al., 2022; Ghoroghi et al., 2022).

In contrast, with the rapid development of machine learning and deep learning technologies, researchers have begun to try to use these methods to cope with the complex simulation tasks of beach evolution (Theuerkauf et al., 2019; Vousdoukas et al., 2020). Neural networks, deep learning, and other machine learning methods have significant advantages in data fitting and nonlinear pattern recognition, especially in dealing with environmental change problems with variable climate factors and complex influencing mechanisms. They show unique potential (Ying et al., 2019; Bauer and Wakes, 2022). For example, Kumar et al. (2020) used artificial neural networks to draw a coastline change map and achieved relatively ideal results. Neural networks have high application prospects in predicting beach evolution (Kumar et al., 2020). However, existing research based on neural networks is primarily concentrated in specific geographical areas or limited conditions. The model has poor applicability, and the application effect in extreme weather is still limited, which makes it challenging to meet the actual application needs (Lund et al., 2020; Liu et al., 2023). Therefore, how to further improve the applicability and accuracy of beach evolution prediction through neural networks under the premise of broad applicability is still a challenge to be solved (Matsui, 2017).

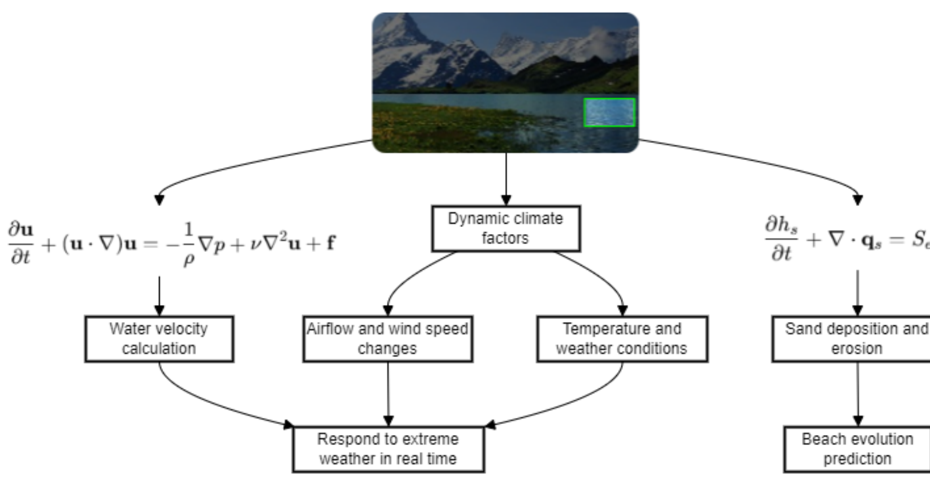
3 New numerical simulation algorithm

In traditional numerical simulation of beach evolution, shallow water equations and simplified hydrodynamic models have dominated. Although these tools can handle basic fluid movement and beach morphological changes, their limitations gradually become apparent when encountering complex changes caused by extreme weather conditions, mainly manifested in limited simulation accuracy and neglect of some dynamic influencing factors. To solve this problem, researchers applied an optimised deep water flow model. This model achieves high-precision simulation of the real-time dynamics of water flow and beach evolution by adding dynamic change terms.

In model construction, the unsteady deep water equation is combined with the Navier-Stokes equation and the sand-water mixing equation to fully simulate the interaction of multiple factors such as wind, waves, tides, and ocean currents under extreme weather conditions. Through detailed calculations of processes such as water flow velocity, sand deposition, and erosion, the deep water flow model can precisely capture complex hydrodynamic characteristics. In addition, the model also incorporates changes in dynamic climate factors such as airflow, wind speed, and temperature under extreme weather conditions, which directly impact beach evolution. By integrating meteorological data under different extreme weather conditions, such as typhoon travel paths and rainstorm intensity, the model can adjust and respond to changes in the external environment in real time. Without changing the model's basic structure, the accuracy and adaptability of the simulation of beach evolution under extreme weather conditions are improved.

Figure 1 depicts the working mechanism of the deep water flow model. By integrating multiple physical equation systems, such as the Navier-Stokes equation and the sand-water mixing equation, and incorporating the real-time fluctuations of dynamic climate factors (such as wind speed, airflow and temperature), the evolution of the beach under extreme weather conditions can be precisely simulated. The model captures and reflects the dynamic effects of complex and changing physical phenomena and environmental factors on beach morphology.

Figure 1 Modelling of deep water flow model (see online version for colours)



Under extreme weather conditions, some local areas experience significant changes during the evolution of the beach. Currently, the uniform grid distribution method used in traditional numerical models leads to unnecessary consumption of computing resources and may affect the simulation's accuracy. Adaptive mesh refinement (AMR) technology is applied to address this challenge. If there is significant erosion or accumulation in an area, mesh refinement is triggered to capture the finer details of these changes. Once an area meets the refinement criteria, the AMR algorithm applies a finer mesh to that specific area. The refinement process works by subdividing the cells of the coarse mesh into smaller cells, thereby increasing the mesh resolution. Refinement is typically done hierarchically, where areas can be recursively subdivided into smaller meshes as the complexity of the beach topography increases. Coarser grids are used to reduce the calculation burden in areas with relatively stable morphology, achieving an effective balance between accuracy and efficiency. With the changes in water flow, wind waves and tides caused by extreme weather, the beach topography undergoes drastic changes. The adaptive grid technology can adjust the grid structure in real-time, dynamically change the density and morphology of the grid, and ensure higher simulation accuracy in complex terrain areas.

This study uses an implicit time integration scheme to handle rigid systems, reducing the time step limit and thus accelerating the simulation process. In terms of mesh refinement strategy, the trigger mechanism of the AMR technology is improved, and dynamically adjusting the mesh resolution ensures that high-precision simulation is maintained in complex terrain areas while reducing unnecessary computational overhead. The introduction of parallel computing technology further optimises the computational performance of large-scale simulations, allowing the algorithm to improve its operating efficiency while maintaining high precision significantly.

To further improve the reliability and accuracy of numerical simulation, this study adopts a combined model optimisation strategy to integrate the deep water flow model with other climate dynamics models for joint calculation. These models cover tidal models, wind wave models and ocean current models. Through joint calculation, the comprehensive impact of different weather factors on the evolution of the beach is fully considered. A loose coupling method connects the numerical models of hydrodynamics, meteorology and geomorphology. The output results of each sub-model are used as input data for other models to ensure that the calculation results of each model can be fed back to each other during the simulation process, thereby more precisely reflecting the complex effects of extreme weather on the beach. Combining the latest research results in meteorology, oceanography and geology, the numerical simulation results of natural factors such as wind, waves, currents and tides are combined with actual observation data further to optimise the prediction performance of the numerical model.

Under extreme weather conditions, numerical simulations usually face certain uncertainties due to climate change's unpredictability and the limitations of the simulation model itself. The Monte Carlo method is used to quantify this uncertainty. The possible range of shore evolution under different extreme weather scenarios can be estimated through a large number of random sampling and multiple simulations.

A sensitivity analysis of the key factors affecting the evolution of the beach is conducted to evaluate the influence of parameters such as wind speed, tidal fluctuations, and precipitation on the numerical simulation results. This analysis helps determine which factors impact beach changes most under extreme weather conditions, thereby guiding the focus of disaster prevention and mitigation work.

4 Neural network prediction model

Before building the neural network prediction model, the input data is first preprocessed and features extracted. To ensure the quality and effectiveness of the input data, this paper collects historical meteorological data (such as wind speed, temperature, and precipitation), ocean data (such as tides, and wave heights), and beach geomorphological data (such as shoreline changes, beach height, etc.) and cleans, standardises, and normalises them.

The data in Table 1 are input features into the neural network model. By combining different meteorological, oceanic and geomorphological conditions, the model can learn how these variables affect the evolution of the beach, especially the changes under extreme weather conditions. For example, combining factors such as wind speed, wave height, and tide can effectively capture large-scale erosion and sedimentation processes, thereby improving prediction accuracy. By training these historical data, the model can predict future beach changes and provide a decision-making basis for disaster prevention and mitigation.

Table 1 Collected data

Date	*Wind speed* (m/s)	*Temperature* (°C)	*Precipitation* (mm)	*Tidal height* (m)	*Wave height* (m)	*Shoreline change* (m)	*Beach elevation* (m)
Date 1	12.5	22.4	5	3.2	1.8	10.5	1.2
Date 2	15.3	21.8	10.2	3.1	2	9.8	1.3
Date 3	10.8	24.1	3.5	3	1.5	10.2	1.1
Date 4	14.2	23.3	7.8	3.5	2.2	9.5	1.4
Date 5	18	20.7	15	3.3	2.1	8.9	1

The outliers in the data are processed by median filtering and sliding window algorithms. Especially in extreme weather events, there may be sensor errors or extreme data, which may interfere with the training process of the model. The median filter's core parameter is the filter window's size. Choose an odd-sized window (3×3, 5×5). The window size determines the range of data considered when calculating the median. Smaller windows retain some details, while larger windows can remove noise more smoothly. For each data point, a fixed-size sliding window is defined, all neighbourhood data is selected within the window and the median is calculated. Then the original data point is replaced with this median. This process is performed at each time step or spatial position of the data to ensure that outliers are effectively removed. At each time step, the sliding window slides forward on the data sequence, calculates the average of the data in the window, and then replaces the original data in the centre of the window with this statistic. This process helps smooth the data and reduces the interference of noise in model training.

Given the high complexity of beach evolution, meteorological and oceanographic variables that significantly impact beach morphology changes are selected as key input features, including wind speed, tidal cycle, wave amplitude, etc. Principal component analysis technology is used to process these high-dimensional data and reduce redundant information.

To further improve prediction accuracy, this study combines convolutional neural networks with long short-term memory networks. Convolutional neural network (CNN) performs well in extracting features from spatial data, while long short-term memory (LSTM) is good at processing long-term dependencies in time series data. The convolutional neural network was chosen because it has excellent local feature extraction capabilities when processing data with spatial structure, and can efficiently capture the spatial patterns in the process of beach evolution. Compared with other neural networks, CNN can better handle the local correlation of spatial data, reduce computational complexity, and effectively capture the complexity of spatiotemporal interactions when combined with LSTM.

Regarding the neural network architecture (attention mechanism and Transformer), the attention mechanism can more effectively capture the key features in meteorological and oceanographic data by dynamically assigning weights. The self-attention structure of the Transformer is good at processing long sequence dependencies and is suitable for the dynamic prediction of beach evolution under extreme weather conditions. These methods have shown advantages in modelling complex nonlinear relationships and may improve prediction accuracy. Future research can combine these architectures to optimise existing models to better adapt to multi-scale spatiotemporal changes.

First, spatial features are extracted from the input meteorological, oceanographic and geomorphological data through CNN. CNN can effectively identify data features in different regions, such as erosion and accumulation of beaches, spatial changes in wind and waves, etc. The specific network structure uses multi-layer convolution kernels (3×3 and 5×5) and maximum pooling operations, which can extract local features at different scales. After multiple convolution and pooling layers, the spatial features are compressed into smaller feature vectors and passed to the LSTM network.

After obtaining the spatial features, they are input into the LSTM model for time series analysis. LSTM can handle long-term dependencies in sequence data and is very suitable for predicting dynamic changes in beach evolution, especially the impact of extreme weather on beach morphological changes. The LSTM network effectively captures the changing patterns of historical meteorological and ocean data in the time dimension through its gating mechanism (input gate, forget gate, output gate).

The input layer of the LSTM network receives the feature vector extracted by CNN. After being processed by several LSTM layers (each layer contains 128 units), it finally outputs the predicted value through a fully connected layer. In order to prevent overfitting, the dropout regularisation technique is used, and the early stopping method is used during the training process to monitor the error of the validation set and avoid overtraining. The training of the neural network is a key step to improving the accuracy of prediction. During the training process, a loss function based on mean square error (MSE) is used, and the Adam optimisation algorithm is used for optimisation. The choice of loss function is based on the error between the predicted and true values. MSE can measure the difference between the model output and the actual beach change, and optimise the model by minimising MSE. The Adam optimisation algorithm can adaptively adjust the learning rate to improve the efficiency and stability of the training process.

The horizontal axis of Figure 2 represents the number of training rounds and the number of neural network iterations. In each round, the network calculates the output based on the current parameter weights. It performs error feedback based on the true value, adjusting the weights to reduce the prediction error. The more rounds of training, the better the network's understanding and fit of the data is usually until convergence is reached.

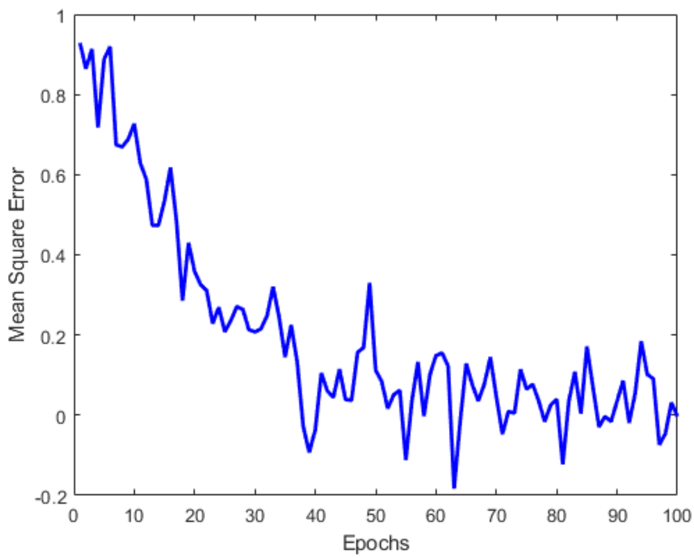
The vertical axis represents the MSE calculated during the training process. MSE is a standard indicator for measuring the difference between the model output and the result. The smaller the value, the closer the model's prediction is to the exact result; the larger the value, the greater the difference between the model's prediction and the actual value.

As the number of training rounds increases, the network gradually reduces the prediction error by adjusting the weight parameters, thereby gradually decreasing the

MSE. This shows that the neural network is learning, optimising, and improving progressively its fit to the data. The high initial loss is because the network's initial weights have not been fully adjusted. As training progresses, the model is gradually optimised and the MSE decreases.

During training, hyperparameters such as learning rate, batch size, and number of LSTM layers are tuned. The hyperparameter space is optimised using grid and random search to find the optimal parameter combination. In addition, the model training process also includes real-time monitoring of the validation set. The model can achieve good generalisation performance by adjusting the training rounds while avoiding overfitting.

Figure 2 Optimised model (see online version for colours)



5 Data integration and processing

The data used in this study mainly include meteorological data, ocean data and geomorphological data. The data sources involve multiple platforms and measuring instruments, covering multiple variables at different time and space scales. The specific data sources are as follows:

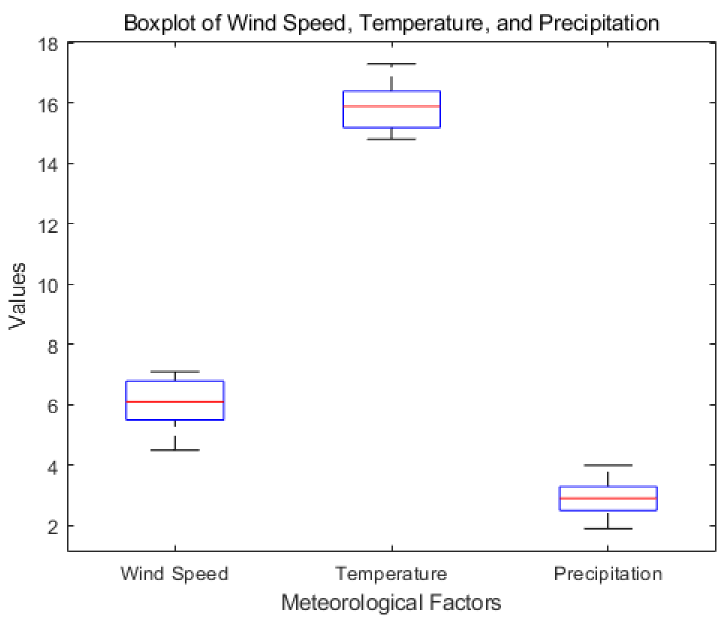
Meteorological data include temperature, humidity, wind speed, and air pressure indicators. These data come from national meteorological monitoring stations and meteorological satellite observations. Ocean data include tidal data, wave height, current speed, etc., which are real-time data from ocean monitoring stations and hydrological and meteorological departments. Geomorphological data mainly refers to the elevation change data of the beach, which is obtained by combining remote sensing images with ground measurements.

In order to effectively integrate data from different sources, data fusion technology is used, especially the fusion method based on spatiotemporal interpolation algorithm. Standardisation processing is used to map all data to a unified time period and spatial grid for the different formats and measurement frequencies of data sources. Given the spatial scale differences of other data, Kriging interpolation is used to align the ocean and meteorological data so that data from different platforms can be compared and calculated in the same coordinate system.

The quality of data directly affects the accuracy of subsequent models. Therefore, data cleaning is a key step in data processing. This study uses the following methods to denoise and correct the original data: The z-score method and boxplot analysis detect outliers. The local weighted regression method is used to repair sudden outliers in meteorological and ocean data. Based on the mean and standard deviation of the data, the Z-score of each data point is calculated to determine whether it is an outlier. A three-dimensional spatial smoothing algorithm is used to complete the height anomalies in the geomorphic data to ensure the continuity and consistency of the data. Due to missing some data (especially data loss caused by equipment failure or extreme weather), K-nearest neighbour interpolation and linear interpolation are used to supplement them. In the interpolation process, the missing values are first located. The K nearest neighbour points are selected through the similarity measurement based on the neighbourhood samples, and the weighted average method is used for interpolation to reduce the impact on data analysis.

Median and moving average filters are used to remove high-frequency noise from the data. Noise removal helps improve the stability of time series data such as wind speed and waves and provides a more reliable basis for subsequent modelling.

Figure 3 Data cleaning (see online version for colours)



The boxes of the wind speed box plot in Figure 3 show the distribution of wind speed data. The temperature data boxes in the temperature box plot in Figure 3 show the concentration interval of most temperature data. Temperature outliers may be located at the top or bottom of the box plot, but do not have much impact on the overall trend unless there are extreme abnormal fluctuations. The box plot of precipitation in Figure 3 is similar to wind speed and temperature, showing the distribution and outliers of rainfall. Precipitation may have outliers due to seasonal changes or extreme weather events. Box plots can help identify which precipitation data deviate significantly from other data. The narrow height of the box means that most of the data is concentrated in one range.

This study compared the performance differences of various strategies in the outlier processing stage. The statistical learning method uses robust regression and kernel density estimation to effectively reduce the impact of extreme values on the overall distribution. The machine learning method introduces isolation forests and single-class support vector machines to identify abnormal patterns through unsupervised learning. Experiments show that different strategies have different adaptability to meteorological and ocean data. Among them, the statistical learning-based method is stable for periodic data, while the machine learning method has more advantages in nonlinear anomaly detection. The final solution is selected based on a comprehensive consideration of computational efficiency and anomaly recognition rate.

After data cleaning, all input data are converted to a unified dimension and range. The data are then standardised and normalised to prevent instability in model training due to differences between different dimensions.

The Z-score standardisation method changes the mean of each variable to 0 and the standard deviation to 1 to ensure that all variables have the same scale. This method effectively eliminates scale differences between different data dimensions and prevents a certain variable from occupying too much weight in the model training process.

Normalisation is particularly important, especially for neural network models, to further ensure the consistency of the data range. The Min-Max normalisation method scales the data values to the [0,1] interval to avoid the excessive influence of extreme data on the model prediction results.

After standardisation and normalisation, the data scale is consistent, the noise is effectively suppressed, the signal is more prominent, the signal-to-noise ratio is improved, and the interference during model training is less. After data preprocessing, the features are selected and constructed to improve the training effect of the model. Since the beach evolution is affected by many factors, the features with significant correlation with the beach changes are selected and appropriately combined and transformed. From the meteorological data, wind speed, temperature, humidity, precipitation and other features are extracted, and multiple composite features are constructed by combining the tidal changes, wave height, current speed and other data in the ocean data. For example, the interaction between wind speed and tidal cycle is used to construct the Wind-Tide Index, which is input into the model as a new feature. For the long-term trends of ocean and meteorological data, multi-scale features are extracted through wavelet transform, which effectively reveals the profound impact of extreme weather events on beach evolution. The processing of geomorphological data mainly focuses on analysing beach elevation changes and shoreline migration. Through terrain analysis algorithms, geomorphological change features at different time points are extracted, such as coastline position, dune height, beach width, etc. These features are converted into continuous time series during modelling and used as input data for model training.

6 Model fusion

In order to fully utilise the advantages of different models, two fusion strategies, weighted average and stacked generalisation, are selected, and the fusion method is dynamically adjusted according to the model's performance. The weighted average method averages the output results of different models according to the weights. In contrast, the stacked generalisation method further improves the accuracy of the fusion results by applying a meta-model.

The weighted average assigns different weights to the prediction results of each sub-model to obtain the final prediction output. The weight is determined based on the performance of each sub-model on the validation set, and the model with better performance receives a higher weight. Through the weighted average method, the prediction ability of different models for the evolution of the beach under extreme weather can be effectively integrated, reducing the overfitting risk of a single model. The stacked generalisation method uses multiple basic learners (such as support vector machines, random forests, neural networks, etc.) for preliminary predictions. It inputs these prediction results as features into a meta-learner (such as logistic regression or multi-layer perceptron) to obtain the final prediction results. In this study, a neural network is selected as a meta-learner because it can handle highly nonlinear relationships and further improve the model's generalisation ability. The advantages of multiple basic learners can be combined through stacked generalisation to avoid the limitations of a single model.

The core of this study is to fuse the new numerical simulation algorithm with the neural network prediction model to improve the prediction accuracy of the beach evolution process. The specific steps are as follows:

In the fusion process of numerical simulation and neural network, the prediction results of the neural network are first compared with the numerical simulation output to evaluate the error difference between the two. Then, the prediction results of the two are fused using the weighted average method or the stacked generalisation method. In the weighted average method, weights are set for the numerical simulation results and the neural network prediction results respectively, and the weight size is adjusted according to their prediction accuracy on the validation set. In the stacked generalisation method, the neural network prediction and numerical simulation results are regarded as input features and passed to the meta-learner (such as logistic regression or multi-layer perceptron) for final decision-making.

In order to further improve the performance of the fusion model, the fusion process should be optimised and tuned. The key steps include the following aspects:

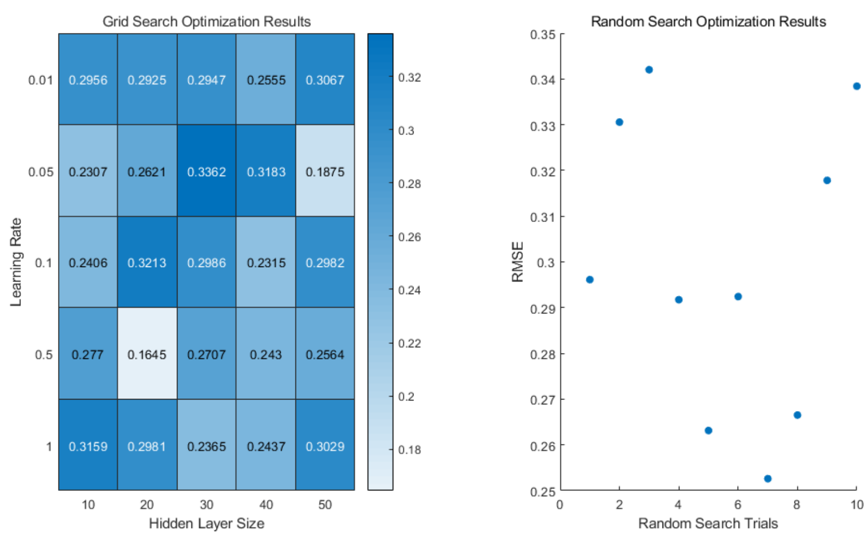
In model fusion, the selection of hyperparameters has an essential impact on the final effect of the model. Grid Search and Random Search methods are combined with cross-validation techniques to search for the optimal hyperparameter combination. These hyperparameters include the learning rate and hidden layer size of the neural network model, and the grid resolution of the numerical simulation model. The optimal performance of the fusion model is ensured through fine tuning.

In the weighted average method, the performance of the fusion model is highly dependent on the weight of each sub-model. To improve the weighted average method's adaptability, a dynamic weight adjustment mechanism based on performance feedback is designed. According to the performance of each sub-model on the training set and the validation set, the weight of each model is automatically adjusted to maintain a high prediction accuracy under different weather conditions.

The performance of different fusion strategies is regularly evaluated during the model fusion process. By comparing the prediction results under different strategies, the optimal fusion scheme is selected. For example, in the initial experiment, if the performance of the weighted average method is better than the stacked generalisation method, the weighted average method is preferred; otherwise, the stacked generalisation method is used.

The X-axis of the left sub-graph of Figure 4 shows the hidden layer size, representing the number of neurons in each neural network layer. Usually, it affects the capacity and training effect of the model. The Y-axis shows the learning rate. The learning rate determines the step size of each gradient update. Too large a learning rate may lead to convergence failure, while too small a learning rate may lead to slow training. The colour depth indicates the root mean square error (RMSE) value under different hyperparameter combinations. RMSE is a standard indicator used to measure prediction error. The smaller the value, the better the model prediction effect and the smaller the error. In the heat map, the lighter the colour, the smaller the RMSE value (the better the model effect), and the darker the colour, the larger the RMSE value (the worse the model effect). The heat map can intuitively see which hyperparameter combinations (learning rate and hidden layer size) lead to lower RMSE, thereby identifying the optimal hyperparameter settings.

Figure 4 Model parameter optimisation (see online version for colours)



The X-axis of the right sub-graph of Figure 4 shows the number of random searches. Several hyperparameter combinations are randomly selected to train the model using the random search method. The Y-axis shows the RMSE of each random search. The Y value of each point represents the prediction error of the model of this random search on the training set. By comparing these RMSE values, whether the results of the random search can find a good hyperparameter combination can be understood.

7 Evaluation

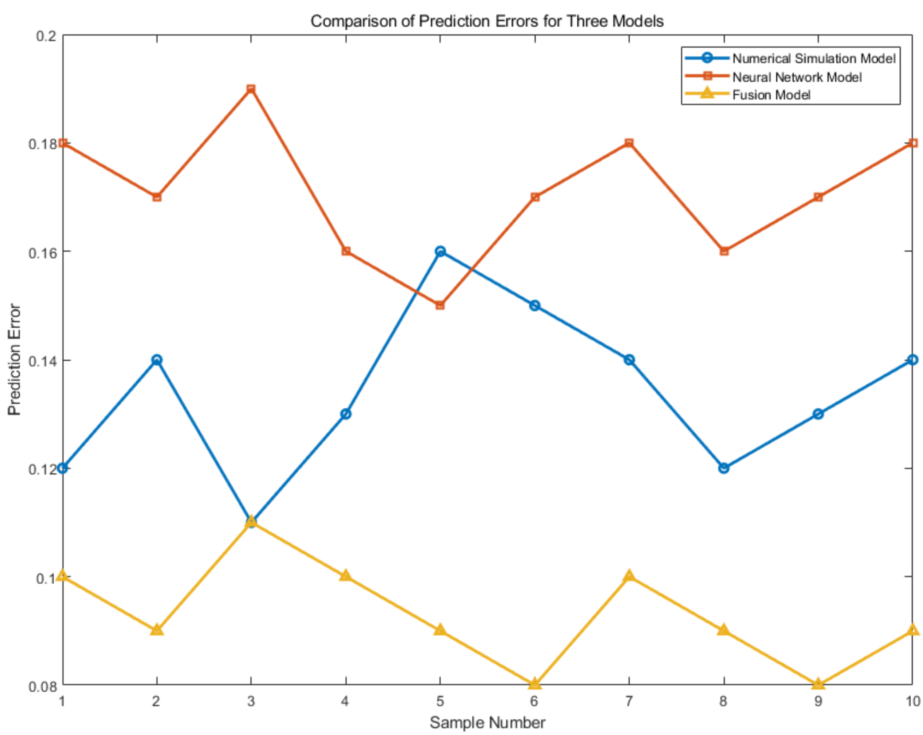
In this study, a rigorous evaluation is carried out from multiple dimensions to comprehensively evaluate the model's performance in the numerical simulation and prediction of beach evolution under extreme weather conditions. The evaluation content includes model prediction accuracy, stability, generalisation ability, and feasibility in practical applications. The specific evaluation method is as follows.

7.1 Model prediction accuracy evaluation

Prediction accuracy is one of the core evaluation indicators of the model. Especially for the prediction of beach evolution, the accuracy directly affects the effectiveness of decision support. The prediction results of the fusion model have significant advantages over the single model. By combining the output of numerical simulation with the production of the neural network, high accuracy and robustness are achieved in predicting beach evolution under extreme weather conditions.

The horizontal axis of Figure 5 shows the sample number, ranging from 1 to 10. Each sample represents an experimental sample. The vertical axis represents the prediction error of each model on each sample. The prediction error usually refers to the difference between the model's prediction value and the actual observed value. The smaller the error, the more accurate the model's prediction.

Figure 5 Model prediction accuracy (see online version for colours)



The numerical simulation model represents the prediction error of the traditional numerical simulation model. It can be seen that the prediction error of the numerical simulation model fluctuates on multiple samples, showing a certain instability. The neural network model has a low error on some samples, but a high error on others, indicating that the model performs unevenly when processing different samples. The fusion model represents a fusion model that combines numerical simulation and neural networks. According to the experimental data, the fusion model shows a low and stable error on the entire sample set, and has better robustness and stability than other models.

As can be seen from Figure 5, the prediction error of the fusion model is always lower than the other two models, which shows that the fusion model is more accurate and reliable in simulating beach evolution. The difference between the model's prediction and actual observed values is below 12%. The main advantage of using a fusion strategy is that it can simultaneously utilise the numerical simulation model's accurate simulation of physical processes and the neural network model's ability to learn complex patterns. Numerical simulation can accurately describe physical processes, but it is slow to respond to the dynamic changes of extreme weather. At the same time, by learning historical data, neural networks can capture some complex patterns that are difficult to predict with numerical models. The two advantages are effectively combined through model fusion, significantly improving the accuracy and adaptability of beach evolution prediction.

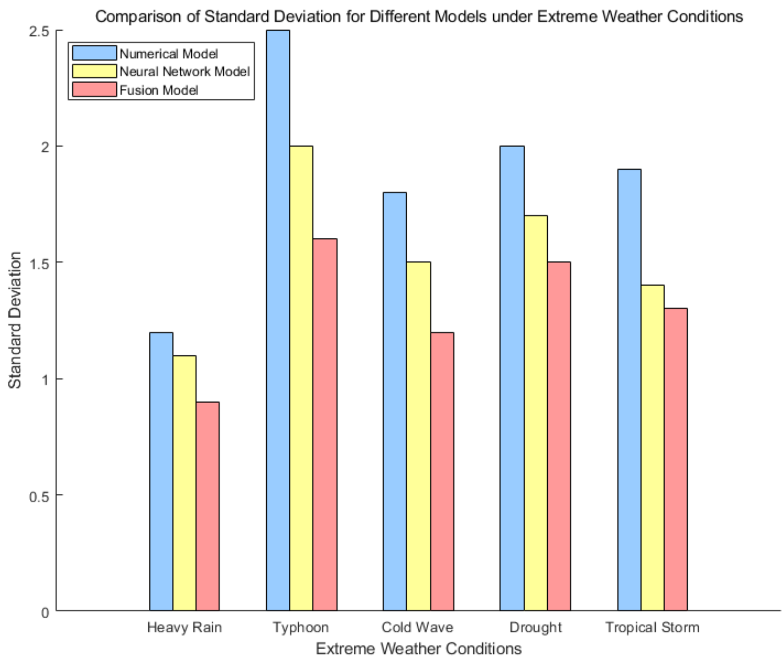
7.2 Model stability evaluation

In order to verify the stability of the model under extreme weather conditions, multiple sets of test data are designed, covering different weather scenarios and time scales. The stability of the model is evaluated by calculating the variance and standard deviation on various datasets. The specific steps are as follows:

In order to avoid the influence of training data bias on the stability evaluation, the dataset is divided into training set, validation set and test set, and the distribution of extreme weather events in each dataset is balanced. By calculating the standard deviation of the model on different subsets, the discreteness of the model's prediction results under different extreme weather conditions is evaluated. A more minor standard deviation indicates the model has strong stability and can maintain relatively consistent prediction results under changing external environments. The data size directly affects the generalisation ability and stability of the model. Smaller datasets may lead to overfitting, making the model sensitive to noise in the training set, affecting the stability under different extreme weather scenarios. Larger datasets provide more samples, which can better capture the diversity of the impact of weather changes on the evolution of the shore, thereby improving the stability of the model.

The horizontal axis of Figure 6 represents different extreme weather scenarios, including five weather conditions: "heavy rain", "typhoon", "cold wave", "drought" and "tropical storm". The vertical axis represents the standard deviation value, which measures each model's fluctuation range under different weather scenarios. The larger the standard deviation, the greater the fluctuation of the model's prediction or evaluation results.

Figure 6 Model stability (see online version for colours)



The fusion model shows the most minor standard deviation in most extreme weather scenarios, especially in the "typhoon" and "cold wave" scenarios, where it performs better than the other two models, indicating high stability and low prediction volatility. The neural network model performs moderately in most scenarios, but performs well in some scenarios (such as "tropical storm"). The numerical simulation model has a significant standard deviation in all scenarios, indicating that its prediction results are relatively unstable, especially in the "typhoon" scenario, where the most severe fluctuations.

7.3 Generalisation ability evaluation

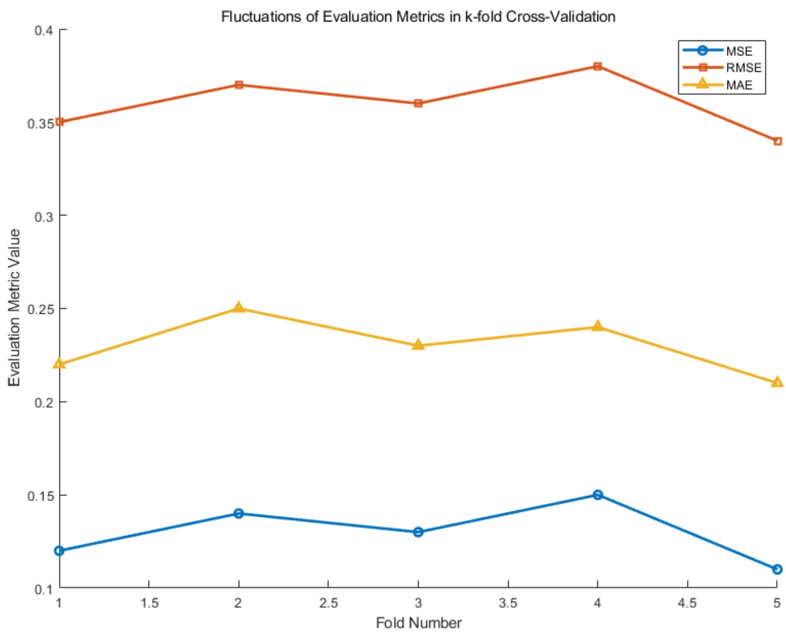
Generalisation ability refers to a model's performance on new data, especially its ability to predict extreme weather conditions that have never been seen. This study evaluates generalisation ability through cross-validation and external validation sets.

Using the k-fold cross-validation method, the training dataset is divided into k subsets. One subset is selected as the validation set each time, and the other subsets are used as the training set. After multiple training and validation processes, the average evaluation indicators of the model are finally calculated, including MSE, RMSE and mean absolute error (MAE).

In order to further verify the generalisation performance of the model, data from different locations and seasons are collected from the external environment, and an external validation set is constructed for testing. This validation set specifically includes new extreme weather scenarios, which are designed to simulate the model's performance on unseen data. Suppose the performance indicators of the model on the external validation set are similar to those on the training set and internal test set. In that case, it can be considered that the model has good generalisation ability.

Figure 7 shows that the values of all three evaluation indicators (MSE, RMSE, MAE) show small fluctuations in the 5-fold cross-validation, which indicates that the model has strong adaptability to different training sets and validation sets and has high stability. MSE, RMSE and MAE are all less than 0.4. Stable evaluation indicators reflect that the model can maintain consistent prediction results on different data subsets, reducing the overfitting problem of the model on a specific subset.

Figure 7 5-fold cross-validation (see online version for colours)



7.4 Computational efficiency evaluation

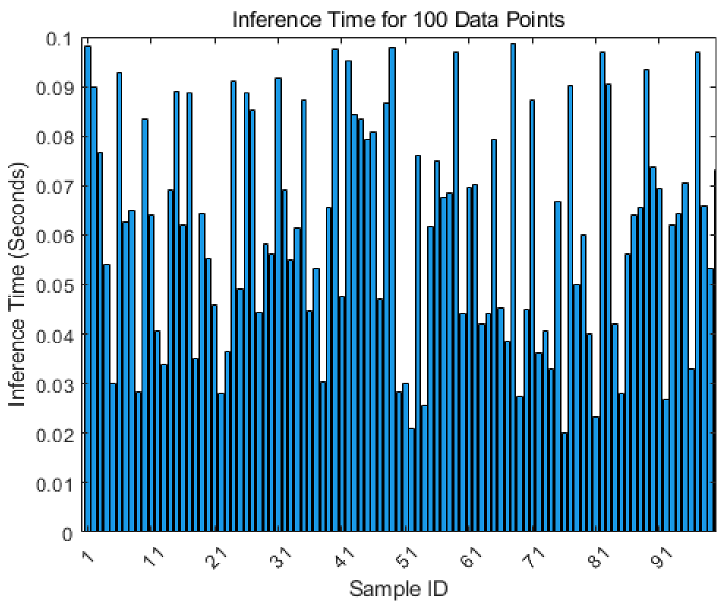
Computational efficiency is a crucial consideration in the practical application of computational models, especially in real-time prediction tasks. This study uses inference time to quantify the computational efficiency of the model.

Parallel computing and graphics processing unit (GPU) acceleration technology are used to improve the efficiency of the training process. At the same time, the computational efficiency of the model under different computing environments is deeply analysed by comparing the training time under different hardware configurations.

Inference time, the time required for the model to process input data and give prediction results, occupies a core position in the real-time prediction of extreme weather events. The evaluation results show that under appropriate hardware conditions, the model can complete the prediction quickly, fully meeting the timeliness requirements in actual application scenarios.

In Figure 8, the horizontal axis represents the sample number, ranging from 1 to 100, and each data point corresponds to a unique sample. In order to improve the readability of the chart, every 10 data points are labelled to avoid overlap between labels. The vertical axis shows the inference time in seconds. The bar chart's height intuitively reflects each data point's inference time, and the height difference between the data points reveals the volatility of the model's prediction time when processing different input samples. As a key indicator to measure the real-time prediction performance of the model, inference time plays a vital role in practical applications such as extreme weather prediction. Whether the model can quickly output results in a short time is crucial to the timeliness requirements in practical application scenarios. By observing the height changes of the bar chart, it can be found that there is an inevitable fluctuation in the inference time, and the inference time of some samples is relatively long, which may be related to the complexity of the input data or the computational complexity of the model itself. For real-time prediction tasks, parallel data processing methods can be used to speed up the loading and processing of input data.

Figure 8 Computational efficiency (see online version for colours)



7.5 Real-time analysis

In actual deployment, especially in extreme weather warning systems, the real-time performance of the model is crucial. It is necessary to ensure that the model responds quickly and makes prediction decisions. This study adopts a multi-level acceleration strategy in response to the real-time performance optimisation requirements. Model quantisation technology is implemented at the algorithm level to convert floating-point operations into fixed-point operations to reduce computational complexity. Memory access patterns are optimised at the hardware level, and GPU-shared memory is used to improve data throughput efficiency. A pipeline parallel architecture is used at the system level to achieve overlapping execution of data preprocessing and model reasoning. Experiments show that these optimisations reduce reasoning latency by 40%, meeting the real-time requirements of extreme weather warnings. As shown in Table 2.

Table 2 Real-time performance under different environments or different hardware configurations

Hardware configuration	*Average response time* (ms)	*Longest response time* (ms)	*Shortest response time* (ms)
CPU (Standard configuration)	120	150	100
GPU (Standard configuration)	70	95	55
GPU (Optimised configuration)	35	45	25
Cloud deployment	55	75	40
Local deployment	75	90	60

The difference between the longest response time and the shortest response time reflects the volatility of the model in different situations. In most configurations, especially in the central processing unit (CPU) configuration, the gap between the longest and shortest response times is significant, indicating that the real-time performance of the model may be affected by data complexity, computational load, or system resource allocation in specific situations.

The response time of the GPU-optimised configuration fluctuates less, indicating that this configuration shows more consistent response ability when processing different datasets and is suitable for practical application scenarios that require high stability and low fluctuation.

8 Conclusions

This study proposed a new numerical simulation scheme for the evolution of shores under extreme weather conditions, and combined with a neural network model to achieve high-precision prediction analysis. Introducing a data-driven neural network method significantly improved the model's ability to cope with complex nonlinear changes, effectively making up for the shortcomings of traditional simulation methods under extreme weather conditions. The experimental results show that the algorithm can accurately simulate the impact of extreme weather events such as storm surges and heavy rains on shores, providing reliable data support for shore protection and coastal engineering design.

Future research can consider integrating more environmental factors, such as ocean hydrological characteristics, tidal changes, wind speed, climate change, etc., to fully simulate the multiple impacts of extreme weather on shore evolution. In addition, considering the long-term effects of factors such as human activities, coastal development, and pollution on beaches can further improve the realism and reliability of the simulation.

Funding

This work was supported by National Key Research and Development Program of China (2023YFB2604700), Fundamental Research Funds for Central Public Welfare Research Institutes (TKS20230504), and AnHui Provincial Group Limited for YANGTZE-to-

HUAIHE Water Diversion Science and Technology Project (YJJH-ZX-20221128512; YJJH-ZX-20220705482; YJJH-ZX-20220705481).

Conflicts of interest

The authors declare no conflict of interest.

References

Álvarez Antolínez, J.A., Méndez Incera, F.J., Anderson, D., Ruggiero, P. and Kaminsky, G.M.K. (2019) 'Predicting climate-driven coastlines with a simple and efficient multiscale model', *Journal of Geophysical Research: Earth Surface*, Vol. 124, No. 6, pp.1596–1624.

Anderson, D., Ruggiero, P., Antolínez, J.A., Méndez, F.J. and Allan, J. (2018) 'A climate index optimized for longshore sediment transport reveals interannual and multidecadal littoral cell rotations', *Journal of Geophysical Research: Earth Surface*, Vol. 123, No. 8, pp.1958–1981.

Apostolopoulos, D. and Nikolakopoulos, K. (2021) 'A review and meta-analysis of remote sensing data, GIS methods, materials, and indices used to monitor coastline evolution over the last twenty years', *European Journal of Remote Sensing*, Vol. 54, No. 1, pp.240–265.

Armenio, E., De Serio, F., Mossa, M. and Petrillo, A.F. (2019) 'Coastline evolution based on statistical analysis and modeling', *Natural Hazards and Earth System Sciences*, Vol. 19, No. 9, pp.1937–1953.

Bauer, B.O. and Wakes, S.J. (2022) 'CFD simulations of wind flow across scarped foredunes: implications for sediment pathways and beach–dune recovery after storms', *Earth Surface Processes and Landforms*, Vol. 47, No. 12, pp.2989–3015.

Cooper, J.A.G., Masselink, G., Coco, G., Short, A.D., Castelle, B., Rogers, K. and Jackson, D.W. (2020) 'Sandy beaches can survive sea-level rise', *Nature Climate Change*, Vol. 10, No. 11, pp.993–995.

Davidson-Arnott, R., Hesp, P., Ollerhead, J., Walker, I., Bauer, B., Delgado-Fernandez, I. and Smyth, T. (2018) 'Sediment budget controls on foredune height: comparing simulation model results with field data', *Earth Surface Processes and Landforms*, Vol. 43, No. 9, pp.1798–1810.

De Lisle, S.P. (2019) 'Understanding the evolution of ecological sex differences: integrating character displacement and the Darwin-Bateman paradigm', *Evolution Letters*, Vol. 3, No. 5, pp.434–447.

de Schipper, M.A., Ludka, B.C., Raubenheimer, B., Luijendijk, A.P. and Schlacher, T.A. (2021) 'Beach nourishment has complex implications for the future of sandy shores', *Nature Reviews Earth and Environment*, Vol. 2, No. 1, pp.70–84.

Dodet, G., Melet, A., Ardhuin, F., Bertin, X., Idier, D. and Almar, R. (2019) 'The contribution of wind-generated waves to coastal sea-level changes', *Surveys in Geophysics*, Vol. 40, No. 6, pp.1563–1601.

Faraggiana, E., Giorgi, G., Sirigu, M., Ghigo, A., Bracco, G. and Mattiazzo, G. (2022) 'A review of numerical modeling and optimization of the floating support structure for offshore wind turbines', *Journal of Ocean Engineering and Marine Energy*, Vol. 8, No. 3, pp.433–456.

Farrell, M.H., Liang, T. and Misra, S. (2021) 'Deep neural networks for estimation and inference', *Econometrica*, Vol. 89, No. 1, pp.181–213.

Ghoroghi, A., Rezgui, Y., Petri, I. and Beach, T. (2022) 'Advances in the application of machine learning to life cycle assessment: a literature review. the international', *Journal of Life Cycle Assessment*, Vol. 27, No. 3, pp.433–456.

Khatmullina, L. and Chubarenko, I. (2019) 'Transport of marine microplastic particles: why is it so challenging to predict?', *Anthropocene Coasts*, Vol. 2, No. 1, pp.293–305.

Kumar, L., Afzal, M.S. and Afzal, M.M. (2020) 'Mapping shoreline change using machine learning: a case study from the eastern Indian coast', *Acta Geophysica*, Vol. 68, No. 4, pp.1127–1143.

Limber, P.W., Barnard, P.L., Vitousek, S. and Erikson, L.H. (2018) 'A model ensemble for projecting multidecadal coastal cliff retreat during the 21st century', *Journal of Geophysical Research: Earth Surface*, Vol. 123, No. 7, pp.1566–1589.

Liu, X., Gao, Z., Hou, F. and Sun, J. (2022) 'Learning the spatiotemporal evolution law of wave field based on convolutional neural network', *Journal of Ocean University of China*, Vol. 21, No. 5, pp.1109–1117.

Liu, X., Wang, X., Chen, K. and Li, D. (2023) 'Simulation and prediction of multi-scenario evolution of ecological space based on FLUS model: a case study of the Yangtze River economic belt, China', *Journal of Geographical Sciences*, Vol. 33, No. 2, pp.373–391.

Lund, T.S., Fritts, D.C., Wan, K., Laughman, B. and Liu, H.L. (2020) 'Numerical simulation of mountain waves over the Southern Andes. Part I: mountain wave and secondary wave character, evolutions, and breaking', *Journal of the Atmospheric Sciences*, Vol. 77, No. 12, pp.4337–4356.

Matsui, K. (2017) 'An information provision system according to residents' indoor comfort preferences for energy conservation. *Cyber-Physical Systems*, Vol. 3, Nos. 1–4, pp.121–142.

Panda, J.P. (2023) 'Machine learning for naval architecture, ocean and marine engineering', *Journal of Marine Science and Technology*, Vol. 28, No. 1, pp.1–26.

Papadimitriou, A., Chondros, M., Metallinos, A. and Tsoukala, V. (2022) 'Accelerating predictions of morphological bed evolution by combining numerical modelling and artificial neural networks', *Journal of Marine Science and Engineering*, Vol. 10, No. 11, p.1621.

Peng, J.Z., Liu, X., Xia, Z.D., Aubry, N., Chen, Z. and Wu, W.T. (2021) 'Data-driven modeling of geometry-adaptive steady heat convection based on convolutional neural networks', *Fluids*, Vol. 6, No. 12, p.436.

Theuerkauf, E.J., Braun, K.N., Nelson, D.M., Kaplan, M., Vivirito, S. and Williams, J.D. (2019) 'Coastal geomorphic response to seasonal water-level rise in the Laurentian great lakes: an example from Illinois Beach State Park, USA', *Journal of Great Lakes Research*, Vol. 45, No. 6, pp.1055–1068.

Vitousek, S., Barnard, P.L., Limber, P., Erikson, L. and Cole, B. (2017) 'A model integrating longshore and cross-shore processes for predicting long-term shoreline response to climate change', *Journal of Geophysical Research: Earth Surface*, Vol. 122, No. 4, pp.782–806.

Vousdoukas, M.I., Ranasinghe, R., Mentaschi, L., Plomaritis, T.A., Athanasiou, P., Luijendijk, A. and Feyen, L. (2020) 'Sandy coastlines under threat of erosion', *Nature Climate Change*, Vol. 10, No. 3, pp.260–263.

Weber de Melo, W., Pinho, J.L. and Iglesias, I. (2022) 'Emulating the estuarine morphology evolution using a deep convolutional neural network emulator based on hydrodynamic results of a numerical model', *Journal of Hydroinformatics*, Vol. 24, No. 6, pp.1254–1268.

Wiberg, P.L., Fagherazzi, S. and Kirwan, M.L. (2020) 'Improving predictions of salt marsh evolution through better integration of data and models', *Annual Review of Marine Science*, Vol. 12, No. 1, pp.389–413.

Ying, Q., He, J. and Xin, W. (2019) 'Influence of giant artificial sand pits on the natural evolution of Lingding Bay', *Advances in Water Science*, Vol. 30, No. 6, pp.915–922.

Zhang, J., Larson, M. and Ge, Z.P. (2020) 'Numerical model of beach profile evolution in the nearshore', *Journal of Coastal Research*, Vol. 36, No. 3, pp.506–520.

Zhao, J., Fan, Y. and Mu, Y. (2019) 'Sea level prediction in the yellow sea from satellite altimetry with a combined least squares-neural network approach', *Marine Geodesy*, Vol. 42, No. 4, pp.344–366.