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Analysis and prediction of typical sea ecological environment change characteristics based on machine learning

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SUMMARY: *Marine ecological environment monitoring is shifting from single-index empirical judgment to dynamic identification and trend prediction driven by multi-source observation data. In order to solve the problems of strong coupling, significant temporal fluctuation, and prominent spatial heterogeneity of ecological variables in typical inshore waters, and it is difficult for traditional methods to simultaneously consider state discrimination and continuous prediction, this paper takes the inshore waters of Jiaxing and Ningbo as objects, and constructs a machine learning model combining sliding time window, spatial neighborhood weight, unified expression of multi-source features and joint output of dual tasks. The model takes remote sensing observation, bubue monitoring, water quality investigation, meteorological and Marine data and human activity information as input, and realizes a comprehensive description of the evolution process of Marine ecology through spatio-temporal feature fusion, state semantic mapping, category discrimination and trend prediction. The experimental results show that the contribution of inorganic nitrogen in Jiaxing sea area reaches 0.24, and the proportion of degraded and high-risk samples is 52.9%. The RMSE of the model under 1-step and 12-step prediction conditions is 0.028 and 0.086, respectively, the F1 value is still 0.833 under 40% missing rate, and the accuracy of cross-region transfer reaches 0.887 and 0.873, which is better than that of XGBoost, LSTM and SVR. The research can provide effective technical support for typical sea ecological environment monitoring, risk early warning and fine governance.*

KEYWORDS: *Machine learning; Marine ecological environment; Spatio-temporal feature analysis; Trend forecasting*

1 Introduction

Marine ecological environment is an important foundation to maintain the sustainable utilization of Marine resources and the high-quality development of coastal areas. Its change process is simultaneously affected by multiple factors such as sea surface temperature, salinity, chlorophyll concentration, dissolved oxygen, nutrient transport, human development activities and climate fluctuations, which has obvious characteristics of time series fluctuation, spatial heterogeneity and coupled evolution [1, 2]. Due to differences in geographical location, seawater exchange conditions, ecosystem structure and external disturbance intensity, typical sea areas often show complex and diverse change laws in the evolution of ecological environment [3]. How to extract key features from multi-source observation information, accurately identify the change state of ecological environment, and make reasonable

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predictions for the future evolution trend have become important issues in Marine ecological monitoring, resource management and risk early warning [4].

Traditional sea ecological environment research relies more on statistical analysis, empirical interpretation and single-index evaluation, which play a certain role in describing local phenomena and explaining phased changes. However, it is often difficult to fully reveal the deep laws of ecological environment changes when facing long-term series, multi-dimensional monitoring variables and nonlinear coupling relationships [5-7]. With the continuous accumulation of data from remote sensing observations, ocean buoys, cross-sectional surveys, automatic monitoring platforms and reanalysis, Marine ecological environment research has entered a new stage of collaborative analysis of multi-source heterogeneous data. Massive data provides conditions for fine recognition and dynamic prediction, and also puts forward higher requirements for data fusion, feature expression and model generalization ability [8].

Machine learning methods have strong advantages in complex system modeling, pattern recognition and trend prediction, which can mine potential associations from multidimensional samples, establish the mapping relationship between environmental variables and ecological states, and improve the ability to depict nonlinear change processes [9, 10]. The introduction of machine learning into the study of typical Marine ecological environment change not only helps to realize the efficient processing of multi-source Marine data, but also enhances the identification accuracy and prediction ability of the ecological evolution process, and provides more targeted technical support for Marine ecological restoration, environmental governance and Marine space development [11]. Based on this, this paper focuses on the analysis and prediction of typical sea ecological environment change characteristics, combines machine learning methods to construct a research framework, and focuses on the spatio-temporal feature expression, state discrimination and trend prediction process of multi-source Marine ecological environment data. The effectiveness and applicability of the model in the analysis of ecological environment change are verified through experiments.

2 Theoretical basis and key technologies

2.1 Theoretical basis for analysis of typical sea ecological environment change characteristics

The change of typical sea ecological environment is not the result of the fluctuation of a single index, but a comprehensive response process formed by the joint action of water temperature, salinity, chlorophyll concentration, dissolved oxygen, nutrients, suspended particles and human development activities. From the perspective of ecological mechanism, the Marine ecological state has obvious multi-factor coupling characteristics. On the one hand, the Marine hydrological conditions determine the intensity of material transport and energy exchange. On the other hand, biogeochemical processes in turn affect water quality and ecological stability. Therefore, the analysis of the characteristics of Marine ecological environment change should be comprehensively described from three dimensions: multi-index collaborative change, time series evolution and spatial differentiation.

In order to quantitatively characterize the ecological state of the sea area, a comprehensive index of ecological environment can be usually constructed. Let the standardized value of the ith ecological index at time t be $z_{i,t}$, and its weight be w_i, then the comprehensive index of Marine ecological environment can be expressed as follows:

$$E_t = \sum_{i=1}^{n} w_i z_{i,t}, \quad \sum_{i=1}^{n} w_i = 1 \tag{1}$$

Here, E_t represents the comprehensive ecological environment level at time t, and n is the number of indicators. Equation (1) can map multi-dimensional variables such as sea surface temperature, salinity, chlorophyll concentration and dissolved oxygen into the same evaluation framework, and provide basic representation for subsequent change identification and trend prediction.

In the time dimension, the evolution of the Marine ecological environment usually shows the coexistence of stage fluctuations and long-term trends. In order to measure the change intensity of ecological status in adjacent periods, the change rate can be further defined as follows:

$$R_t = \frac{E_t - E_{t-1}}{E_{t-1}} \tag{2}$$

Among them, R_t reflects the relative change amplitude of the comprehensive state of the ecological environment between adjacent moments. When $R_t>0$, the ecological status is relatively improved. When $R_t<0$, it indicates that there is a degradation trend of the ecological environment. Equation (2) can better reveal the dynamic response characteristics of typical sea areas under seasonal transformation, climatic anomalies or external disturbances.

In general, the theoretical basis for the analysis of the change characteristics of typical sea ecological environment is to comprehensively characterize the ecological state by multi-source indicators, describe the evolution process by change rate, and identify the ecological response law of different sea units by combining spatial differences. This theoretical framework not only provides support for the explanation of Marine ecological change mechanism, but also lays a foundation for data expression and indicator modeling for subsequent machine learning models to carry out state discrimination and trend prediction.

2.2 Key technologies of Marine ecological environment prediction driven by machine learning

In the study of typical Marine ecological environment, the value of machine learning is mainly reflected in the mining of complex relationships, nonlinear law modeling and collaborative processing of multi-source heterogeneous data. Compared with traditional analysis methods that rely on empirical thresholds or linear statistical relationships, machine learning can extract discriminative high-dimensional features from remote sensing images, buoy monitoring, cross-sectional surveys, and meteorological and hydrological records, and establish the mapping relationship between the state of the ecological environment and the future evolution trend. Due to the temporal continuity, spatial correlation and variable coupling of Marine ecosystem, the model not only needs to identify the differences in current state, but also retains historical evolution information to improve the prediction ability of short-term fluctuations and long-term trends.

At the level of data representation, multi-source observation variables at the same time are usually organized as feature vectors, which are used as the input of machine learning models. Let the sea ecological environment observation sample at time t be expressed as follows.

$$x_t = [x_{1,t}, x_{2,t}, \dots, x_{m,t}] \tag{3}$$

Here, x_t denotes the input feature vector at time t, m is the total number of input variables. The vector can comprehensively contain information such as sea surface temperature, salinity, chlorophyll concentration, dissolved oxygen, pH value, nutrient concentration and human activity intensity, so as to provide a unified data representation basis for subsequent model training.

At the prediction level, machine learning performs state discrimination or trend prediction by establishing a functional mapping between the input features and the target variable. The general form can be written as follows:

$$\hat{y}_{t+\Delta}=f(x_t;\theta) \tag{4}$$

where $\hat{y}_{t+\Delta}$ represents the prediction result of the ecological environment state or change trend at time t+Δ in the future, $f(\cdot)$ represents the machine learning model, and θ represents the model parameters. If the research goal is continuous value prediction, random forest regression, support vector regression, or long short-term memory network can be used. If the research goal is ecological status classification or anomaly recognition, it can be transformed into a classification task, and the discriminative output is completed by an ensemble learning model or neural network.

In order to make the model learn a more stable mapping relationship, it is usually necessary to measure the error between the predicted value and the true value through the loss function in the training process, and constantly update the parameters. For continuous ecological index prediction, the mean square error loss can be used:

$$L=\frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2 \tag{5}$$

Here, L is the model loss value, N is the number of samples, yi and $\hat{y}_i$ represent the true value and predicted value respectively. The smaller the loss is, the stronger the fitting ability of the model to the evolution law of the Marine ecological environment is. Based on the above technology path, machine learning can not only improve the accuracy of typical sea ecological environment change recognition, but also enhance the trend prediction ability of complex ocean processes, which provides reliable method support for subsequent model design and experimental analysis.

3 Analysis and prediction model design of typical sea ecological environment change characteristics based on machine learning

3.1 Analysis and prediction model of typical sea ecological environment change characteristics

In order to improve the accuracy of typical sea ecological environment change recognition and the stability of trend prediction, this paper constructs a feature analysis and prediction model for multi-source Marine ecological environment data. The model takes remote sensing observation, bubue monitoring, water quality investigation, meteorological and Marine data and human activity information as joint input, and completes a comprehensive description of the evolution process of Marine ecology through four levels of data alignment, feature fusion, state discrimination and trend output. Compared with the single variable analysis method, the proposed model emphasizes the unified expression of time continuity, spatial proximity and multi-factor coupling relationship, and can simultaneously consider the identification of the state of the Marine ecological environment and the prediction of the future change trend.

The input of the model organizes the multi-source ecological environment observation sequence with a sliding time window. Let the multi-source observation matrix of the study sea area at time t be $Xt \in R^{n\times m}$, where n denotes the number of spatial units and m denotes the dimension of ecological environment variables. In the feature layer, the model encodes the data from different sources into a unified representation, and forms a comprehensive ecological representation vector through weighted fusion:

$$F_t = \sum_{k=1}^{K} \alpha_k H_t^{(k)}, \quad \sum_{k=1}^{K} \alpha_k = 1 \tag{6}$$

Here, $H_t^{(k)}$ represents the hidden features extracted from the KTH data source at time t, α_k is the corresponding weight, and k is the number of data source categories. Equation (6) reflects the collaborative integration ability of the model for remote sensing, hydrology, ecology, meteorology and human disturbance information, which can avoid the deviation of ecological state judgment caused by single data source.

On this basis, in order to highlight the temporal dependence and spatial propagation of Marine ecological evolution, the model further introduces the spatio-temporal joint representation mechanism, and couples the current fusion feature with the neighborhood unit response to obtain the ecological state representation vector:

$$Z_t = \phi\left(W_f F_t + W_s \sum_{j\in N(i)} \beta_{ij} F_{j,t} + b\right) \tag{7}$$

Here, Z_t is the ecological state representation after spatio-temporal coupling, $N(i)$ represents the spatial neighborhood set, β_{ij} represents the spatial correlation weight, W_f and W_s are the temporal feature and spatial feature mapping matrices, respectively, and $\phi(\cdot)$ is the nonlinear activation function. Equation (7) enables the model not only to retain the ecological environment information of the unit itself, but also to capture the diffusion effect and linkage change characteristics between adjacent sea areas.

At the output end, this paper adopts a dual-task structure of "state discrimination + trend prediction". State discrimination is used to identify the level of the sea ecological environment at the time of study, and trend prediction is used to describe the evolution direction and change range in the future period. The state discrimination result can be expressed as follows.

$$P_t = \mathrm{Softmax}(W_c Z_t + b_c) \tag{8}$$

Here, P_t is the probability distribution that the ecological environment state belongs to each category, and W_c and b_c are the classification layer parameters. When the maximum probability corresponds to the categories of "stable", "fluctuation" or "degradation", the phased identification of the ecological state of the sea area can be completed. Trend prediction takes the form of regression output:

$$\hat{y}_{t+\tau} = W_r Z_t + b_r \tag{9}$$

Here, $\hat{y}_{t+\tau}$ represents the predicted value of ecological environment change at time τ in the future, and W_r and b_r are the parameters of the regression layer. This output can correspond either to a comprehensive ecological index or to future levels of core variables such as chlorophyll concentration, dissolved oxygen, or eutrophication risk.

In order to balance classification and prediction accuracy, a joint objective function is constructed in the model training stage:

$$L=\lambda_1 L_{cls}+\lambda_2 L_{reg} \tag{10}$$

Here, L_{cls} represents the state discrimination loss, L_{reg} represents the trend prediction loss, and λ_1 and λ_2 are the trade-off coefficients. Equation (10) enables the model to maintain the fitting ability to the continuous change trend while learning the ecological state boundary, thus improving the overall analysis effect.

The relationship between the different levels is shown in Figure 1. In the figure, the model is divided into data input layer, preprocessing layer, spatio-temporal feature expression layer, state discrimination layer and trend output layer, which can clearly reflect the complete realization path of the proposed model from multi-source observation to ecological prediction results.

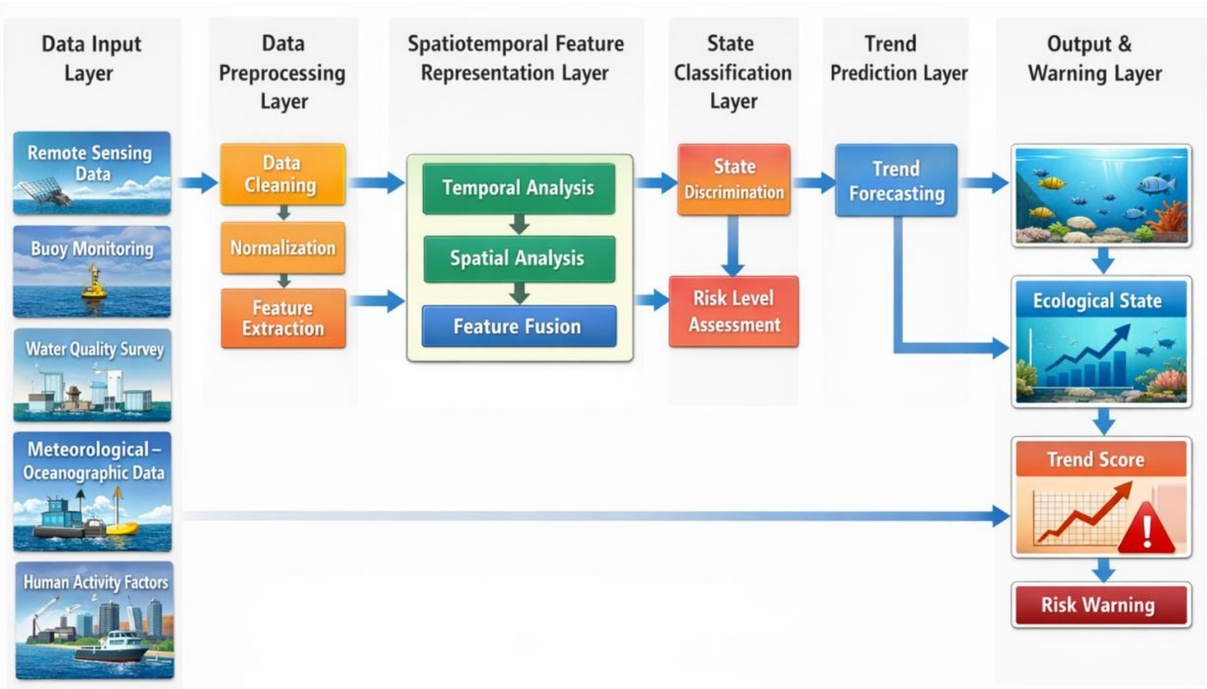

Figure 1: The overall architecture diagram of the analysis and prediction model of typical sea ecological environment change characteristics

To further illustrate the functional positioning of various variables in the model, the description of input and output variables of the model is shown in Table 1.

Table 1: Description table of model input and output variables

Variable Category	Variable Name	Data Source	Variable Function
Input Variable	Sea Surface Temperature	Remote Sensing Retrieval, Buoy Monitoring	Characterizes thermal variation features of the sea area
Input Variable	Sea Surface Salinity	Buoy Monitoring, Marine Survey	Reflects water mass exchange and salinity structure variation
Input Variable	Chlorophyll Concentration	Remote Sensing Retrieval, Water Quality Monitoring	Describes primary productivity and algal activity level
Input Variable	Dissolved Oxygen	Water Quality Monitoring, Transect Survey	Reflects the ecological health status of the water body
Input Variable	Nutrient Concentration	Marine Ecological Survey	Characterizes the driving intensity of eutrophication
Input Variable	Suspended Particulate Matter	Remote Sensing Data, Field Sampling	Reflects water turbidity and transport processes
Input Variable	Wind Speed and Precipitation	Meteorological Reanalysis Data	Characterizes the influence of external meteorological disturbances
Input Variable	Human Activity Intensity	Statistical Data, Shoreline Development Information	Characterizes the level of anthropogenic disturbance
Intermediate Variable	Fused Feature Vector	Generated by Model Computation	Comprehensively represents multi-source ecological information
Intermediate Variable	Spatiotemporal State Vector	Generated by Model Computation	Describes the spatiotemporal coupling state of the ecological environment
Output Variable	Ecological State Category	Model Classification Output	Identifies whether the sea area is in a stable, fluctuating, degraded, or high-risk state
Output Variable	Trend Prediction Value	Model Regression Output	Predicts the magnitude of future ecological environmental change
Output Variable	Risk Early Warning Level	Threshold-Based Output	Supports ecological risk identification and management decision-making

Table 1 shows that the proposed model realizes the systematic description of the typical sea ecological environment change process by constructing the analysis framework of multi-source input, fusion expression and dual-task output. This structure enhances the adaptability of the model to complex ecological disturbances, and also provides a unified data support for subsequent change characteristics analysis and trend prediction.

3.2 Spatial and temporal feature expression for multi-source Marine ecological environment data

Typical sea ecological environment data have the characteristics of diverse sources, different scales, continuous time and spatial coupling. It is difficult to accurately reflect the ecological evolution process by only relying on a single monitoring index. In order to enhance the model's ability to describe complex ocean processes, based on the unified preprocessing of multi-source data, this paper constructs the spatio-temporal feature representation method for time dimension, space dimension and variable dimension, and maps remote sensing inversion results, buoy monitoring sequences, water quality survey data, meteorological and Marine data and human activity information into the same feature space. This method emphasizes the unified expression of historical sequence information, neighborhood association information and cross-source collaboration information, so as to improve the reliability of subsequent state discrimination and trend prediction. The process of spatio-temporal feature representation of multi-source Marine ecological environment data includes data acquisition, quality control, time window construction, spatial neighborhood coding, feature fusion and unified output.

Let the multivariate observation vector of the ith spatial cell in the study sea area at time t be x_i^t. Within a time window of length l, the time-series sample tensor can be constructed as follows:

$$S_i^t = [x_i^{t-l+1}, x_i^{t-l+2}, \dots, x_i^t] \tag{11}$$

Among them, Sit represents the historical ecological environment sequence of spatial unit i at time t, which can simultaneously retain the change trajectories of variables such as temperature, salinity, chlorophyll, dissolved oxygen and nutrient salts in continuous periods. Compared with the static input method, Equation (11) enables the model to perceive the cumulative change and time series fluctuation characteristics of the Marine ecological environment.

In order to further highlight the evolution trend of ecological variables, this paper constructs the difference sequence based on the original window sequence, and jointly generates the time representation vector:

$$h_i^t = \phi(W_1 S_i^t + W_2 \Delta S_i^t + b_1) \tag{12}$$

where ΔS_i^t represents the difference sequence of adjacent moments in the window, hit is the time evolution feature, W_1 and W_2 are the mapping parameters, and $\phi(\cdot)$ is the nonlinear transformation function. This formula not only retains the original level of the variable, but also strengthens the expression ability of the stage change and mutation information of the ecological environment.

The ecological environment change of the sea area also has obvious spatial correlation, and the adjacent sea areas often show linkage response under the action of water exchange, pollution diffusion and ecological disturbance propagation. To this end, this paper introduces spatial neighborhood weights to aggregate ecological information in the surrounding sea area of the study unit. Let the spatial correlation weights between spatial unit i and neighborhood unit j be as follows:

$$a_{ij} = \frac{\exp\left(-\frac{d_{ij}}{\sigma_d}\right)\exp\left(-\frac{\|\bar{x}_i - \bar{x}_j\|_2}{\sigma_f}\right)}{\sum_{J\in N(i)} \exp\left(-\frac{d_{ij}}{\sigma_d}\right)\exp\left(-\frac{\|\bar{x}_i - \bar{x}_j\|_2}{\sigma_f}\right)} \tag{13}$$

where d_{ij} is the space distance between units, $\bar{x}_i$ and $\bar{x}_j$ are the average ecological attribute vector, and σ_d and σ_f are the adjustment parameters. In Equation (13), geographical proximity and ecological similarity are simultaneously included in the weight calculation, so that the expression of spatial relationship is no longer limited to distance constraints, but more in line with the actual propagation law of the Marine ecosystem.

After obtaining the temporal and spatial weights, the remote sensing features, monitoring sequence features, meteorological disturbance features and human activity features are further unified and projected to form a multi-source spatio-temporal fusion representation:

$$r_i^t = \mathrm{ReLU}\left(W_r\left[h_i^t \| \sum_{j\in\mathcal{N}(i)} a_{ij}\, x_j^t \| m_i^t\right] + b_r\right) \tag{14}$$

Here, r_i^t is the final spatio-temporal feature representation, m_i^t represents auxiliary features of meteorology, ocean and human activities, $\|$ represents vector concatenation operation. Equation (14) realizes the collaborative integration of time dependence, spatial neighborhood and cross-source information, and provides a unified and discriminative input representation for subsequent state discrimination and trend prediction.

Figure 2 shows the spatio-temporal feature expression framework of multi-source Marine ecological environment data in this paper. The figure starts from raw data access, and then goes through quality control, time window construction, spatial correlation coding, multi-source feature fusion and feature output, which reflects the realization path of extracting high-level ecological semantic representation layer by layer from raw observation.

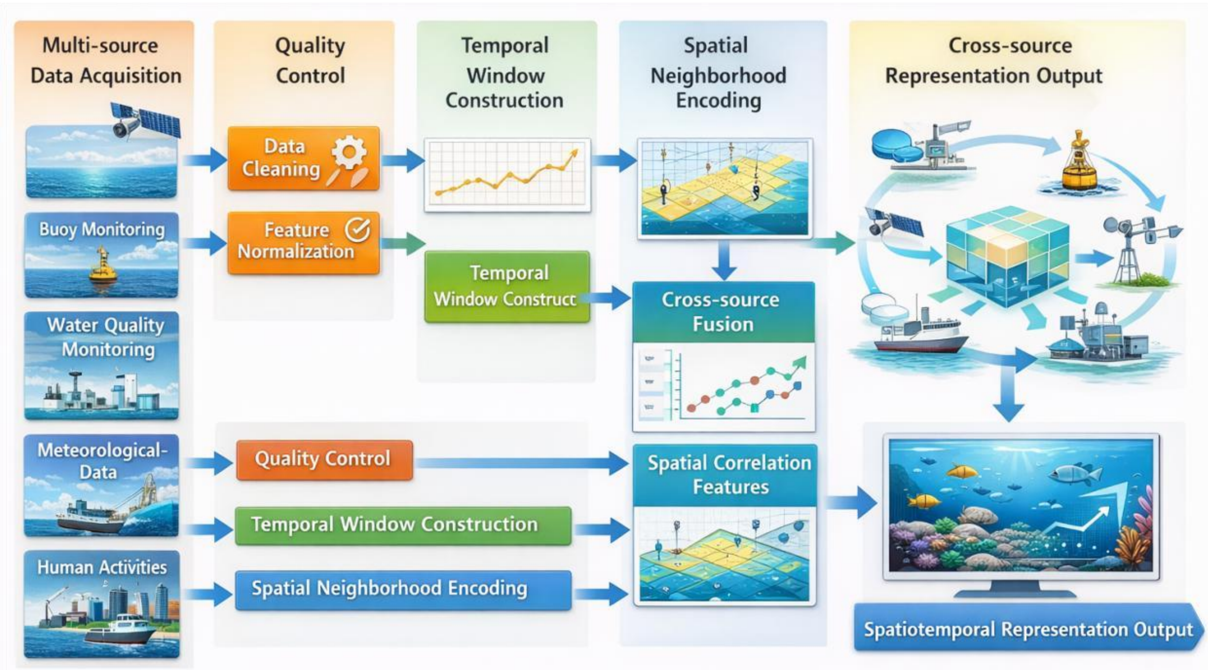

Figure 2: Framework diagram of spatio-temporal feature expression of multi-source Marine ecological environment data

To illustrate the specific composition of the feature expression layer, the composition of multi-source Marine ecological environment features is shown in Table 2.

Table 2: Composition Table of multi-source Marine ecological environment characteristics

Feature Dimension	Specific Indicators	Temporal Scale	Spatial Scale	Processing Method
Hydrodynamic Features	Sea Surface Temperature, Sea Surface Salinity, Flow Velocity, Flow Direction	Daily Scale, Weekly Scale	Grid Cell, Sea Area Unit	Missing Value Completion, Normalization, Window Construction
Water Quality Environmental Features	Dissolved Oxygen, Nutrients, Suspended Particulate Matter, pH Value	Daily Scale, Monthly Scale	Monitoring Transect, Sea Area Unit	Outlier Removal, Standardization, Differential Calculation
Ecological Productivity Features	Chlorophyll Concentration, Primary Productivity Index	Weekly Scale, Monthly Scale	Remote Sensing Pixel, Grid Cell	Remote Sensing Retrieval, Smoothing, Temporal Encoding
Meteorological Forcing Features	Wind Speed, Precipitation, Air Temperature, Radiation	Daily Scale	Regional Scale, Grid Cell	Alignment Interpolation, Trend Decomposition
Remote Sensing Texture Features	Water Color Index, Turbidity Texture, Surface Reflectance Features	Weekly Scale, Monthly Scale	Pixel Scale	Convolutional Extraction, Statistical Aggregation
Human Activity Features	Shoreline Development Intensity, Emission Pressure, Port Disturbance	Monthly Scale, Seasonal Scale	Bay Unit, Nearshore Unit	Index-Based Processing, Hierarchical Encoding
Temporal Evolution Features	Sliding Window Sequence, Change Gradient, Periodic Fluctuation Term	Continuous Time Series	Unit Scale	Sequence Construction, Differential Enhancement
Spatial Correlation Features	Neighborhood Mean, Spatial Weight, Local Similarity	Synchronous Time Point	Neighborhood Unit	Adjacency Encoding, Weight Aggregation

Table 2 shows that the spatio-temporal feature expression in this paper constructs a feature system with temporal continuity and spatial correlation around multiple dimensions such as hydrology, water quality, ecology, meteorology and human activities. Through this way of expression, the model can more fully identify the potential structure of typical sea ecological environment change, and provide a more explanatory feature basis for the state discrimination and prediction output of the next section.

3.3 State discrimination and prediction output for ecological environment change trend

After obtaining the spatio-temporal feature representation of multi-source Marine ecological environment data, how to effectively transform high-dimensional features into interpretable ecological state categories and trend prediction results is a key link in the application of the model. Different from general environmental monitoring tasks, the evolution of typical sea ecological environment not only has periodic fluctuations, but also may be accompanied by sudden disturbances, continuous degradation or recovery changes. Therefore, the output layer should not only stay in a single numerical prediction, but also complete state discrimination, trend estimation and risk suggestion at the same time. Based on this, this paper builds a state discrimination and prediction output mechanism for ecological environment change trend based on spatio-temporal feature representation, and realizes the comprehensive expression of the change process of Marine ecological environment through the three-level output path of "category identification-trend estimation - early warning generation".

The state discrimination link is mainly used to identify the development stage of the Marine ecological environment at the current time. Considering the differences in the coupling response strength of indicators such as sea surface temperature, salinity, chlorophyll and dissolved oxygen in different sea units, this paper first performs nonlinear projection on the spatio-temporal fusion features obtained in the previous section to generate the state discrimination score vector:

$$u_i^t = \tanh(W_u r_i^t + b_u) \tag{15}$$

Here, r_i^t represents the spatio-temporal feature representation of spatial cell i at time t, u_i^t is the state semantic vector, and W_u and b_u are mapping parameters. This formula compresses the complex ecological environment features into a more discriminative semantic space, which provides a basis for subsequent state classification.

On this basis, the model further constructs a category response function to judge different ecological states. Assuming that the research objects are divided into four kinds of states: "stable", "fluctuation", "degradation" and "high risk", the discrimination results can be expressed as follows:

$$c_i^t = \arg\max(W_c u_i^t + b_c) \tag{16}$$

where c_i^t is the ecological state category of unit i at time t, W_c and b_c are the parameters of the discriminant layer. Compared with the traditional hard decision method based on threshold, Equation (16) can automatically identify the ecological state boundary according to the joint response relationship of multi-source features, which is suitable for nonlinear classification tasks in complex sea environment.

In the process of trend prediction, this paper does not directly perform static regression on single time feature, but further introduces the coupling of pre and post time period features to enhance the ability to describe the evolution inertia. Let the features at the current time and the last time be rit and rit−1 respectively, then the trend representation vector is defined as follows:

$$q_i^t=\gamma_i^t \odot r_i^t+(1-\gamma_i^t)\odot r_i^{t-1} \tag{17}$$

Here, ⊙ represents the element-wise product and γ_i^t is the dynamic weight vector, which is used to balance the contribution of current and historical features to trend prediction. This formula can highlight the continuous change information and avoid the amplification of short-term fluctuations caused by only making predictions based on the observed values at a single time. Based on the trend representation vector, the model further outputs the range of ecological environment change in the future stage, and combines the setting threshold to generate a risk early warning index:

$$\omega_i^{t+\tau}=\eta_1\hat{y}_i^{t+\tau}+\eta_2 d_i^t+\eta_3 v_i^t \tag{18}$$

Here, $\omega_i^{t+\tau}$ is the comprehensive risk early warning index at the future time $t+\tau$, $\hat{y}_i^{t+\tau}$ represents the trend prediction result, d_i^t represents the degradation intensity of the current state, v_i^t represents the recent fluctuation amplitude, and η_1, η_2, and η_3 are weight parameters. This index brings trend level, state change and volatility features into a unified framework, which helps to promote model output from "predicted value" to "decisionable outcome".

Figure 3 shows the output process of ecological environment state discrimination and prediction. The figure starts from spatio-temporal feature input, and then goes through state semantic mapping, category discrimination, trend estimation, risk index generation and result output, which reflects the process of layer-by-layer transformation from high-dimensional features to ecological state, trend level and early warning information.

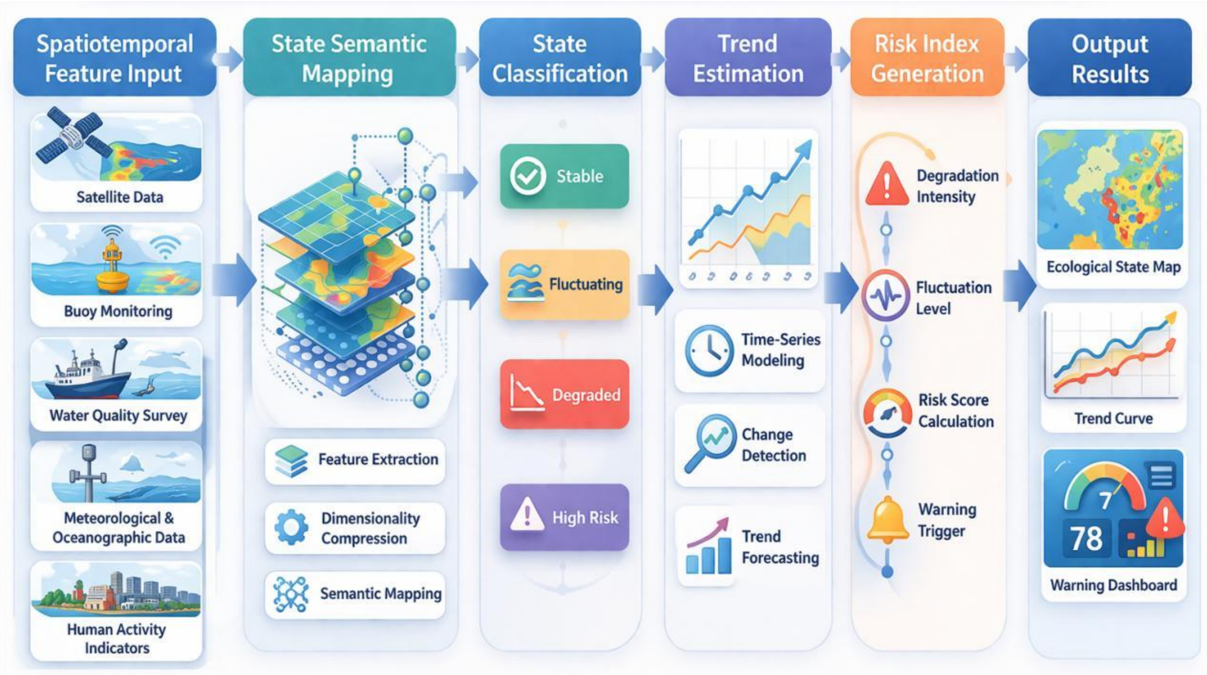

Figure 3: Output flowchart of ecological environment state discrimination and prediction

Figure 3 shows that the output layer of this paper does not simply give the future value of an ecological index, but completes the comprehensive identification of the evolution process of the Marine ecological environment through the cooperation of state discrimination and trend prediction. On the one hand, the state discrimination results can reflect the ecological level of the study area at the current stage. On the other hand, the trend prediction and risk index provide a more forward-looking basis for subsequent ecological management, resource scheduling and early warning decision-making. Through this hierarchical output mechanism, the model can simultaneously take into account the classification interpretation ability and the predictive application value, which lays a direct foundation for the result analysis and model performance verification in Chapter 4.

4 Experiment and result analysis

4.1 Research area, data sources and experimental environment configuration

In order to verify the effectiveness of the model in the analysis of the characteristics and trend prediction of the ecological environment change in the coastal waters, the experiment selected the Hangzhou Bay and the typical coastal waters on both sides of Hangzhou Bay in Zhejiang province as the research object, focusing on the coastal waters of Jiaxing and Ningbo. This region is located in the transition zone between the south of the Yangtze River estuary and the central and northern coastal areas of Zhejiang Province. Due to the joint influence of estuary runoff input, gulf water exchange, port shipping activities, shoreline development and monsoon climate, the ecological environment changes have strong spatio-temporal heterogeneity and regional representative. Water quality fluctuation, nutrient input and coastal development disturbance were more prominent in the coastal waters of Jiexing, while the coastal waters of Ningbo showed more complex ecological response characteristics under the effects of port activities, bay exchange and air-sea coupling factors. Therefore, the joint inclusion of the two areas in the experimental framework was conducive to testing the adaptability of the model to different environmental conditions in the sea.

The research data mainly consists of remote sensing observation data, on-site monitoring data, meteorological and Marine data and human activity statistical data. Remote sensing data were used to extract chlorophyll concentration, sea surface temperature and water color. Field monitoring data were used to obtain water quality variables such as dissolved oxygen, inorganic nitrogen, reactive phosphate, pH and suspended particles. Meteorological and Marine data are used to describe wind speed, precipitation, temperature, and sea level changes. Human activity data are used to describe the intensity of external disturbances such as shoreline development, port throughput and nearshore discharge. The experimental environment uses Python 3.10 and PyTorch deep learning framework to complete data preprocessing, model training and result output. All the samples are divided into training set, validation set and test set according to the time order to ensure that the trend prediction process conforms to the real time series scenario. To further illustrate the study area and the composition of data sources, the relevant information is shown in Table 3.

Table 3: Description of study area and data sources Table

Region Name	Coverage Area	Data Type	Time Range	Spatial Scale	Main Indicators	Data Source
Jiaxing Nearshore Sea Area	Typical nearshore sea area on the northern coast of Hangzhou Bay	Remote sensing data, in-situ monitoring data, meteorological data, human activity data	2020–2024	Combination of grid scale and station scale	Chlorophyll concentration, sea surface temperature, dissolved oxygen, inorganic nitrogen, reactive phosphate, wind speed, precipitation	Remote sensing imagery, nearshore monitoring records, meteorological statistical data
Ningbo Nearshore Sea Area	Typical nearshore sea area on the southern coast of Hangzhou Bay and around Ningbo	Remote sensing data, in-situ monitoring data, marine meteorological data, human activity data	2020–2024	Combination of grid scale and station scale	Chlorophyll concentration, sea surface temperature, suspended particulate matter, dissolved oxygen, nutrients, sea level, port activity intensity	Remote sensing imagery, sea area monitoring records, marine meteorological data
Integrated Experimental Dataset	Combined samples from Jiaxing and Ningbo	Multi-source fused data	2020–2024	Input into the model after unified resampling	Hydrological features, ecological features, meteorological features, human activity features	Results of data collation and unified preprocessing

Table 3 shows that the experimental data in this paper have obvious characteristics of multi-source and spatio-temporal fusion, which can not only reflect the ecological environment differences between Jiexing and Ningbo typical coastal waters, but also provide a relatively complete input variable system for model training, so as to support the development of subsequent change characteristics analysis and trend prediction experiments.

4.2 Evaluation index and design of comparative experiment scheme

In order to comprehensively test the effectiveness of the proposed model in the identification and trend prediction of typical sea ecological environment change, an evaluation system is constructed from two levels of state discrimination performance and continuous value prediction performance. For the task of ecological environment state discrimination, accuracy, precision, recall and F1 value are selected as the core indicators. The precision reflects the reliability of the model in identifying degraded or high-risk samples, the recall reflects the model's ability to capture abnormal ecological states, and the F1 value is used to comprehensively evaluate the balance between precision and recall. For the task of ecological environment trend prediction, the root mean square error, mean absolute error and determination coefficient are selected as the main indicators to describe the prediction effect of the model on the range of ecological environment change, the trend direction and the overall fitting degree. The above indicators can comprehensively reflect the comprehensive performance of the model in classification interpretation ability and numerical prediction ability.

In terms of the design of comparative experimental scheme, this paper takes the proposed model as the core, and compares three typical methods of setting XGBoost, LSTM and support vector model. Among them, the support vector model uses support vector regression in continuous prediction tasks and support vector classification in state discrimination tasks, which are collectively referred to as SVR hereafter for the convenience of unified expression. XGBoost is used to test the performance of ensemble learning methods in multi-source environmental feature modeling, LSTM is used to compare the adaptability of time-series deep models in continuous prediction tasks of Marine ecology, and SVR is used to reflect the benchmark performance of traditional few-shot nonlinear modeling methods. All models use the same data input range and consistent data partition method, and the training set, validation set and test set are kept unified to avoid the deviation of results caused by the difference of sample partition. In order to ensure the fairness of comparison, the parameters of each model are adjusted by the validation set in the training phase, and the experimental runs are completed in the same hardware and software environment.

In addition to the horizontal comparison, this paper also complements the validation of the model from three perspectives: feature contribution analysis, missing rate perturbation experiment and cross-region transfer experiment. The feature contribution analysis is used to illustrate the influence of different ecological variables on the state recognition results, the missing rate perturbation experiment is used to investigate the robustness of the model under the condition of incomplete observation information, and the cross-regional transfer experiment is used to test the generalization ability of the model between the coastal waters of Jiaxing and Ningbo. Through the experimental design of "performance comparison-stability verification-regional migration test", the advantages of the proposed model in the analysis and trend prediction of sea ecological environment change can be more clearly explained.

4.3 Analysis Results of typical sea ecological environment change characteristics

In order to verify the ability of the model to identify the characteristics of the ecological environment change in the typical coastal waters of Jiexing-Ningbo, this paper statistically analyzed the importance of multi-source input variables, and classified and summarized the ecological state discrimination results of different sea units. The comparison of the contribution of different features in the two types of typical sea areas is shown in Figure 4.

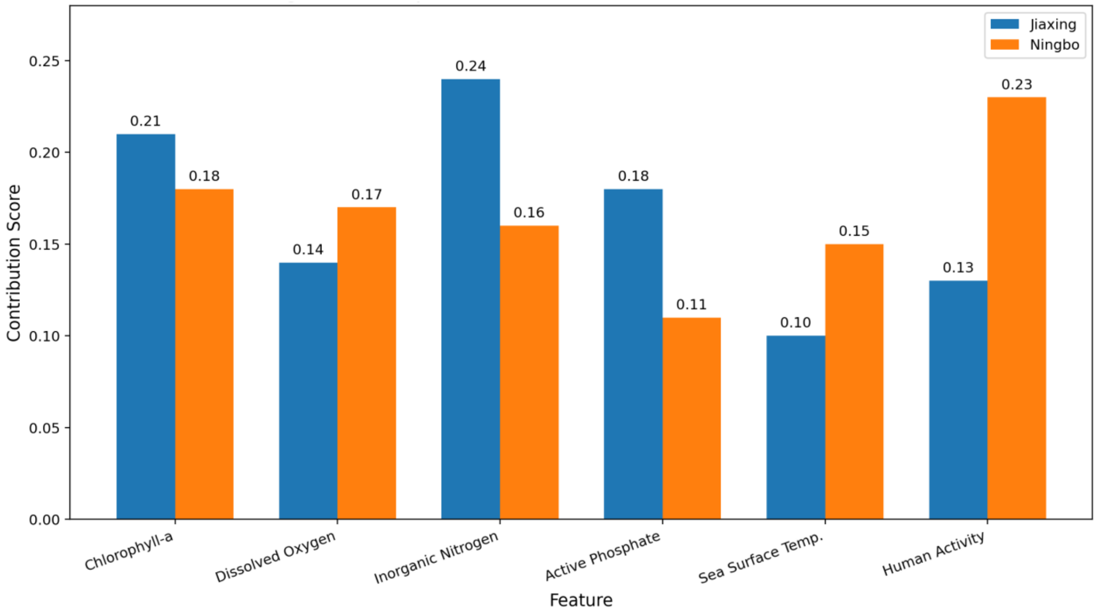

Figure 4: Bar chart of multi-source feature contribution comparison

It can be seen from Figure 4 that the coastal waters of Jianxing are more sensitive to the response of nutrient salt-related factors, in which the contribution of inorganic nitrogen reaches 0.24, chlorophyll concentration and active phosphate are 0.21 and 0.18, respectively, indicating that the terrestrial input and eutrophication process have a stronger driving effect on the ecological changes in this region. The contribution of human activity intensity was the highest (0.23), sea surface temperature (SST) and dissolved oxygen (DO) were 0.15 and 0.17, respectively, indicating that port activities, bay exchange and sea-air disturbance jointly affected the change of ecological status. In general, the Jiaxing sea area shows the characteristics of "nutrient driven", and the Ningbo sea area is more prominent in the characteristics of "human-hydrodynamic coupling", which reflects that the model can clearly distinguish the dominant factors of ecological environment evolution in different regions.

To further illustrate the distribution of state discrimination results in different sea areas, the statistics of ecological state discrimination results in typical sea areas are shown in Table 4.

Table 4: Statistical table of ecological state discrimination results for typical sea areas

Sea Area	Stable / Samples	Fluctuating / Samples	Degraded / Samples	High-Risk / Samples	Total Samples
Jiaxing Nearshore Sea Area	42	71	82	45	240
Ningbo Nearshore Sea Area	58	84	67	31	240
Total	100	155	149	76	480

Table 4 shows that a total of 127 samples were classified as degraded and high-risk in the coastal waters of Jianxing, accounting for 52.9% of the total samples in the region, which is significantly higher than the 40.8% in the coastal waters of Ningbo, indicating that the ecological pressure in the waters of Jianxing is more concentrated. There were 142 samples of stable and fluctuating states in the coastal waters of Ningbo, accounting for 59.2%, which was higher than that of Jiaxing (47.1%), indicating that the overall ecological status of Ningbo was relatively stable, but there were still local high-risk units. Combined with Figure 4 and Table 4, it can be concluded that the proposed model can not only identify the spatial differences of typical sea area ecological states, but also reveal the dominant driving sources of ecological changes in different regions, which provides a more reliable result basis for subsequent trend prediction analysis.

4.4 Prediction results of typical sea ecological environment change trend

In order to further test the ability of the model to describe the evolution process of the typical sea ecological environment, this paper predicts and analyzes the change trend of the comprehensive ecological index in the coastal waters of Jiexing and Ningbo respectively, and compares the predicted results with the real observation sequence. Figure 5 shows the trend prediction curve of typical sea area ecological environment.

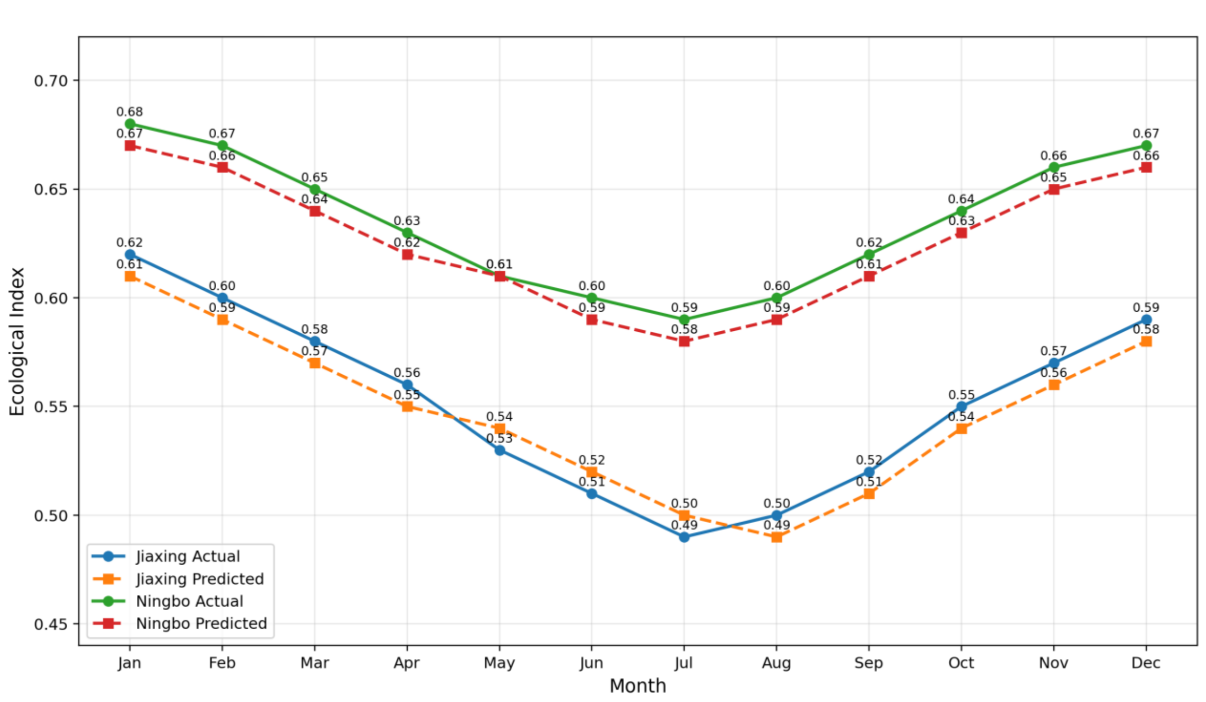

Figure 5: The trend prediction curve of typical sea area ecological environment

It can be seen from Figure 5 that the proposed model can better track the change trend of the ecological environmental index in the two types of typical sea areas. From May to August, the ecological index of Jiaxing coastal waters decreased more obviously, the actual value decreased from 0.53 to 0.49, and the predicted value decreased from 0.54 to 0.50, and the maximum deviation between them was only 0.01. From October to December, the index gradually rebounded, with the actual value rising from 0.55 to 0.59, and the predicted value rising from 0.54 to 0.58. The overall direction of change remained consistent. The trend curve of the coastal area of Ningbo is relatively flat, the fluctuation range of the real value is 0.59-0.68, and the fluctuation range of the predicted value is 0.58-0.67, which indicates that the model also has a good fitting ability to the evolution process of the relatively stable sea area. In general, the model in this paper can simultaneously capture the strong seasonal fluctuation characteristics of the Jiaxing sea area and the stable ecological evolution trajectory of the Ningbo sea area, reflecting a better trend response ability.

To further compare the performance of the models under different prediction step sizes, the comparison of prediction results for multiple time steps is shown in Figure 6.

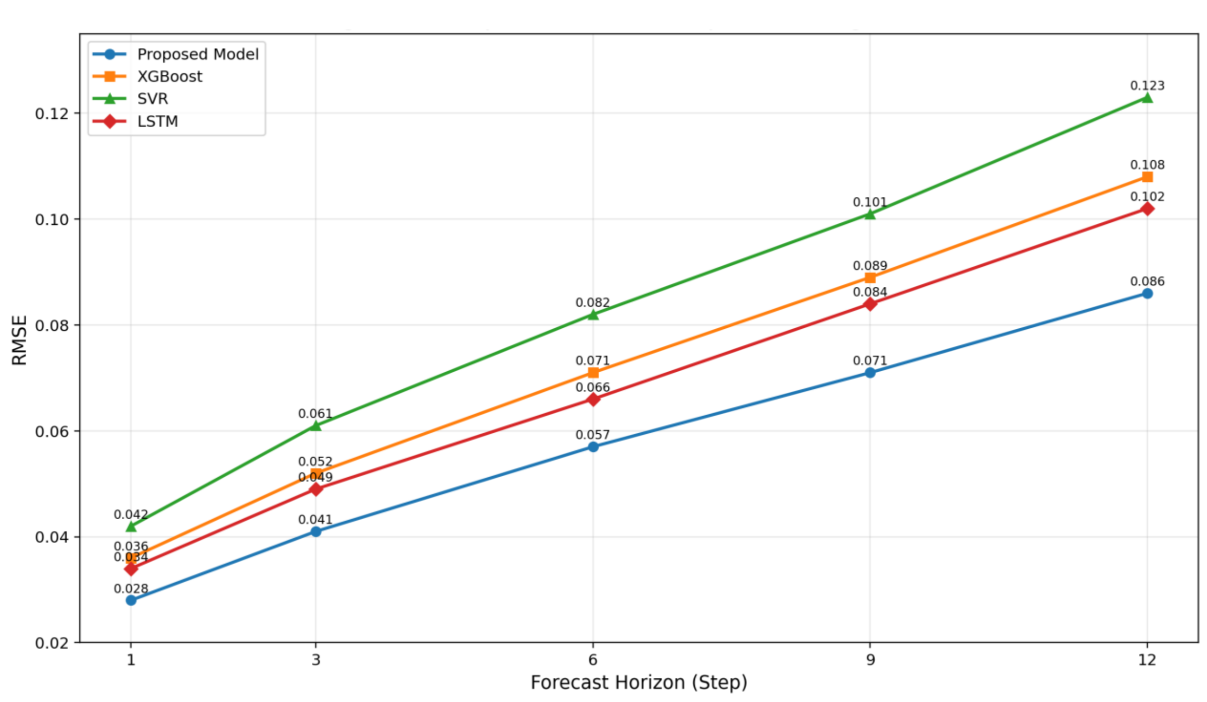

Figure 6: Comparison plot of prediction results for multiple time steps

Figure 6 shows that as the prediction step size increases, each model error shows an upward trend, but the proposed model always maintains the lowest RMSE. In the 1-step prediction, the RMSE of the proposed model is 0.028, which is lower than 0.036 of XGBoost, 0.034 of LSTM and 0.042 of SVR. When the prediction step is extended to 6 steps, the RMSE of the proposed model is 0.057, which is 0.014, 0.009 and 0.025 lower than that of XGBoost, LSTM and SVR, respectively. Under the condition of 12-step prediction, the RMSE of the proposed model is still controlled at 0.086, while the error of the comparison model increases to 0.108, 0.102 and 0.123, respectively. It can be seen that the model in this paper shows better stability and accuracy advantages in short-term prediction and medium-and long-term prediction, indicating that the spatio-temporal feature expression and state discrimination mechanism constructed by the model can effectively enhance the continuous prediction ability of the evolution law of typical sea ecological environment.

4.5 Model robustness and Generalization performance analysis

In order to further test the stability and cross-regional application ability of the proposed model under complex observation conditions, this paper analyzes the robustness and generalization performance from two aspects of data missing disturbance and cross-regional transfer. The former is used to investigate the anti-interference ability of the model under the condition of incomplete input information, and the latter is used to verify the adaptation level of the model when it is transferred and applied between the coastal waters of Jiexing and Ningbo. Figure 7 shows the curve of model performance variation under different missing rates.

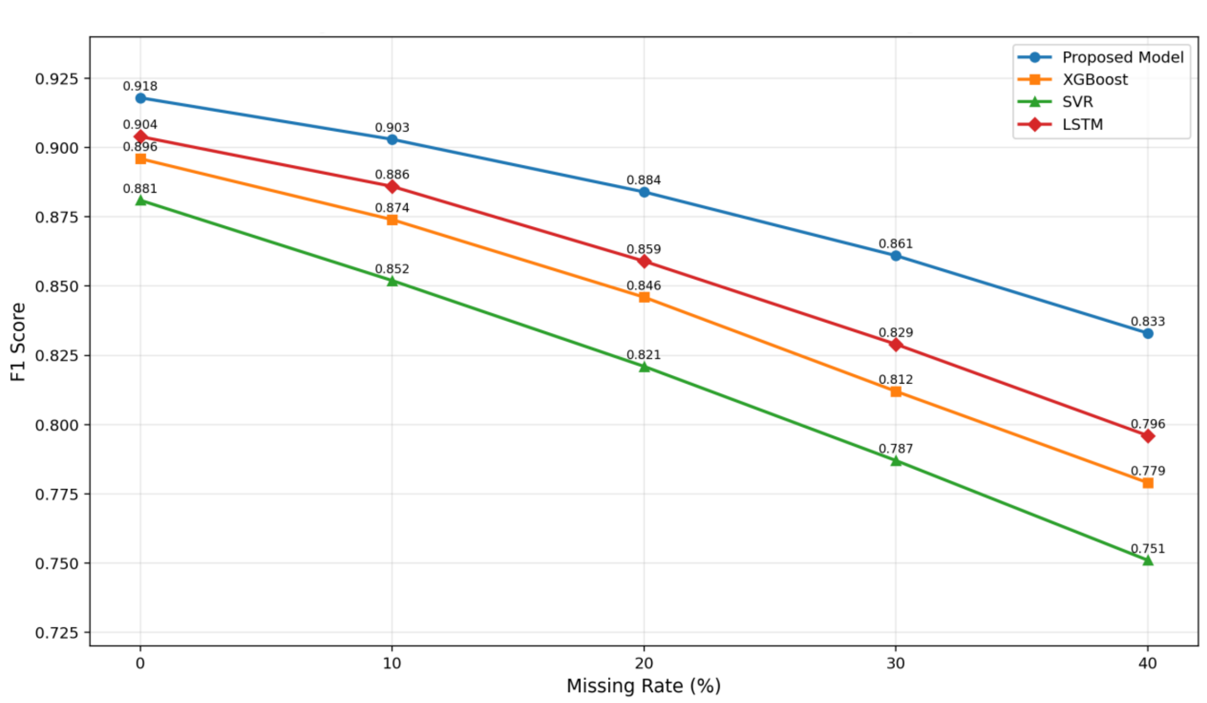

Figure 7: Plot of model performance variation for different missing rates

As can be seen from Figure 7, as the data missing rate increases from 0% to 40%, the F1 values of each model show a downward trend, but the proposed model always maintains the optimal performance. Under the condition of no missing data, the F1 value of the proposed model is 0.918, which is higher than that of XGBoost (0.896), LSTM (0.904) and SVR (0.881). When the missing rate increases to 20%, the F1 value of the proposed model still reaches 0.884, which is 0.038, 0.025 and 0.063 higher than that of XGBoost, LSTM and SVR, respectively. Under the condition of 40% missing rate, the F1 value of the proposed model still remains at 0.833, while the comparison models have dropped to 0.779, 0.796 and 0.751, respectively. The results show that the proposed model has a stronger adaptability to the incompleteness of multi-source observation data, and can maintain the accuracy of ecological state discrimination relatively stable, especially in the scenario of medium and high missing rate.

In order to further investigate the transfer applicability of the model between different sea areas, this paper sets up two types of cross-regional experiments: "Jiaxing training-Ningbo test" and "Ningbo training-Jiaxing test", and the cross-regional generalization ability comparison is shown in Figure 8.

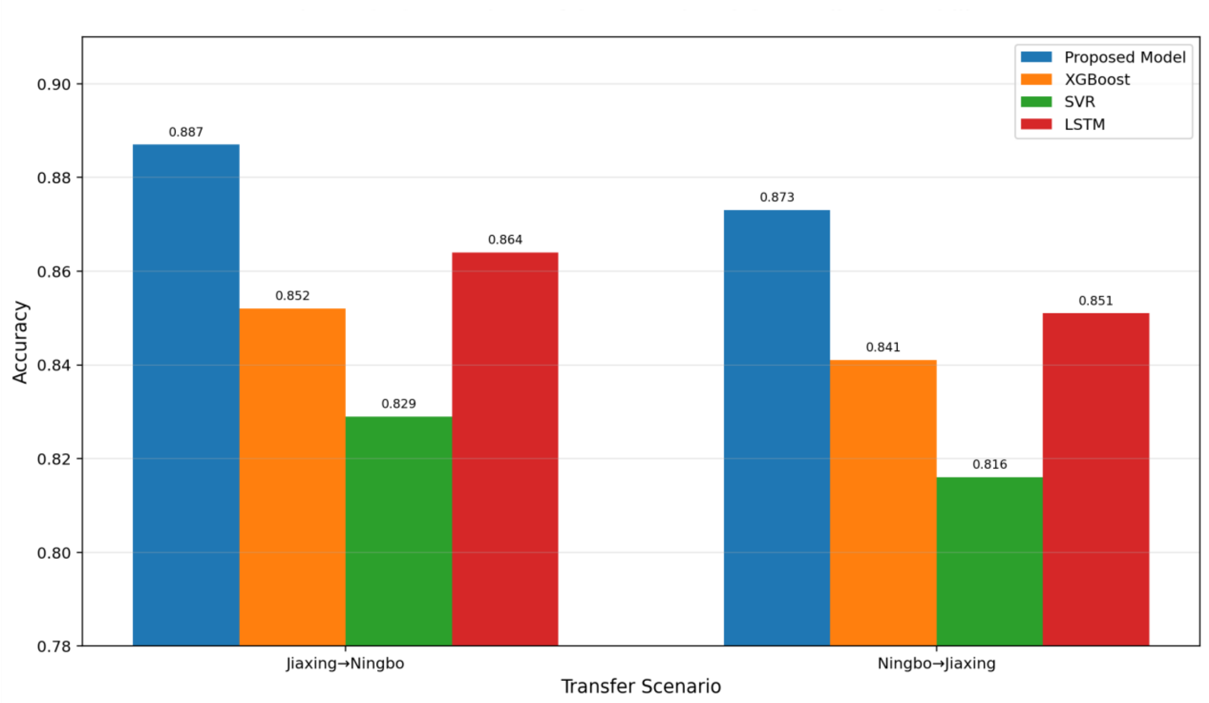

Figure 8: Comparison plot of generalization ability across regions

Figure 8 shows that the proposed model achieves the highest accuracy in both types of cross-region migration scenarios. Under the condition of "Jiaxing → Ningbo", the accuracy of the proposed model reaches 0.887, which is 0.035, 0.023 and 0.058 higher than that of XGBoost, LSTM and SVR, respectively. Under the condition of "Ningbo → Jiaxing", the accuracy of the model in this paper is 0.873, which is still higher than that of XGBoost (0.841), LSTM (0.851) and SVR (0.816). It should be noted that the overall accuracy of "Ningbo → Jianxing" is slightly lower than that of "Jianxing → Ningbo", indicating that the Jianxing sea area is more strongly affected by nutrient input and near-shore disturbance, and the ecological state boundary is relatively more complex, so the migration identification is more difficult. Based on Figure 7 and Figure 8, it can be concluded that the proposed model not only maintains good robustness under the condition of missing data, but also shows strong generalization ability among different coastal waters, which provides a reliable method support for the subsequent monitoring of Marine ecological environment and regional promotion and application.

5 Discussion

In this paper, a machine learning model is constructed around the analysis and trend prediction of typical sea ecological environment change characteristics, and a comparative verification is carried out in the coastal waters of Jiaxing and Ningbo. Combined with the results in Chapter 4, it can be seen that the model can not only identify the dominant factors of different sea ecological environment changes, but also stably complete trend fitting and cross-regional migration prediction. This indicates that integrating multi-source data fusion, spatio-temporal feature expression and state discrimination mechanism into the same framework is an effective way to improve the analysis ability of sea ecological environment.

The results of characteristic analysis showed that the contribution of inorganic nitrogen reached 0.24, chlorophyll concentration and active phosphate were 0.21 and 0.18, respectively, and the proportion of degraded and high-risk samples reached 52.9%, indicating that the ecological change in this region was more likely to be driven by terrigenous input and eutrophication process. In the coastal waters of Ningbo, the contribution of human activity intensity was the highest, which was 0.23, and the proportion of stable and fluctuating samples was 59.2%, indicating that port activities, bay exchange and air-sea factors jointly shaped the complex but relatively stable ecological evolution pattern in this region. This regional difference is highly consistent with the nearshore environmental background of the two places, which also indicates that the features extracted by the model in this paper have certain ecological explanatory power, rather than relying solely on numerical fitting results.

From the trend prediction results, the proposed model can well track the change process of the Jiaxing sea area decreasing in summer and rising in autumn and winter, and can also maintain the fitting accuracy of the stable fluctuation characteristics of the Ningbo sea area. In the multi-time step prediction, the RMSE of the model under 1-step and 12-step conditions are 0.028 and 0.086, respectively, which are better than those of the comparison models, indicating that the spatio-temporal fusion expression has a positive effect on the medium-and long-term trend maintenance. At the same time, the F1 value of the model still reaches 0.833 under the condition of 40% missing rate, and the accuracy of "Jiaxing → Ningbo" and "Ningbo → Jiaxing" in the cross-region experiment are 0.887 and 0.873, respectively, indicating that the model has strong adaptability to data missing disturbance and regional differences. This result means that the method is not only suitable for local sea area state analysis, but also has the potential to be extended to adjacent inshore sea areas.

Of course, this paper still needs to be further improved. First, although the experimental data cover the typical sea areas of Jiaxing and Ningbo, the time span is still limited, and it is not sufficient to describe the long-term response to extreme weather, concentrated red tide outbreaks or sudden pollution events. Second, existing models emphasize more on the unified expression of multi-source data, and are still weak in reflecting the causal chain and mechanism constraints in ecological processes. Third, although the state discrimination and trend output have achieved good results, the risk level classification still has a certain experience, which can be dynamically corrected by combining with more detailed business standards. Future research can be further deepened in terms of expanding the sample period, introducing higher resolution Marine remote sensing data, and enhancing the mechanism constraint modeling, so as to further improve the practical value of the model in Marine ecological monitoring and early warning.

6 Conclusion

This paper constructs a multi-source data-driven machine learning research framework for the analysis and prediction of typical sea ecological environment change characteristics, and completes the experimental verification of Jiaxiing-Ningbo coastal waters. The results show that the model can map multiple types of information such as remote sensing, water quality, meteorology and oceanography, and human activities into the spatio-temporal feature space, and then realize the comprehensive recognition of the Marine ecological evolution process through the dual-task output of state discrimination and trend prediction. The results showed that Jiaxing sea area was more easily driven by nutrient input and eutrophcation process, and the contribution of inorganic nitrogen, chlorophyll concentration and active phosphate reached 0.24, 0.21 and 0.18, respectively. In Ningbo sea area, the coupling effect of human activity and hydrodynamic force is more prominent. The model can not only well track the trend of the decline in summer and the rise in autumn and winter of Jiaxing sea area, but also maintain a low error in multi-time step prediction, and still show strong robustness and generalization ability under the condition of data missing and cross-regional migration. In general, the method in this paper has a good potential in the identification of Marine ecological state, trend prediction and regional promotion and application, and the practical value can be further improved by combining longer time series and stronger mechanism constraints in the future.

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