

Environmental Parameters Prediction of Marine Ranching Based on Fuzzy Neural Network

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Abstract: Environmental factors in marine ranch waters feature nonlinearity, time variability and uncertainty. Traditional empirical monitoring methods are difficult to realize accurate prediction of environmental parameters and ecological risk early warning. Taking a typical marine ranch in Laizhou Bay as the research area, this paper selects dissolved oxygen (DO), chlorophyll a (Chl-a) and chemical oxygen demand (COD) as core monitoring indicators, and constructs a prediction and ecological early warning model for marine ranch environmental parameters using the Takagi Sugeno (T-S) fuzzy neural network. Based on monthly monitoring data from January 2023 to December 2024 collected from 22 monitoring stations covering the core artificial reef zone, transition buffer zone and offshore control zone of the marine ranch, MATLAB platform was adopted for data normalization, network initialization, training simulation and case prediction. Seventy percent of samples were randomly selected as the training set and the remaining 30% as the test set. Model predicted outputs were compared with field measured values to analyze model errors and fitting performance. The results show that the T-S fuzzy neural network prediction model achieves high fitting degree for time series variations of DO, Chl-a and COD, with test set errors maintained at a low level. The model can effectively capture precursors of ecological risks such as summer autumn hypoxia and abnormal increase of chlorophyll a in the Laizhou Bay marine ranch. Water quality in most periods of the artificial reef core area meets Grade II standards for seawater quality, while local stations exhibit elevated chlorophyll a and decreased dissolved oxygen in summer and autumn. The proposed model supports short term prediction of key environmental parameters and hierarchical ecological early warning for marine ranches, providing technical support for intelligent monitoring and risk prevention of Laizhou Bay marine ranches.

Keywords: T-S Fuzzy Neural Network, Marine Ranch, Laizhou Bay, Dissolved Oxygen, Chlorophyll-a, Chemical Oxygen Demand.

1. Introduction

Marine ranches restore offshore fishery habitats through artificial reef deployment, stock enhancement and release, representing a vital mode for conservation of offshore fishery resources in China [1]. Laizhou Bay is a semi enclosed shallow gulf in the southern Bohai Sea. Restricted by weak water exchange capacity, it is significantly affected by terrigenous runoff, seasonal thermohaline variation and phytoplankton blooms. Hypoxia and eutrophication events occur frequently, which directly threaten organism survival and ecological security of marine ranches.

Current marine ranch environmental monitoring mainly relies on field sampling and buoy based online data acquisition [2]. Conventional water quality prediction approaches include water quality index methods, multiple regression and grey prediction. Nevertheless, the marine ranch ecosystem involves complex multi factor coupling; marine water environments exhibit strong nonlinear characteristics, which limit prediction accuracy of traditional statistical models and fail to satisfy demands for real time ecological early warning [3]. The back propagation (BP) neural network possesses powerful nonlinear fitting capacity, yet suffers from slow convergence and easy trapping in local optima. The T-S fuzzy neural network integrates fuzzy logic and neural networks [4]. It inherits interpretability from fuzzy inference as well as self-learning capability of neural networks, with advantages of fast convergence and high prediction accuracy. It has been widely applied in prediction and evaluation of offshore and aquaculture water quality [5].

Existing intelligent prediction studies for marine ranches

mostly focus on comprehensive water quality grade evaluation. Research on simultaneous multi parameter prediction targeting dissolved oxygen, chlorophyll a and COD, together with model application for ecological disaster early warning, remains to be further improved. Accordingly, this study takes Laizhou Bay marine ranch as research object, constructs a T-S fuzzy neural network based prediction model for key environmental parameters, realizes time series prediction of critical environmental factors, and establishes an ecological early warning threshold system. It provides technical references for intelligent monitoring and pre disposal of ecological disasters for marine ranches.

2. Materials and Methods

2.1. Overview of the Study Area

Laizhou Bay lies in the southern Bohai Sea (37°05' 37°45' N, 119°05' 120°00' E). It is a semi enclosed shallow gulf with average water depth of 6-8 m, subject to terrigenous runoff inputs from the Yellow River, Weihe River and other rivers. Distinct seasonal cycles are observed. Water column stratification occurs in summer under high water temperature, which easily triggers bottom water dissolved oxygen depletion. Phytoplankton proliferates vigorously during summer and autumn with large fluctuations in chlorophyll a concentration, leading to potential risks of red tide and hypoxia [6]. The study area covers the marine ranch demonstration zone near Furong Island in Laizhou Bay, where large scale artificial reefs are deployed for fishery habitat restoration [7, 8]. Monitoring zones are divided into artificial reef core zone, transition buffer zone and offshore

control zone without artificial reefs for comparative research.

2.2. Sample Collection and Station Layout

Monthly field monitoring was conducted from January 2023 to December 2024. A total of 22 monitoring stations were laid out in accordance with Technical Specification for Marine Ranch Monitoring (SC/T 9112 2023): Artificial reef core zone (10 stations): Dense sampling stations were arranged at the center and boundaries of artificial reef groups to represent primary habitats of the marine ranch. Transition buffer zone (7 stations): Stations were set 2.5 km outside reef areas to reflect environmental gradients radiating from the marine ranch. Offshore control zone (5 stations): Stations were deployed 12.18 km away from the ranch in non-farming waters without artificial reefs to serve as background references. Sample collection, preservation and laboratory

measurement followed Specifications for Oceanographic Survey (GB/T 12763 2007). Measured indicators included dissolved oxygen (DO), chlorophyll a (Chl-a) and chemical oxygen demand (COD). Water temperature and salinity were synchronously recorded as auxiliary variables.

2.3. Evaluation Indicators and Early warning Thresholds

Dissolved oxygen (DO), chlorophyll a (Chl-a) and chemical oxygen demand (COD) were selected as core model input indicators. Grading criteria and ecological early warning thresholds were established referring to Seawater Quality Standard (GB 3097 1997) and relevant specifications for fishery water environments (Table 1).

Table 1. Grading criteria and ecological early-warning thresholds for environmental parameters of Laizhou Bay marine ranch

Grade	DO mg·L ⁻¹	Chl-a μg·L ⁻¹	COD mg·L ⁻¹	Ecological status	Warning level
I	>6	≤2	≤2	Excellent ecology	No warning
II	5-6	2-4	2-3	Good ecology	Attention
III	4-5	4-7	3-4	Fair ecology	Yellow warning
IV	3-4	7-10	4-5	Slight ecological damage	Orange warning
V	<3	>10	>5	Severe ecological damage	Red warning

Decreasing DO and sharp increase of Chl-a indicate potential risks of hypoxia and red tide, which will trigger corresponding ecological early-warning levels.

2.4. Principle of T-S Fuzzy Neural Network Prediction Model

The T-S fuzzy neural network consists of four layers: input layer, fuzzification layer, fuzzy rule layer and output layer. In this study, historical time-series samples of DO, Chl-a and COD are taken as model inputs, and predicted values of environmental parameters at future moments are regarded as outputs. The network adopts a 3-8-1 structure: 3 neurons in input layer, 8 neurons in hidden fuzzification layer and 1 neuron in output layer. Separate sub-models are constructed for each of the three environmental parameters.

(1) Error Loss Function

Squared error is adopted as training loss function:

$$e = \frac{1}{2} (y_d - y_c)^2$$

Where y_d is expected model output from field measurements, y_c is predicted output of neural network, e is training error.

(2) Network Parameter Updating

Gradient descent algorithm is applied for back-propagation updating of membership-function centers, widths and consequent coefficients:

$$p_j^i(k) = p_j^i(k-1) - \alpha \frac{\partial e}{\partial p_j^i}$$

$$c_j^i(k) = c_j^i(k-1) - \beta \frac{\partial e}{\partial c_j^i}$$

$$b_j^i(k) = b_j^i(k-1) - \beta \frac{\partial e}{\partial b_j^i}$$

Where p_j^i is consequent coefficients of network; c_j^i and

b_j^i is center and width of Gaussian membership function, respectively; α and β are learning rates.

2.5. Model Construction Procedures

The T-S fuzzy neural network was implemented on MATLAB platform with the following steps:

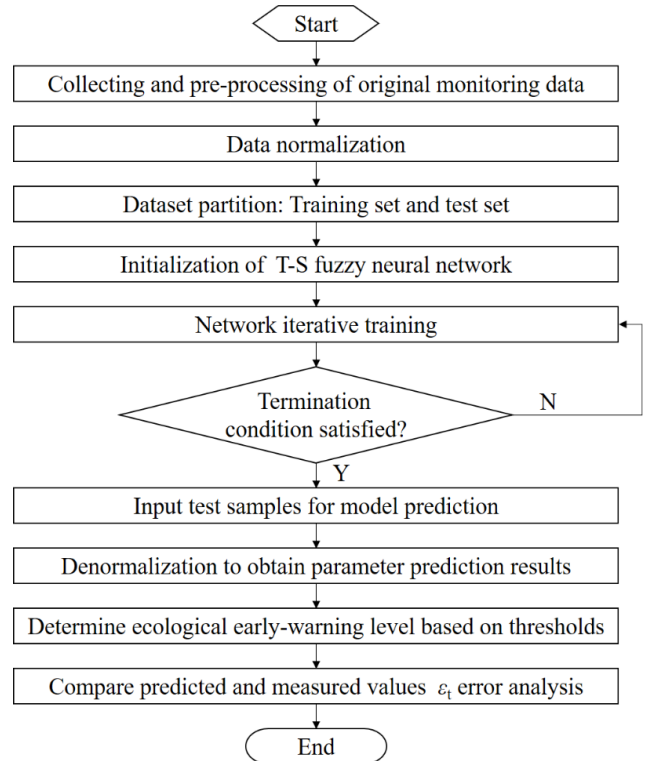


Figure 1. Workflow of T-S fuzzy-neural-network-based prediction and ecological early-warning for marine-ranch environmental parameters

(1) Data preprocessing: The ‘mapminmax’ function was used to normalize raw monitoring data of DO, Chl-a and COD into the range [-1, 1]. Outliers were eliminated and small

amounts of missing data were interpolated using adjacent time series values.

(2) Dataset partition: Seventy percent of total time series samples were randomly selected as training set and 30% as test set.

(3) Network initialization: Membership functions, network weights and learning rates were initialized; maximum iteration number was set as 200.

(4) Network training: Training samples were fed into the network. Output errors were calculated, and network parameters were iteratively updated via gradient back propagation until convergence or maximum iterations were reached.

(5) Simulation and model testing: Test set samples were imported into the trained network to obtain predicted environmental parameter values, which were denormalized to restore real physical magnitudes.

(6) Ecological early warning judgment: Predicted DO, Chl-a and COD values were compared with thresholds in Table 1 to output ecological early warning levels.

(7) Result comparison: Predicted values were compared against measured values. Root mean square error (RMSE), mean absolute error (MAE) and coefficient of determination (R²) were calculated to evaluate model performance.

General technical workflow of the model is shown in Figure 1.

3. Results and Analysis

3.1. Spatiotemporal Characteristics of Environmental Parameters in Laizhou Bay Marine Ranch

Monitoring results from January 2023 to December 2024 are summarized below:

Artificial reef core zone: DO mostly ranged from 5.1-8.4 mg/L throughout the year. Bottom water DO decreased significantly in July August summer, dropping to 4.2 mg/L at some local stations. Chlorophyll-a exhibited prominent summer autumn fluctuations, reaching 5.8-7.2 $\mu\text{g/L}$ at several stations. COD values were mostly lower than 3 mg/L. Water quality generally satisfied Grade-II seawater criteria, with yellow warning risks in summer autumn.

Transition buffer zone: Influenced by diffusion of terrigenous runoff, Chl-a and COD concentrations were slightly higher than those in the artificial reef core zone. Some stations reached orange warning thresholds during summer and autumn.

Offshore control zone: Environmental parameters remained relatively stable. DO stayed within 5.6-8.7 mg/L

and chlorophyll a was mostly below 3.5 $\mu\text{g/L}$. Water quality was overall better than that of the ranch buffer zone.

Obvious seasonal variations existed for Laizhou Bay marine ranch. Summer high temperature and water column stratification constitute high risk periods for hypoxia. Sufficient nutrients in summer autumn stimulate phytoplankton proliferation, raising chlorophyll-a concentration and bringing potential risks of eutrophication and red tide, which calls for prediction driven early warning.

3.2. Training and Simulation Results of T-S Fuzzy Neural Network

Independent T-S fuzzy-neural-network sub-models were built respectively for DO, Chl-a and COD. After 200 iterations, training-set error decreased rapidly and converged. Statistical performance metrics for training-set and test-set predictions are listed in Table 2.

Table 2. Prediction-performance metrics of T-S fuzzy neural network

Predicted parameter	Dataset	RMSE	MAE	R ²
DO/(mg·L ⁻¹)	Training set	0.273	0.211	0.942
	Test set	0.341	0.264	0.915
Chl-a/($\mu\text{g}\cdot\text{L}^{-1}$)	Training set	0.416	0.327	0.927
	Test set	0.508	0.392	0.894
COD/(mg·L ⁻¹)	Training set	0.182	0.143	0.951
	Test set	0.235	0.176	0.923

As shown by performance indicators, the coefficient of determination R² of all three environmental-parameter test sets exceeded 0.89; RMSE and MAE remained at low levels. Predicted temporal trends were basically consistent with field-measurement time series. Due to disturbance from abrupt phytoplankton blooms, prediction errors of chlorophyll-a were slightly larger than those of DO and COD.

Time-series comparison between predicted outputs and measured values of test samples indicates that the model well captures abrupt events such as rapid summer DO decline and sharp Chl-a elevation, showing capability to identify precursors of ecological risks.

3.3. Case Study of Marine Ranch Ecological Early warning

Time-series data (June-September 2024) of a typical station within artificial-reef core zone of Laizhou Bay marine ranch were selected for case prediction. Model-predicted DO, Chl-a and COD values were input into the threshold system to generate early-warning outputs.

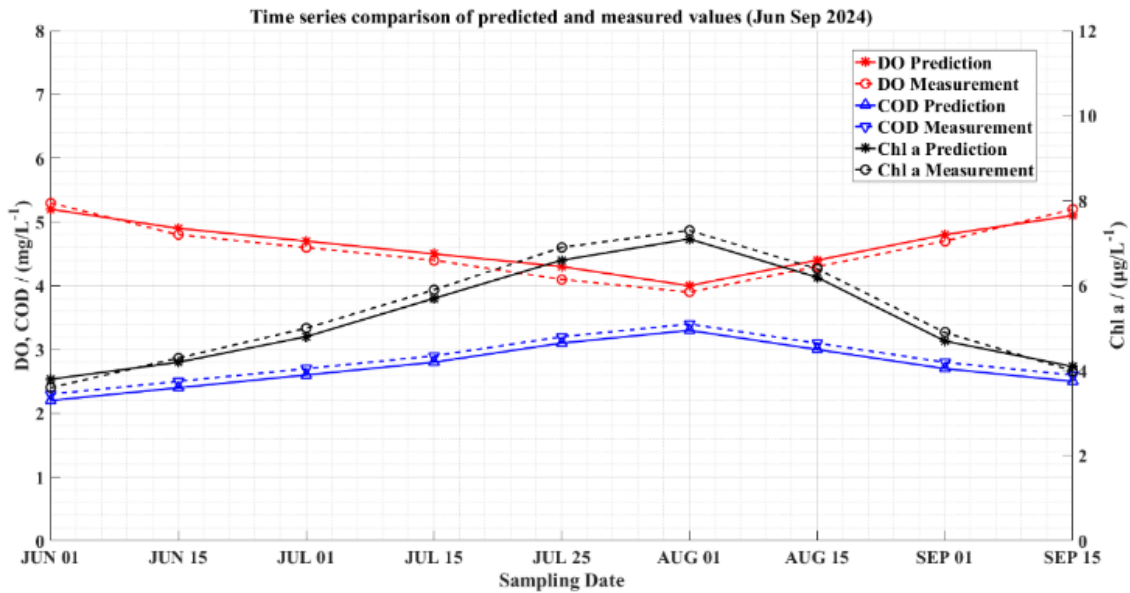


Figure 2. Time-series comparison of predicted and measured DO, Chl-a and COD at typical station in artificial-reef core zone of Laizhou Bay marine ranch (June-September, 2024).

Figure 2 shows the time-series comparison between model-predicted values and field-measured values of DO, Chl-a and COD at the typical station in the artificial-reef core zone from June to September 2024. As can be seen from Figure 2, the variation trends of predicted curves for the three environmental parameters are highly consistent with measured curves. Around July 25, chlorophyll-a rose rapidly and dissolved oxygen decreased obviously, and this abrupt process was captured in advance by the model. At this moment, the predicted DO was 4.3 mg/L and predicted Chl-a was 6.6 µg/L, triggering the yellow ecological early-warning. The measured DO was 4.1 mg/L and measured Chl-a was 6.9 µg/L, which also met the threshold of yellow warning. COD fluctuated mildly throughout the period with minor deviation between prediction and measurement. In early August, dissolved oxygen reached its minimum value in this monitoring period. The model predicted a potential evolution toward orange warning, which was consistent with field observation results. The above results further verify that the T-S fuzzy neural network possesses favorable predictive capacity for sudden ecological risks in marine ranches.

3.4. Discussion on Model Applicability

Compared with traditional BP neural networks, T-S fuzzy neural networks combine fuzzy inference rules and exhibit stronger robustness for noisy, uncertain marine-environmental time-series data with fewer convergence iterations. Nevertheless, as a data-driven model, its prediction accuracy will decrease under rare extreme events such as short-term massive terrigenous-pollutant inputs. Future model optimization can incorporate water temperature and salinity as auxiliary input variables.

4. Conclusions

Targeting ecological monitoring and early warning requirements for Laizhou Bay marine ranch, this study constructed a T-S fuzzy neural network based multi environmental parameter prediction model. Dissolved oxygen, chlorophyll a and chemical oxygen demand were selected as core indicators. Multi station monthly time series monitoring data (2023 2024) of the marine ranch were used for network training, simulation validation and early warning

case analysis.

(1) The T-S fuzzy neural network delivers favorable prediction performance for DO, Chl-a and COD of Laizhou Bay marine ranch, with test set (R^2) all above 0.89. It can effectively capture precursors of summer autumn ecological risks including hypoxia and abnormal chlorophyll a elevation, and realize hierarchical ecological early warning (yellow, orange and red warning).

(2) Water quality in artificial reef core zone of Laizhou Bay marine ranch meets Grade II seawater standards for most of the monitoring period. Summer (July August) represents a high risk ecological window: bottom water dissolved oxygen declines and chlorophyll a rises, triggering yellow warnings at some stations which should be prioritized for monitoring.

(3) The proposed prediction early warning model can be embedded into intelligent marine ranch monitoring platforms. Short term environmental parameter prediction can be realized using buoy online time series data, providing decision making support for ecological disaster prevention and fishery production management for marine ranches.

Future research may introduce more auxiliary input factors including water temperature, salinity and nutrients. High frequency hourly buoy time series data can be adopted to optimize network architecture and further improve prediction performance under extreme ecological events.

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