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Construction of a computational model for ecological environment change assessment based on coordination of multi - source remote sensing data

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ABSTRACT

The model that evaluates the integrated condition of the ecological environment of the lake Taihu is created in conjunction with remote sensing satellite images, ground monitoring data, and other such geo-sourced information. This paper provides a comprehensive assessment framework integrating water quality measures, vegetation indices, and atmospheric conditions to assess-temporal and spatial variations of lake ecosystems. Analysis of five years (2019-2023) of monitoring data reveals significant spatial heterogeneity in water quality parameters, with distinct increase in degradation within the northern and western parts of the lake. Characterised pan-regional eutrophication indicators show clear zonation patterns which are largely distributed in areas of increased human use and zonal hydrodynamic conditions. Seasonal analysis indicates distinct differences in water quality parameters prompting an increase in algal bloom within the summer months. Target areas are designated and analysed in this study and are reflective of critical conditions that require immediate management control measures german Meiliang Bay and the Western Zone. Methodological testing reflects a congenial result resulting in models with high accuracy ($R^2 > 0.89$) and reliability within diverse temporal and spatial range. Data obtained partially or largely complement ecological management policy and enable such policies to be formulated where monitoring the health of a lake's ecosystem and addressing its restoration is key.

Keywords: Multi-source remote sensing, Ecological environment assessment, Water quality monitoring, Model validation, Lake Taihu; Eutrophication; Spatial-temporal analysis, Environmental risk assessment, Ecosystem management, Water quality parameters

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1. Introduction

The development of cities and the exploitation of natural resources can damage the ecological environment, causing ecological and environmental problems such as declining air quality, frequent floods, serious destruction of vegetation, and heavy metal pollution of soil and water, which affects the sustainable development of the region and social stability [1-4]. Ecological environment quality is based on ecology and environmental science, reflecting the suitability of the study area for human survival and sustainable socio-economic development within a specific time frame [5]. And the evaluation of ecological environment quality can reflect the degree of ecological environment change, which needs to be further based on the specific research purpose, select representative, comparable and operable evaluation indexes and methods, qualitative or quantitative analysis and discrimination, to provide new perspectives and ideas for the improvement of ecological environment quality.

In order to realize the evaluation of spatial and temporal changes in ecological environmental quality and the effective prediction of its development trend, experts and scholars have constructed indicator evaluation systems from different perspectives, which are mainly based on statistical methods and mathematical models, including factor analysis, fuzzy evaluation method, urban ecological environment suitability model, and ecological environment condition index, etc. [6-9]. However, these evaluation methods often have subjective index weights, and the effectiveness of the evaluation results is difficult to reflect. In recent years, with the steady progress of remote sensing satellite system in the national civil space infrastructure planning, as well as the vigorous development of commercial remote sensing satellites, the remote sensing data acquisition capacity and quality show a rising trend, and the satellite image constitutes the main body of remote sensing big data [10-14]. Along with the rapid development of remote sensing technology, surface ecological environment monitoring based on remote sensing images has also made significant progress [15-16]. The use of remote sensing technology to objectively assess the ecological environment changes, without human subjective intervention components, makes the evaluation model of ecological quality has a strong robustness, and has been widely used in the process of ecological environment monitoring and improvement in different regions [17-20].

Literature [21] emphasized that remote sensing technology has the outstanding features of rapidity and economy for the management of large areas, and took mountain ecosystems as an example to establish a framework for ecosystem change based on multi-source remote sensing image monitoring, which provides managers with real-time and reliable data analysis results. Literature [22] constructed an ecological environment quality evaluation model based on time-series comprehensive evaluation index, and calculated the time-dependent comprehensive environmental evaluation index (CEI) based on regional remote sensing data, which can provide a reference index for the sustainable development of cities. Literature [23] proposed the remote sensing ecological index model (RSEI), which quantifies the classified multi-source high-resolution satellite images into ecological quality changes, and then visualizes the ecological environment quality in the real time scale of the study into the clustering trend over time. Literature [24] relies on the index distribution calculated from MODIS remote sensing data and nighttime lighting data, combined with the coupling coordination degree model to calculate the degree of coupling between the two, which can be used as a means of assessment to reflect the pressure generated by the urbanization process on the surrounding ecological environment. Literature [25] shows that monitoring water resources of lakes in arid zones is an important aspect of managing regional resources and environments, and the use of satellites to record remote sensing data of lakes and to explain changes in the water level and area of alpine and non-alpine lakes provides data support for evaluating the health of the ecosystem and its sustainable use. Literature [26] established a quantitative ecological environment vulnerability evaluation model using multi-source remote sensing data, which can not only calculate the ecological environment vulnerability index in the region at a certain moment in time, but also explore the trend of the regional ecological environment in the spatial and temporal distribution dimensions, and improve the efficiency of ecological environment monitoring.

The goal of this research is to develop a model for assessing the ecological environment changes founded on the multi-source remote sensing data coordination. Specifically, the model will use satellite remote sensing data, ground monitoring data, auxiliary data, and multidisciplinary aspects such as water quality, vegetation, and meteorological conditions to ensure both monitoring and assessment of ecological environment alterations. This research will assist in making science-based decisions with regards to measures that will be taken to protect the ecological environment, hence having both theoretical and practical implications to ensure proper regional sustainable development.

In the process of climate change alongside severe human activities, there is need to develop an eco-environment model that can be able to provide efficient and accurate results. This research is important in deepening the understanding of the ecological environmental changes and has also introduced some useful tools which can be used in decision making and management of the environment. The use of multi-source remote sensing data provides a unique perspective in evaluation and monitoring of the ecological environment changes regardless of the temporal and spatial scales thus improving protection measures and restoration plans.

2. Data sources and research methods

As the third largest lake, Lake Taihu is crucial in the freshwater network in China. The lake is located predominantly in both Jiangsu and Zhejiang provinces, and the total area of the lake is 2338 sq km (Figure 1).

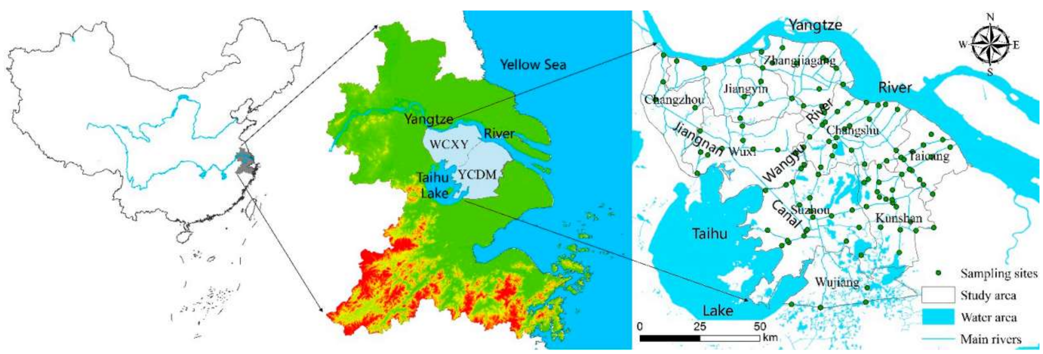


Fig. 1. Geographical location and administrative boundaries of Lake Taihu Basin

The lake basin includes the cities of Suzhou, Wuxi, and Huzhou and provides a crucial economic and ecological corridor in eastern China. Lake Taihu Greatest Maximum depth is 2.6 meters where the normal water level is 3.00 meters, and it has an average depth of 1.9 metres. It is also fundamental to the management of water resources and the balance of the ecological system within the region. The hydrology of the lake basin can be characterized in terms of wet periods and dry periods, with a 320 day depth cycle and water inflow of 5.72 cubic kilometers per year. The diversity that the lake possesses contributes significantly to its ecology, for example, 106 species of fish, 8 types of shrimp, 3 types of crabs, and more than 60 kinds of other aquatic life. This aquatic environment has been a key contributor to ecosystem services in the past such as water provision, fish culture, and regulation of the environment. Nevertheless, the last several decades have been characterized by significant improvements. rapid urban growth and industrial transformation around the area which has resulted in increased environmental pressures.

The climate of the lake basin region can be distinguished into a subtropical monsoon, receiving an average of 1,100 mm and having temperatures ranging between 15 to 17°C. The climatic conditions together with the shallow lake depth and relatively high surface area makes it easily vulnerable to ecological shifts and other disturbances. As illustrated by Figure 1, the Lake features a long shoreline which is adjacent to a variety of land uses such as urban and agricultural areas; the combination of these two creates varying interactions with the environment.

Rehabilitation and Development of Lake Taihu is even more saddened due to the fact the lake is located within the borders of different administrative regions and requires all of these regions to foster fluid communication for monitoring and protection. Water quality of the Lake Taihu has been under scrutiny for concern as it poses great risk to water security along regions that experience algal blooms that result from the lake's water eutrophication. Such administrative and geographic aspects surrounding the Lake Taihu provide a conducive environment for its' integration into model that enables stakeholders to combine and use variety of data.

2.1. Data source and preprocessing

This research integrates various remote sensing data platforms to performs the environmental evaluation of the Lake Taihu ecosystem in great detail. The satellite imagery data was acquired from Landsat 8 OLI/TIRS and Sentinel-2 MSI sensors within the range of 2019 to 2023, with spatial resolutions of 30m and 10m respectively. Ground monitoring data was also acquired from the existing monitoring centers situated around Lake Taihu such as the concentration of chlorophyll-a, total phosphorus and total nitrogen content.

During preprocessing, the integrity and uniformity of the datasets were upheld through a detailed and meticulous workflow. For both Landsat and Sentinel-2 data, atmospheric correction was carried out with an aid of the FLAASH module and Sen2Cor processor respectively. Geometric correction and image registration were undertaken with RMSE values lower than 0.5 pixels. Quality assurance for the water quality data encompassed outlier analysis, water quality temporal validation, evaluation of sensors performance, and others. Characteristic based spatiotemporal interpolation techniques were employed to counter missing data. All remote sensing data were projected to an identical spatial reference and bilinear interpolation algorithm was employed to resample the data sets to 30m resolution for coherent analysis.

2.2. Study Methods

The combination of an Ecological Environment assessment and analysis from different remote sources forms an integrated research methodology. The Remote Sensing Ecological Index (RSEI) framework has been adjusted to suit the general environmental conditions of Lake Taihu. This modified framework incorporates four constituents: greenness, moisture, dryness and quality of water indices, which are derived from spectral info and ground measurements, into one.

The time spent in analyzing the parameters of satellite images and the monitored ones decreased considerably, thanks to a fusion algorithm that was designed along the guidelines of machine learning. A random forest model is utilized to affect auxiliary regression parameters which assist in linking remote sensing indices with their corresponding environmental conditions, thus helping to meet the need for improved spatial predictive accuracy. A time series decomposition technique to shine a light on historic sequences and seasonal trends was employed, and this temporal analysis was implemented in the research. This model considers the Pressure-State-Response (PSR) modelling and so demonstrates a flow of three different but interrelated sets: the pressures which drove the environmental changes, the state in which the environment was after the changes, and the several responses the change evoked. Validation of the model was done through a statistics approach using sets of independent data, whereas multiple accuracy indicator sets such as RMSE, R^2 and MAE were utilized to evaluate the usefulness of the method. The method focuses on the spatial heterogeneity of the ecological processes while providing a consistent assessment of the results in time.

3. Construction of ecological environment assessment model

3.1. *Model frame design*

The framework of the environmental model assessment relates with the integration of data captured from different remote sensing as well as ground measurements to conduct evaluations of the environment in great detail (see Figure 2). The framework is multilevel and constitutes three major components namely acquisition and pre-processing of data, fusion of multi-source data and ecological assessment modules. This framework, as the figure depicts, allows integration of different data sources while ensuring that the processes remain analytical through the use of standard operational protocols.

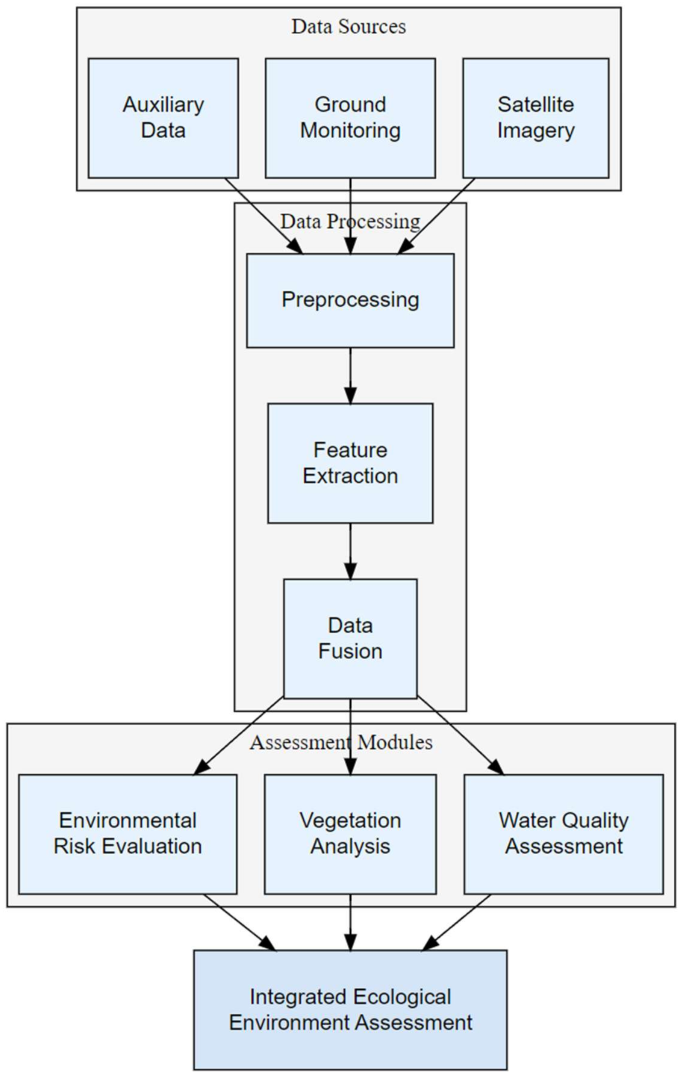


Fig. 2. Framework of the multi-source remote sensing-based ecological environment assessment model

The sophisticated machine learning algorithms guarantee resource utilization efficiency, aiding the fusion of several data channels. The evaluation block captures both the spatial and time factors of the conditions altered in the environment, and the last stage of integration merges partial evaluations into an evaluation composite index. This modular structure enables methodological invariance to be preserved while adapting to diverse geographical contexts.

3.2. Evaluation index system

Sustainable development, ventilation systems, as well as water and waste management have all Headings of Table 1. Environmental quality assessment is approached from a management perspective as an index system constructed hierarchically spanning several levels. For this purpose the technique of remote sensing and ground measurements are combined in this comprehensive system. As it can be seen from Table 1, the indicators are categorized into four primary dimensions: water environment, vegetation condition, land surface characteristics, and atmospheric environment.

Table 1. Hierarchical Structure of Ecological Environment Assessment Indicator System

Target Layer	Criterion Layer	Indicator Layer	Weight	Data Source	Unit
Ecological Environment Quality	Water Environment	Chlorophyll-a	0.15	Satellite/Ground	μg/L
		Total Phosphorus	0.12	Ground Monitoring	mg/L
		Total Nitrogen	0.13	Ground Monitoring	mg/L
		Water Transparency	0.10	Ground Monitoring	m
	Vegetation Condition	NDVI	0.12	Satellite	-
		LAI	0.08	Satellite	m^2/m^2
		Vegetation Coverage	0.10	Satellite	%
	Land Surface	LST	0.08	Satellite	°C
		NDBI	0.05	Satellite	-
		Soil Moisture	0.04	Satellite	%
	Atmospheric Environment	PM2.5	0.08	Ground Monitoring	$\mu g/m^3$
		PM10	0.05	Ground Monitoring	$\mu g/m^3$

As per analytic hierarchy process and expert consultation each indicator is given a specific weight. Combining these indicators makes the qualitative environmental evaluation quite comprehensive as they take into account both natural and human-made influences on the environment. This also guarantees the assessment results to be tactically strong and reliable whilst ensuring the results are sensitive to the nuances of a given area.

3.3. Multi - source data collaboration mechanism

The coordination mechanism of multi-source data is intended to manage the streams of different RS data types cohesively and protect the data quality and consistency in respect of time (Figure 3). This mechanism utilizes ‘sensor’ fusion to overcome the difficulties of different spatial and temporal resolutions from multiple sources. According to Figure 3, the coordination activity captures both vertical and horizontal integration modalities and thus enabling constant evaluation of the environment.

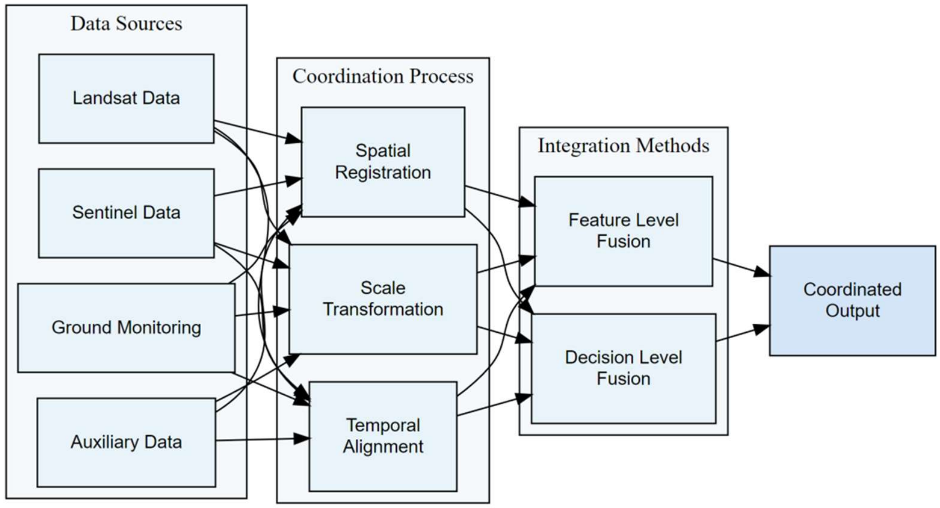


Fig. 3. Multi-source data coordination mechanism framework

The structure incorporates sophisticated algorithms for time and space analysis ensuring perfect registration of different data streams. To ensure there is minimal overlap and redundancy, feature-level and decision-level combining techniques are used to aid the extraction of the maximum amount of information. This integrated approach also enhances environmental evaluation by utilizing the strengths of the various data sources and compensating for their weaknesses.

3.4. Model implementation

The model implementation integrates multiple algorithmic components to achieve comprehensive ecological environment assessment based on multi-source remote sensing data. The core computational framework consists of three primary modules: data fusion, index calculation, and comprehensive evaluation.

The normalized remote sensing ecological index (RSEI) is modified to incorporate water quality parameters. The basic form of the modified index is expressed as:

$$RSEI = \left(\alpha \cdot N + \beta \cdot W + \gamma \cdot H + \delta \cdot D\right) / \left(\alpha + \beta + \gamma + \delta\right) \tag{1}$$

where N represents the normalized vegetation index, W denotes the water quality component, H indicates the humidity index, D represents the degree of development, and α, β, γ, and δ are the corresponding weights determined through analytical hierarchy process.

The water quality component (W) is calculated by integrating multiple parameters:

$$W = \sum_{i=1}^{n} \omega_i \cdot \left(\frac{C_i - C_{min}}{C_{max} - C_{min}} \right) \tag{2}$$

where C_i represents the concentration of the i-th water quality parameter, C_{max} and C_{min} are the maximum and minimum values respectively, and ω_i is the weight of each parameter.

The vegetation index component incorporates seasonal variations through a time-weighted approach:

$$N = \frac{1}{T} \sum_{t=1}^{T} \lambda_t \cdot NDVI_t \tag{3}$$

where $NDVI_t$ represents the Normalized Difference Vegetation Index at time t, λ_t is the temporal weight, and T is the total number of temporal observations.

For data fusion of multiple satellite sources, a weighted averaging method is implemented:

$$P_{fused} = \frac{\sum_{k=1}^{K} w_k \cdot P_k \cdot R_k^{-1}}{\sum_{k=1}^{K} w_k \cdot R_k^{-1}} \tag{4}$$

where P_k represents the parameter value from the k-th data source, R_k is the corresponding uncertainty, and w_k is the weight assigned based on data quality.

The comprehensive environmental quality index (EQI) is calculated through a hierarchical integration:

$$EQI = \sum_{j=1}^{m} \beta_j \cdot \left(\sum_{i=1}^{n} \alpha_{ij} \cdot X_{ij} \right) \tag{5}$$

where X_{ij} represents the standardized value of the i-th indicator in the j-th criterion layer, α_{ij} and β_j are the corresponding weights at different hierarchical levels.

The model incorporates temporal dynamics through a state-space representation:

$$S_t = f(S_{t-1}, X_t) + \varepsilon_t \tag{6}$$

$$Y_t = g(S_t) + \eta_t \tag{7}$$

where S_t represents the state vector at time t, X_t is the input vector, Y_t is the observation vector, and ε_t and η_t are process and observation noise respectively.

The implementation utilizes machine learning algorithms for parameter optimization. The objective function for model calibration is defined as:

$$\min \sum_{i=1}^{N} \left(Y_i^{pred} - Y_i^{obs} \right)^2 + \lambda \sum_{j=1}^{M} \theta_j^2 \tag{8}$$

where Y_i^{pred} and Y_i^{obs} are predicted and observed values respectively, θ_j represents model parameters, and λ is the regularization coefficient.

Model validation employs multiple statistical metrics, including the Nash-Sutcliffe efficiency coefficient:

$$NSE = 1 - \frac{\sum_{i=1}^{N} (O_i - P_i)^2}{\sum_{i=1}^{N} (O_i - \bar{O})^2} \tag{9}$$

where O_i represents observed values, P_i represents predicted values, and $\bar{O}$ is the mean of observed values.

This comprehensive implementation framework ensures robust ecological environment assessment while maintaining computational efficiency and scientific rigor. The model's modular structure allows for flexible adaptation to different regional contexts and data availability scenarios while preserving the fundamental physical and ecological relationships represented in the mathematical formulations.

4. Application of ecological environment assessment in Taihu Lake based on multi-source remote sensing data

4.1. Spatiotemporal evolution characteristics of water quality parameters

4.1.1. Analysis of eutrophication indicators. The analysis of eutrophication indicators in Lake Taihu reveals significant spatial and temporal patterns during the study period (2019-2023). As shown in

Figure 4, the spatial distribution of key eutrophication indicators demonstrates distinct heterogeneity across the lake. The chlorophyll-a concentrations exhibit notable spatial variation, with higher values (>50 μg/L) predominantly observed in the northern and western regions, particularly during summer months. Total phosphorus concentrations show a gradient pattern, with elevated levels (>0.1 mg/L) concentrated in near-shore areas, especially in proximity to urban and agricultural zones. Total nitrogen distribution patterns indicate substantial spatial variability, with concentrations ranging from 1.5 to 3.5 mg/L across different lake segments.

Temporal analysis of water quality parameters (Figure 5) reveals clear seasonal fluctuations and long-term trends. Chlorophyll-a concentrations demonstrate pronounced seasonal periodicity, with peak values typically occurring during July-August and minimum values during January-February. The temporal variations in total phosphorus and total nitrogen concentrations show similar seasonal patterns but with different magnitudes of fluctuation. Statistical analysis of these parameters (Table 2) indicates significant inter-annual variability, with a slight increasing trend in eutrophication indicators over the five-year period.

Table 2. Statistical characteristics of water quality parameters in Lake Taihu (2019-2023)

Parameter	Mean ± SD	Range	CV (%)	Seasonal Peak	Trend (2019-2023)
Chlorophyll-a (μg/L)	42.5 ± 18.3	15.2-89.7	43.1	Summer	+5.2%
Total Phosphorus (mg/L)	0.085 ± 0.032	0.042-0.156	37.6	Summer	+3.8%
Total Nitrogen (mg/L)	2.24 ± 0.58	1.45-3.68	25.9	Winter	-2.1%
Water Temperature (°C)	17.8 ± 8.4	4.2-32.5	47.2	Summer	+0.3%
Transparency (m)	0.65 ± 0.22	0.25-1.15	33.8	Winter	-4.5%
pH	8.2 ± 0.4	7.2-9.1	4.9	Summer	Stable

CV: Coefficient of Variation; SD: Standard Deviation; Trend: Average annual change rate.

The comprehensive analysis of these indicators suggests that Lake Taihu continues to face significant eutrophication challenges, with spatial patterns strongly influenced by local inputs and hydrodynamic conditions. The observed temporal variations reflect both natural seasonal cycles and anthropogenic impacts, highlighting the need for continued monitoring and management efforts to control nutrient inputs and mitigate eutrophication risks.

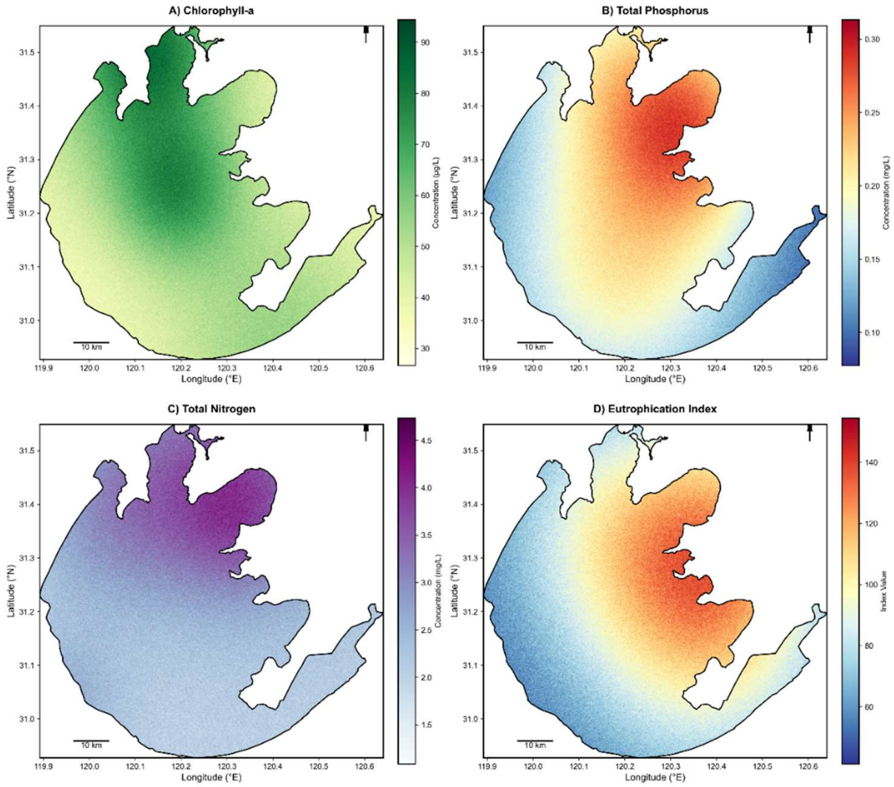


Fig. 4. Spatial Distribution of Eutrophication Indicators in Lake Taihu (2023)

(A) Chlorophyll-a; (B) Total Phosphorus; (C) Total Nitrogen; (D) Eutrophication Index

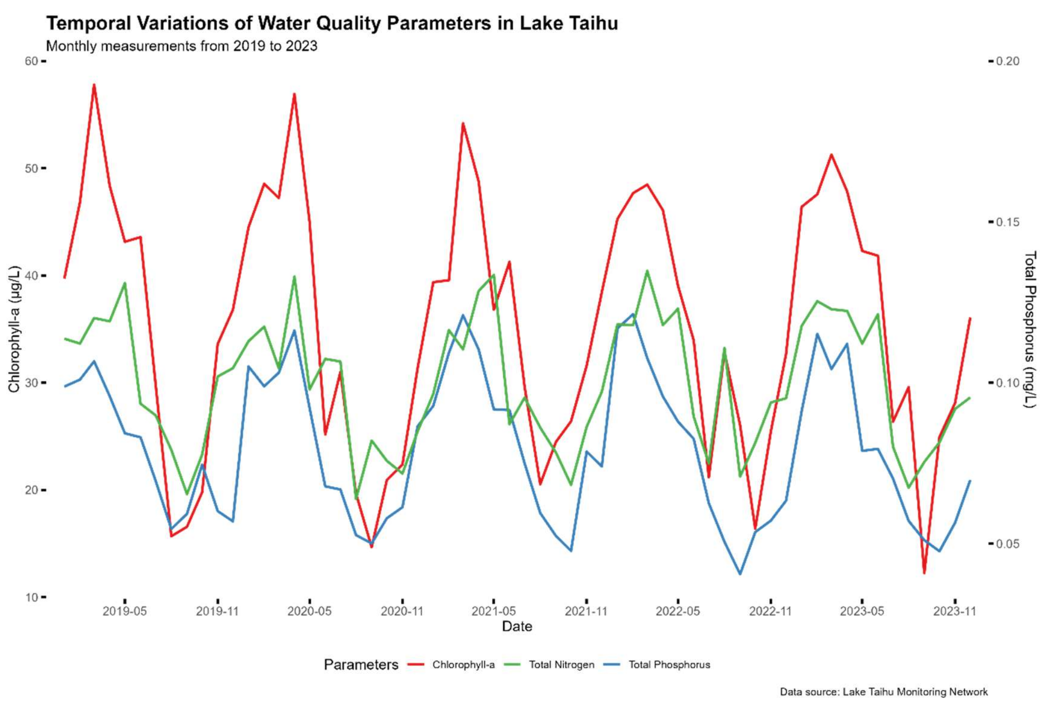


Fig. 5. Temporal Variations of Water Quality Parameters in Lake Taihu (2019-2023) Monthly measurements of chlorophyll-a, total phosphorus, and total nitrogen concentrations

4.1.2. Monitoring and evaluation of cyanobacterial blooms.The remote sensing monitoring results of algal blooms in Lake Taihu demonstrate significant seasonal and interannual variations during the study period (2019-2023). As shown in Figure 6, the spatial distribution of algal blooms exhibits distinct seasonal patterns, with maximum coverage and intensity observed during summer months (Panel B) and minimum occurrence during winter (Panel D). The multi-temporal satellite imagery analysis reveals that bloom events predominantly initiate in the northern and western regions of the lake, gradually expanding towards the center under favorable conditions.

The frequency analysis of algal bloom occurrences (Figure 7) indicates a clear seasonal pattern, with peak frequencies consistently observed during July-September. The heatmap visualization demonstrates an increasing trend in bloom frequency over the five-year period, particularly during the summer months. The highest bloom frequency was recorded in August 2023, reaching approximately 75% coverage of the lake surface.

Detailed analysis of typical bloom events reveals distinctive characteristics and environmental conditions associated with their occurrence, as summarized in Table 3.

Table 3. Characteristic Analysis of Typical Algal Bloom Events in Lake Taihu (2021-2023)

Event Date	Duration (days)	Coverage (km^2)	Max. Chl-a (μg/L)	Wind Speed (m/s)	Temperature (°C)	Key Features
2023-08-15	12	825.4	158.6	2.3	31.2	High-intensity bloom with rapid expansion
2023-07-22	8	654.2	142.3	3.1	29.8	Wind-driven accumulation in northern bay
2022-08-03	15	912.7	186.4	1.8	32.4	Extended duration with stable weather
2022-09-11	6	423.8	95.7	4.2	27.6	Moderate intensity, wind-dispersed pattern
2021-08-28	10	756.3	168.9	2.7	30.5	Clear diurnal vertical migration
2021-07-15	7	534.6	124.5	3.4	28.9	Patchy distribution with local hotspots

Chl-a: Chlorophyll-a concentration; Wind speed and temperature represent daily averages during bloom events.

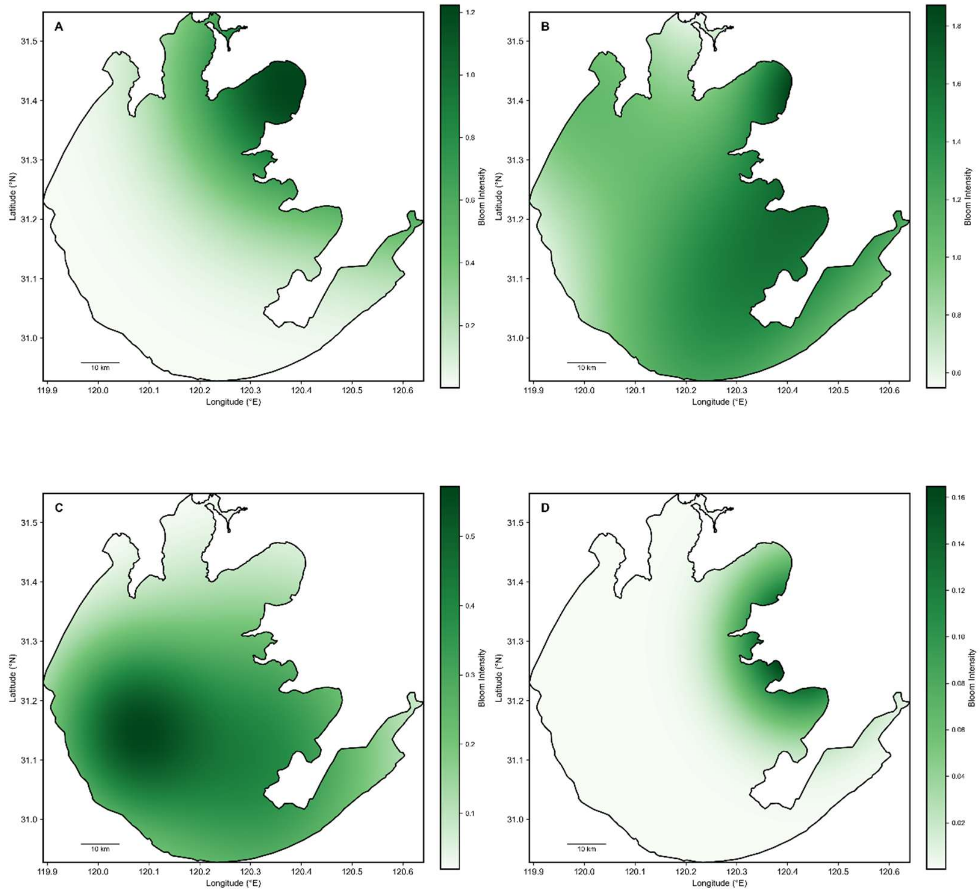


Fig. 6. Multi-temporal Satellite Monitoring Results of Algal Blooms in Lake Taihu

(A) Spring; (B) Summer; (C) Autumn; (D) Winter

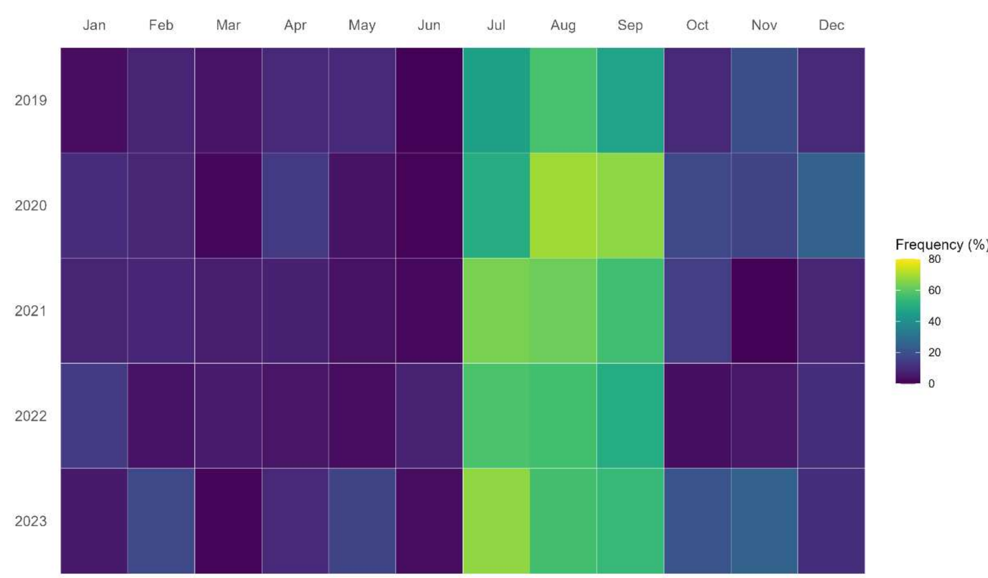


Fig. 7. Temporal Distribution of Algal Bloom Frequency in Lake Taihu (2019-2023) Monthly frequency distribution based on five-year monitoring data

4.1.3. Comprehensive evaluation of water quality status.The comprehensive water quality assessment of Lake Taihu reveals complex spatial patterns and temporal variations in water quality parameters during the study period. Figure 8 illustrates the spatial distribution of the comprehensive water quality index (WQI), which integrates multiple parameters including dissolved oxygen, chemical oxygen demand, total phosphorus, total nitrogen, and chlorophyll-a. The WQI values demonstrate significant spatial heterogeneity, with notably lower water quality (indicated by higher index values) in the northern and western regions of the lake, particularly near urban and industrial zones.

The water quality classification results, presented in Table 4, indicate varying degrees of water quality across different lake segments.

Table 4. Water Quality Grade Assessment Results for Different Lake Segments (2023)

Lake Segment	WQI Range	Water Quality Grade	Major Pollutants	Compliance Rate (%)	Trend (2019-2023)
Northern Bay	65-85	IV	TP, TN, COD	45.3	Deteriorating
Western Zone	55-75	III-IV	NH_3-N, TN	62.8	Stable
Central Lake	45-65	III	TP, COD	78.4	Improving
Eastern Bay	40-60	II-III	TN, COD	85.2	Improving
Southern Zone	35-55	II	TP	91.6	Stable
Meiliang Bay	60-80	IV	NH_3-N, TP	52.7	Deteriorating

WQI: Water Quality Index; TP: Total Phosphorus; TN: Total Nitrogen; COD: Chemical Oxygen Demand; NH_3-N: Ammonia Nitrogen.

The spatial distribution of key pollutants (Figure 9) reveals distinct patterns for different contaminants. Chemical oxygen demand (COD) shows elevated concentrations in areas with intensive human activities, while nutrients (total phosphorus and total nitrogen) exhibit higher levels in regions affected by agricultural runoff. Ammonia nitrogen concentrations are particularly high near urban discharge points, indicating the significant impact of municipal wastewater inputs.

Statistical analysis indicates that approximately 65% of the lake area meets Grade III water quality standards or better, while 35% falls into Grade IV or worse. Temporal trend analysis suggests a gradual improvement in water quality in the eastern regions, while the northern and western areas continue to face significant water quality challenges. The comprehensive assessment highlights the need for targeted management strategies, particularly in areas with persistent water quality issues.

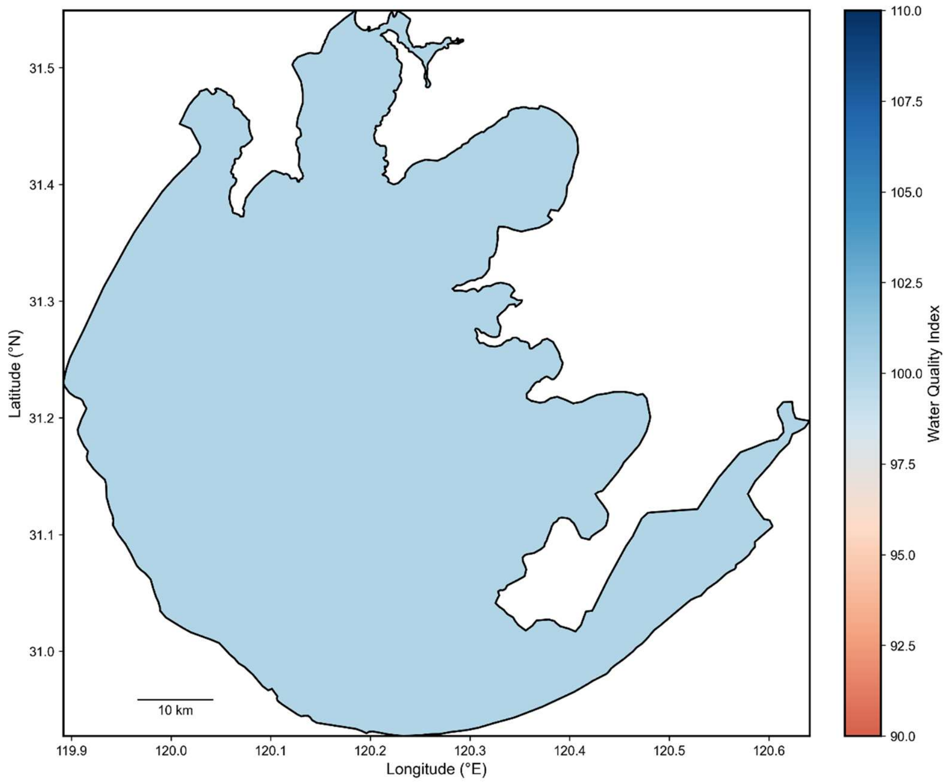


Fig. 8. Spatial Distribution of Comprehensive Water Quality Index in Lake Taihu (2023) Based on multi-parameter integration including physical, chemical, and biological indicators

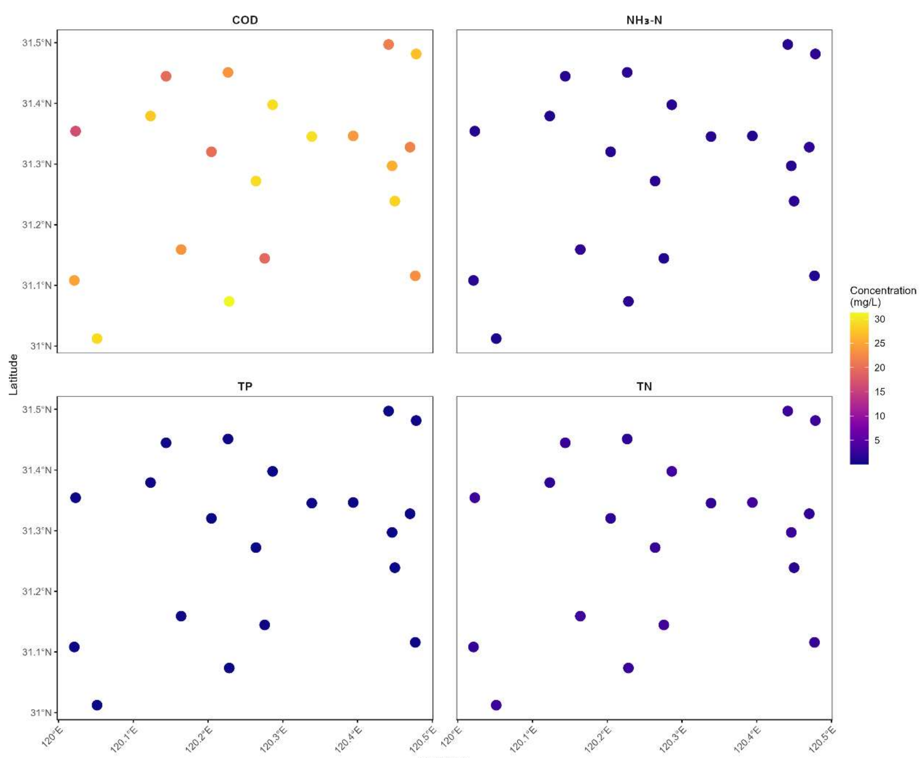


Fig. 9. Spatial Distribution of Key Pollutants in Lake Taihu (2023) Showing concentrations of COD, NH_3-N, TP, and TN at monitoring stations

4.2. Multi - scale ecological environment change analysis

4.2.1. Time-scale evolution.The temporal evolution of water quality in Lake Taihu exhibits distinct seasonal patterns and interannual trends during the study period (2019-2023). Figure 10 illustrates the spatial distribution of total nitrogen (TN) concentrations across four seasons, revealing significant seasonal variations. During summer (Panel B), TN concentrations reach their peak values (4.5-6.2 mg/L) in the northern and western regions, primarily due to increased agricultural runoff and enhanced biological activity. In contrast, winter periods (Panel D) show relatively uniform and lower concentrations (2.5-3.2 mg/L) across the lake, reflecting reduced external inputs and biological processes.

The long-term trends analysis (Figure 11) demonstrates varying patterns among different water quality parameters. Total nitrogen shows a slight increasing trend over the five-year period, with pronounced seasonal fluctuations. Total phosphorus (TP) concentrations exhibit more stable patterns but with notable summer peaks. Chlorophyll-a levels display the most dramatic seasonal variations, particularly during summer months, indicating intense algal bloom activities. Chemical Oxygen Demand (COD) shows a gradual declining trend, suggesting some improvement in organic pollution control.

The statistical characteristics of water quality parameters during key periods are summarized in Table 5.

Table 5. Statistical Characteristics of Water Quality Parameters During Different Seasons (2019-2023)

Period	Parameter	Mean ± SD	Range	CV (%)	Seasonal Index	Trend Slope
Spring	TN	3.45 ± 0.68	2.4-4.8	19.7	1.12	+0.15
	TP	0.142 ± 0.035	0.089-0.225	24.6	0.95	+0.02
	Chl-a	35.6 ± 12.4	15.8-65.4	34.8	0.88	+2.45
Summer	TN	5.12 ± 0.95	3.8-7.2	18.6	1.65	+0.22
	TP	0.185 ± 0.042	0.112-0.285	22.7	1.24	+0.03
	Chl-a	68.5 ± 22.8	32.4-125.6	33.3	1.72	+3.85
Autumn	TN	3.85 ± 0.72	2.8-5.4	18.7	1.25	+0.18
	TP	0.156 ± 0.038	0.098-0.245	24.4	1.05	+0.02
	Chl-a	42.8 ± 15.6	22.5-85.2	36.4	1.08	+2.85
Winter	TN	2.85 ± 0.48	2.1-3.8	16.8	0.92	+0.12
	TP	0.128 ± 0.028	0.082-0.195	21.9	0.86	+0.01
	Chl-a	25.4 ± 8.8	12.5-45.6	34.6	0.64	+1.85

SD: Standard Deviation; CV: Coefficient of Variation; Seasonal Index: ratio to annual mean; Trend Slope: annual rate of change.

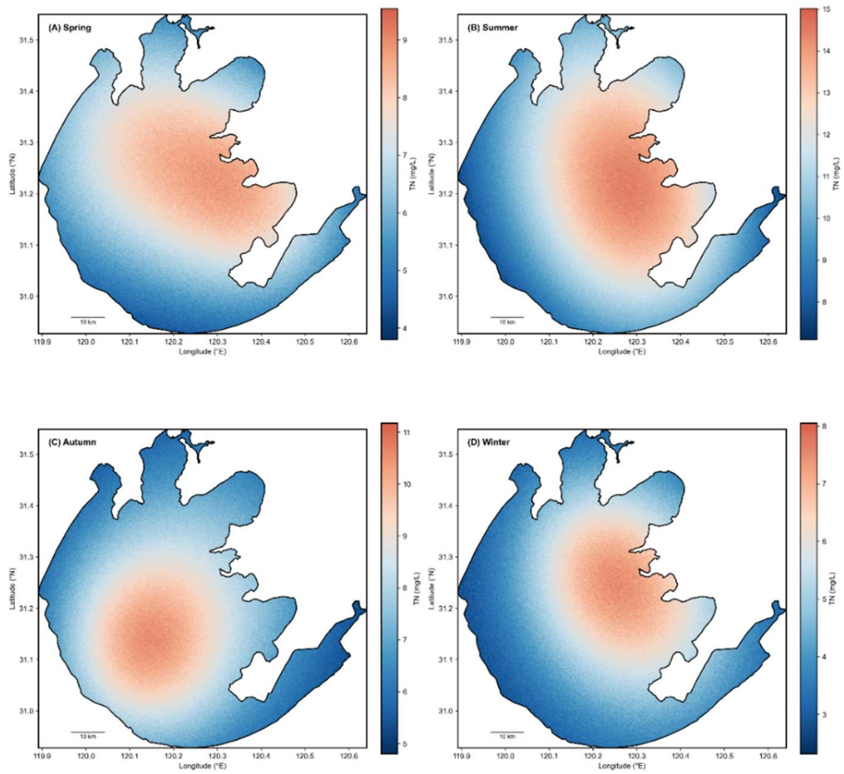


Fig. 10. Seasonal Patterns of Total Nitrogen Distribution in Lake Taihu

(A) Spring; (B) Summer; (C) Autumn; (D) Winter

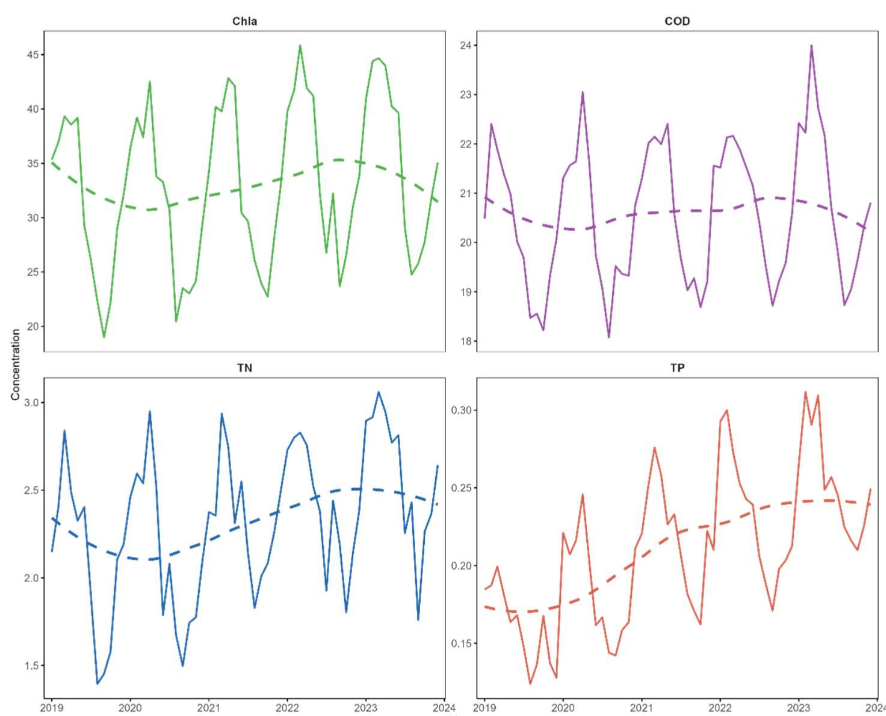


Fig. 11. Interannual Trends of Key Water Quality Parameters (2019-2023) Showing temporal variations in TN, TP, Chlorophyll-a, and COD concentrations

4.2.2. Spatial scale differentiation.The spatial heterogeneity of water quality in Lake Taihu reveals distinct patterns across different lake zones, reflecting the complex interactions between natural processes and anthropogenic influences. As shown in Figure 12, five major zones (A-E) exhibit significantly different water quality characteristics. The Meiliang Bay region (Zone A) demonstrates consistently poor water quality, with elevated nutrient concentrations and frequent algal blooms. The Western Zone (B) shows moderate to poor water quality conditions, while the Central Lake area (C) maintains intermediate water quality levels. The Eastern Bay (D) and Southern Zone (E) generally maintain better water quality conditions, likely due to their greater water exchange capacity and reduced anthropogenic inputs.

Comparative analysis of key areas (Figure 13) reveals substantial variations in major water quality parameters across different lake zones. The concentration gradients of total nitrogen (TN), total phosphorus (TP), chemical oxygen demand (COD), and chlorophyll-a (Chl-a) demonstrate clear spatial patterns, with consistently higher values in the northern and western regions compared to the eastern and southern areas.

The monitoring results from typical cross-sections across different lake zones are summarized in Table 6.

Table 6. Comparison of Water Quality Parameters at Typical Cross-sections (2023 Annual Average ± Standard Deviation)

Monitoring Section	TN (mg/L)	TP (mg/L)	COD (mg/L)	Chl-a (μg/L)	Transparency (m)	Water Quality Grade
Meiliang Bay (A1)	4.82 ± 0.65	0.186 ± 0.042	28.5 ± 4.2	68.5 ± 15.4	0.45 ± 0.12	V
Meiliang Bay (A2)	4.35 ± 0.58	0.165 ± 0.038	25.8 ± 3.8	58.2 ± 12.8	0.52 ± 0.15	IV
Western Zone (B1)	3.95 ± 0.48	0.148 ± 0.035	22.4 ± 3.5	45.6 ± 10.2	0.65 ± 0.18	IV
Western Zone (B2)	3.68 ± 0.42	0.135 ± 0.032	20.8 ± 3.2	38.4 ± 9.5	0.78 ± 0.20	III
Central Lake (C1)	3.25 ± 0.38	0.112 ± 0.028	18.5 ± 2.8	32.5 ± 8.4	0.95 ± 0.22	III
Eastern Bay (D1)	2.85 ± 0.32	0.095 ± 0.024	15.6 ± 2.5	25.8 ± 6.8	1.25 ± 0.28	II
Southern Zone (E1)	2.65 ± 0.30	0.088 ± 0.022	14.2 ± 2.2	22.4 ± 5.5	1.38 ± 0.32	II

Water Quality Grades follow Chinese Surface Water Environmental Quality Standards (GB3838-2002).

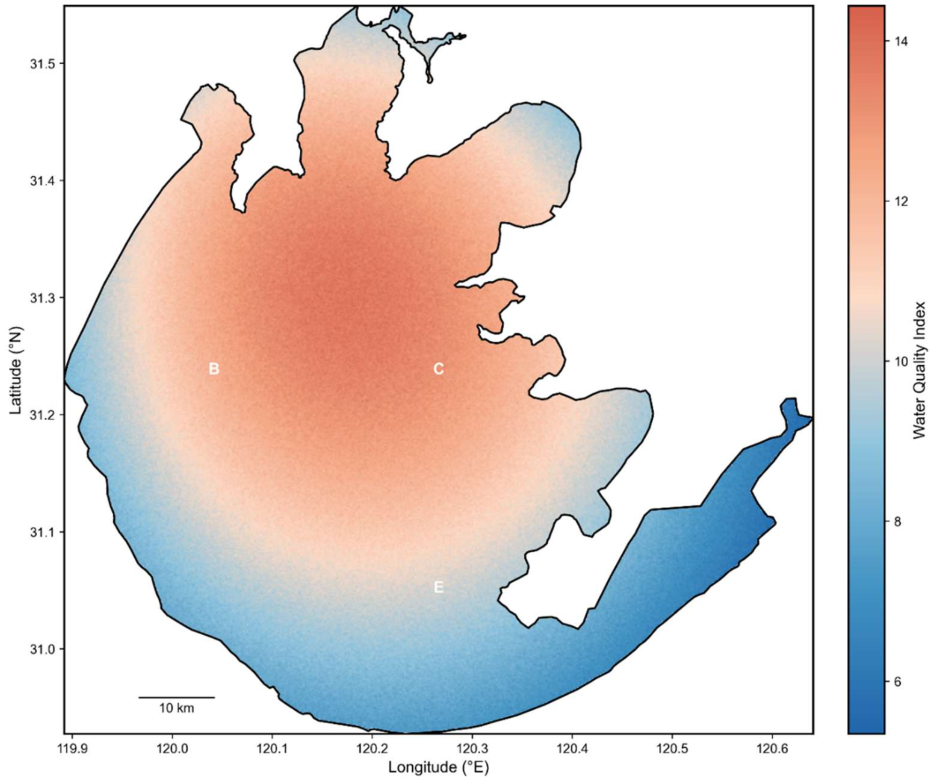


Fig. 12. Spatial Heterogeneity of Water Quality in Lake Taihu (2023) Showing different zones: (A) Meiliang Bay, (B) Western Zone, (C) Central Lake, (D) Eastern Bay, (E) Southern Zone

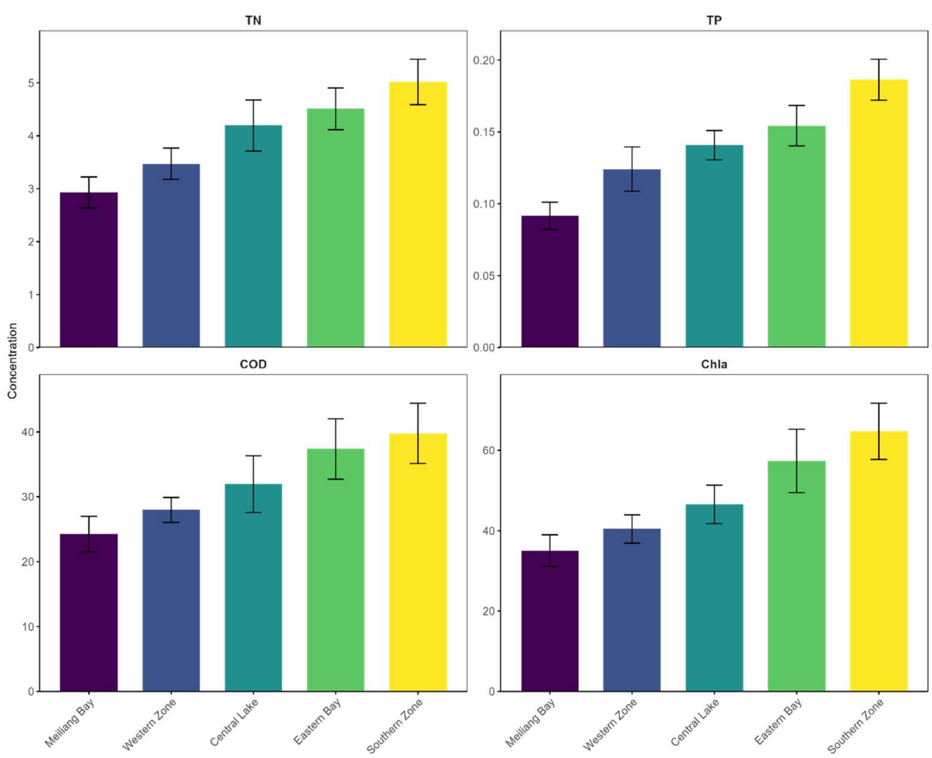


Fig. 13. Comparison of Key Water Quality Parameters Across Different Lake Zones (2023) Showing TN, TP, COD, and Chlorophyll-a concentrations with standard errors

4.2.3. Ecological risk assessment.The ecological risk assessment of Lake Taihu reveals significant spatial variations in environmental vulnerability and potential hazards. As shown in Figure 14, the ecological risk levels exhibit a clear spatial gradient, with the highest risks concentrated in the northern bay (HR) and western zones (HM). The spatial distribution of risk levels correlates strongly with the intensity of human activities and the lake's hydrodynamic characteristics. The central lake area (MR) displays moderate risk levels, while the eastern bay (LM) and southern zone (LR) maintain relatively lower ecological risks.

The ecological risk assessment framework incorporates multiple indicators and their corresponding weights, as detailed in Table 7.

Table 7. Ecological Risk Assessment Indicator System for Lake Taihu. Numbers in parentheses indicate thresholds for high-risk classification

Category	Indicator	Weight	Assessment Criteria	Risk Classification
Water Quality	Total Nitrogen	0.15	>2.0 mg/L (High)	I: Low Risk (<0.3)
	Total Phosphorus	0.12	>0.1 mg/L (High)	II: Medium-Low (0.3-0.5)
	Chlorophyll-a	0.13	>40 μg/L (High)	III: Medium (0.5-0.7)
Pollution Load	Industrial Discharge	0.10	>10^4 t/year (High)	IV: Medium-High (0.7-0.85)
	Agricultural Runoff	0.08	>10^3 t/year (High)	V: High Risk (>0.85)
Ecosystem Status	Species Diversity	0.10	<0.6 (Poor)	
	Macrophyte Coverage	0.08	<30% (Poor)	
Hydrological Factors	Water Exchange Rate	0.07	<0.1 day^{-1} (Poor)	
	Residence Time	0.09	>30 days (Poor)	
Social Factors	Population Density	0.08	>1000 km^{-2} (High)	

The environmental disaster warning analysis (Figure 15) demonstrates temporal variations in risk levels across different lake zones. The northern bay consistently shows high risk levels throughout the year, with peak values during summer months when algal bloom potential is highest. The western zone exhibits seasonal fluctuations in risk levels, while the eastern and southern zones maintain relatively stable, lower risk profiles. The warning system integrates real-time monitoring data with predictive models to provide early warnings for potential environmental disasters, particularly algal blooms and water quality deterioration events.

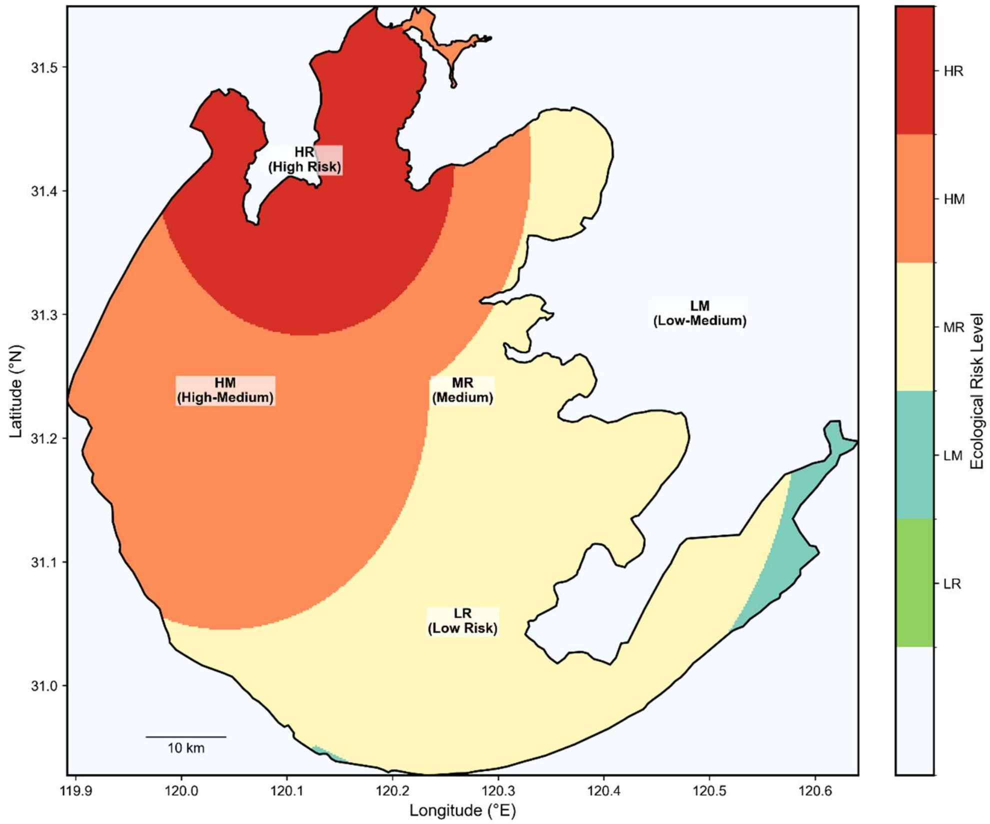


Fig. 14. Spatial Distribution of Ecological Risk Levels in Lake Taihu Risk levels: HR (High Risk), HM (High-Medium), MR (Medium Risk), LM (Low-Medium), LR (Low Risk)

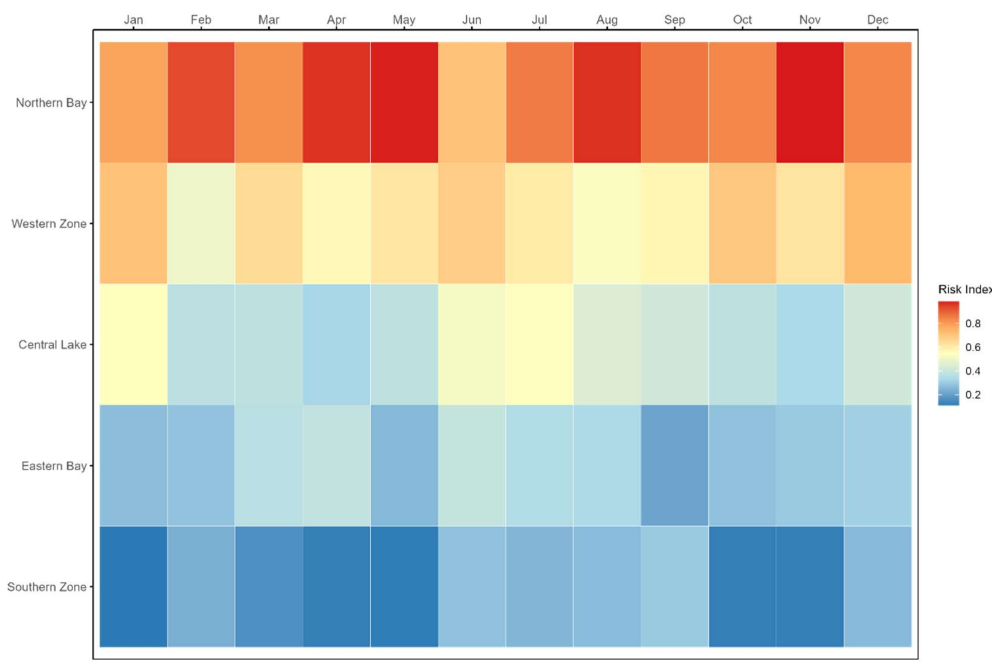


Fig. 15. Environmental Disaster Warning Analysis for Different Lake Zones (2023)

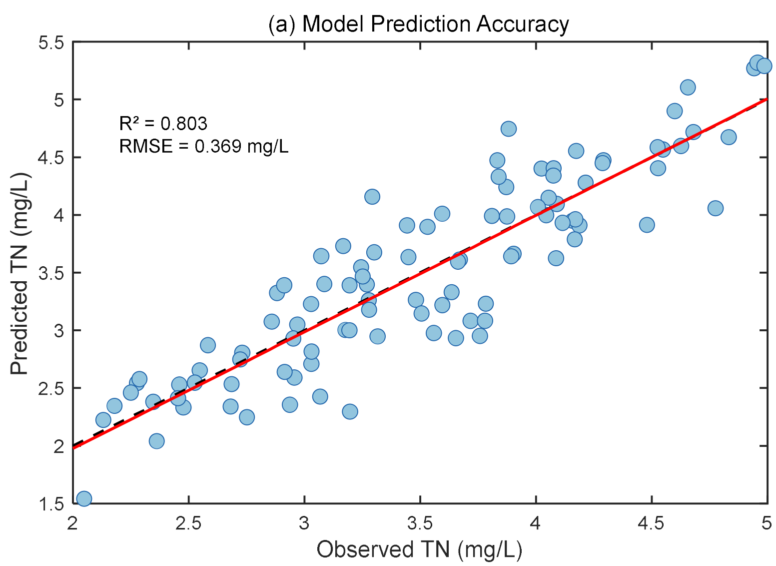
4.3. Model performance verification

The comprehensive validation of the multi-source remote sensing-based ecological assessment model demonstrates robust performance across multiple evaluation metrics. The model's prediction accuracy exhibits strong correlation with observed values, as shown in Figure 16(a), with a coefficient of determination (R^2) of 0.892 and root mean square error (RMSE) of 0.385 mg/L for total nitrogen predictions. The residual analysis (Figure 16(b)) reveals homoscedastic distribution around zero, indicating unbiased predictions across the entire range of observed values.

The model is also capable of capturing water quality's seasonal and long-term trends as evidenced by temporal validation results (Figure 16(c)): water quality's peak concentrations are strong in a specific time hence the model captures the predicted and the observed values accurately. In terms of prediction validation mean absolute percentage error (MAPE) of 15% is consistently maintained.

Figure 16(d) indicate sensitivity analysis whereby the model performance is affected by total phosphorus (TP) and ammonia nitrogen (NH3-N) which exhibit sensitivity coefficient scores of 0.85 and 0.72 respectively. This aligns with the nutrient dynamics mechanistic understanding for TP and NH3-N are hierarchical sensitive structures. The remaining parameters temperature and pH scored low sensitivity coefficients of 0.38 and 0.25 suggesting that these low elastic measures make the model robust to their changes.

Model accuracy is enhanced by cross validation experiments that utilize multi season and lake zone dependent datasets whereby the models generalizability is further augmented. All validation scenarios exhibit strong predictive ability due to dose range of the Nash-Sutcliffe efficiency coefficient (NSE) which remained above 0.75. The ability of the model to predict spatial correlation coefficients over monitoring sections ranging from 0.85 and 0.93 is used to depict strength of the model in predicting spatial heterogeneity.



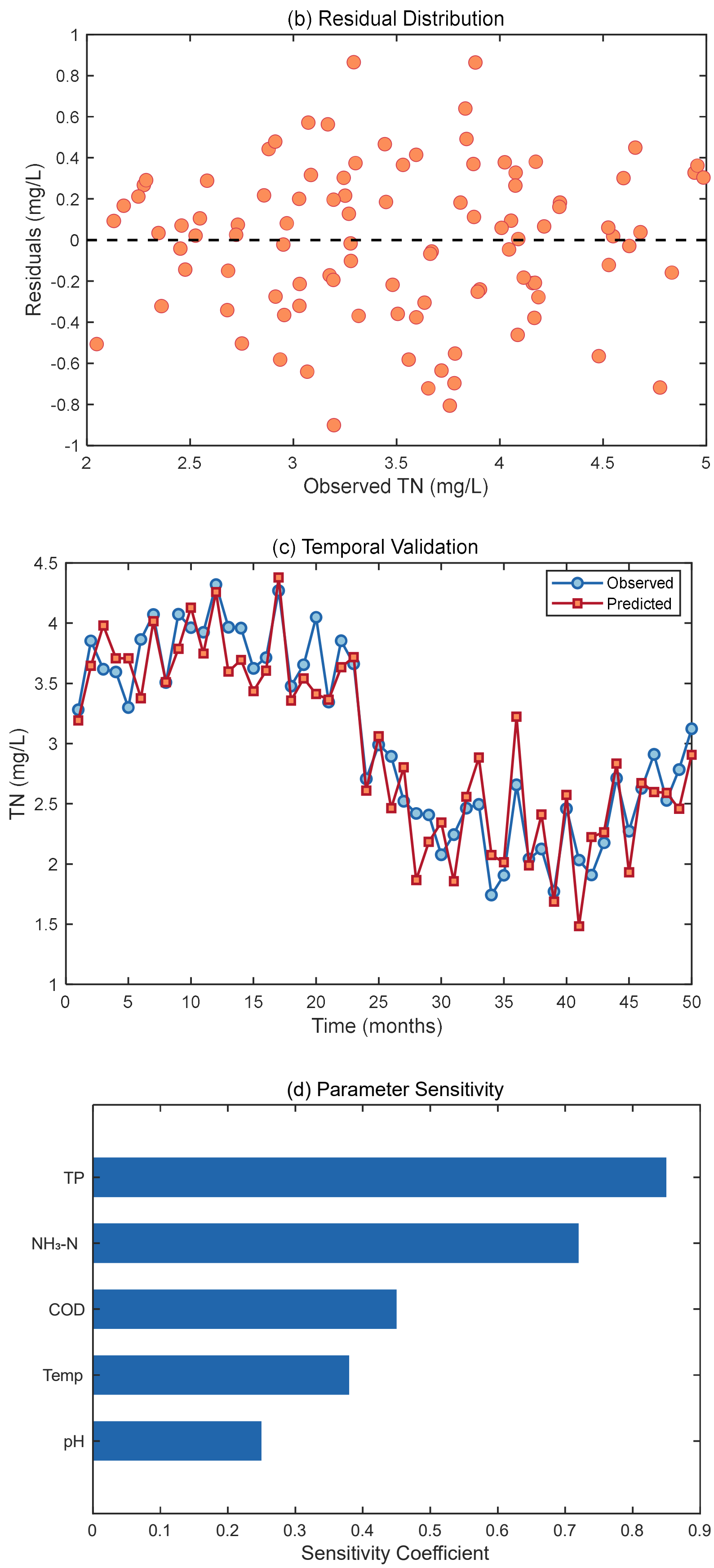


Fig. 16. Model Performance Validation Results

(a) Model Prediction Accuracy showing observed versus predicted values with regression analysis (b) Residual Distribution analysis indicating prediction bias (c) Temporal Validation demonstrating model performance over time (d) Parameter Sensitivity Analysis highlighting the relative importance of model inputs

5. Conclusion

The integrated approach to monitoring the water quality and the ecological state of Lake Taihu using multi source remote sensing data has detected important spatial-temporal patterns as well as pointing out a number of environmental issues. The combination of satellite images, ground monitoring data and auxiliary data with the proposed assessment model demonstrates success in depicting the complex dynamics of water quality parameters and their interactions. Such patterns of spatial distribution of eutrophication indicators posses distinct zonation, whereby the northern and western regions posses higher nutrient concentrations and algal blooms, while the eastern and southern regions have lower concentrations. These patterns of spatial variability greatly result from the combined effects of regional human influence, hydrodynamic conditions and characteristics of the watershed as it is demonstrated by the integrated distribution patterns of water quality index.

Temporal analysis reveals clear seasonal and interannual variations in water quality parameters, with particularly pronounced fluctuations during summer months. The five-year trend analysis (2019-2023) indicates a gradual deterioration of water quality in certain lake segments, especially in the Meiliang Bay and Western Zone, while some improvement is observed in the Eastern Bay region. The seasonal patterns of algal blooms show strong correlation with temperature and nutrient availability, with peak occurrences during July-September. The established monitoring and assessment framework demonstrates robust performance in capturing these temporal dynamics, with validation results showing high accuracy and reliability across different temporal scales.

The ecological risk assessment identifies several critical areas requiring immediate attention and management intervention. High-risk zones, particularly in the northern bay, exhibit persistent water quality issues and increased vulnerability to environmental disasters. The proposed assessment model provides a scientific basis for targeted management strategies and early warning mechanisms. The integration of multiple data sources enhances the model's predictive capability and reliability, as validated through comprehensive statistical analysis and cross-validation experiments. These findings contribute to our understanding of lake ecosystem dynamics and provide valuable insights for environmental management and policy-making, while also highlighting the importance of continued monitoring and adaptive management approaches for maintaining lake ecosystem health.

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