Water Quality Inversion and Spatiotemporal Analysis of Changshu City Based on Multi-source Remote Sensing Data

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Abstract

Rapid urbanization in the plain river network of Changshu City has led to prominent water quality degradation and eutrophication risks. Traditional in-situ monitoring is constrained by sparse sampling and high costs, while conventional remote sensing approaches struggle with accurate water body extraction and stable parameter inversion in turbid, fragmented rivers. This study establishes a targeted remote sensing monitoring framework using 2024 multi-source data (Gaofen-2, Sentinel-2) and field measurements. An optimized modified Normalized Difference Water Index (mNDWI) combined with a spatially weighted adaptive threshold algorithm is adopted to precisely extract complex river networks. Based on Pearson correlation analysis, sensitive spectral bands and band combinations are screened for four key indicators: Chlorophyll-a (CHL-a), Total Nitrogen (TN), Total Phosphorus (TP), and Secchi Depth (SD). Statistical regression and weighted Principal Component Analysis-Random Forest (PCA-RF) models are developed for quantitative inversion, and their accuracy is verified using cross-validation with R^2 and RMSE. A weighted modified Carlson Trophic State Index suitable for plain river networks is applied for eutrophication assessment, and the single-factor pollution index method combined with the worst-factor principle is adopted to conduct comprehensive water quality evaluation in accordance with the national surface water environmental quality standards. The integrated inversion–evaluation–mapping workflow realizes spatially continuous water quality analysis, providing a reliable and region-adapted technical solution for remote sensing monitoring and scientific management of water environment in plain river network areas.

1. Introduction

Inland river networks are core components of terrestrial ecosystems, supporting regional water supply, ecological regulation and sustainable development. As a typical plain river network region in the Yangtze River Delta, Changshu has suffered from severe water quality degradation due to rapid urbanization and industrialization, including nutrient enrichment and frequent eutrophication (Wei et al., 2018). These problems threaten regional ecological security and raise an urgent demand for large-scale, high-efficiency water quality monitoring.

Traditional in-situ monitoring provides accurate point-based data, but it is limited by high costs, sparse sampling sites and insufficient spatiotemporal coverage, which cannot capture the continuous dynamic changes of complex river networks (Ort et al., 2009). Remote sensing technology offers a feasible solution for large-scale water environment observation, yet it still faces key technical bottlenecks: low accuracy of water body extraction in turbid and fragmented rivers, and unstable inversion of non-optically active water quality parameters (Li et al., 2010).

For water body extraction, the modified normalized difference water index (mNDWI) has been widely used in water identification, but it suffers from obvious spectral confusion in highly turbid plain river networks (Han, 2005). For water quality parameter inversion, traditional statistical regression models lack robustness in complex water environments, while machine learning models can better fit nonlinear spectral responses and effectively improve inversion reliability (Wei et al., 2021). In eutrophication assessment, the modified Carlson Trophic State Index is commonly applied in Chinese inland waters, but its fixed coefficient setting easily causes seasonal evaluation bias, and few studies combine land use characteristics to enhance the pertinence of assessment results (Wei et al., 2020).

At present, three critical research gaps remain for water quality remote sensing in Changshu: first, existing water body extraction methods are not fully adapted to the fragmented and turbid characteristics of the local river network; second, stable and season-adapted inversion models for chlorophyll-a (CHL-a), total nitrogen (TN), total phosphorus (TP) and Secchi depth (SD) are insufficient; third, an integrated framework covering water body extraction, quantitative inversion and comprehensive water quality evaluation has not been established.

To fill these gaps, this study constructs a targeted remote sensing monitoring framework based on multi-source satellite data and in-situ measurements. We optimize the mNDWI to realize accurate water body extraction, build a PCA-RF model for the four key water quality parameters, and improve the eutrophication and comprehensive water quality evaluation system with seasonal and land use corrections. This study provides a region-adapted technical solution for water quality monitoring in plain river network areas and supports scientific water environment governance.

2. Study Area and Data Processing

2.1 Study Area Overview

Changshu City is located in the southern part of the Yangtze River Delta, a typical plain river network region with dense, fragmented and interconnected rivers. The area features a

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subtropical monsoon climate, with distinct seasonal variations in temperature and precipitation (Chan and Wang, 2007). Driven by rapid urbanization and industrial development, the inland water bodies in Changshu are disturbed by intensive human activities, resulting in prominent water quality problems such as nutrient enrichment and eutrophication. The spatial and temporal variations of chlorophyll-a (CHL-a), total nitrogen (TN), total phosphorus (TP) and Secchi depth (SD) are significant, which makes the area an ideal representative for water quality remote sensing monitoring in complex plain river networks.

2.2 Data Sources

2.2.1 Remote Sensing Data: Multi-source remote sensing images used in this study were obtained from two official platforms. Gaofen-2 high-resolution satellite data were acquired from the National Remote Sensing Platform of China, providing 0.8 m high spatial resolution images to capture fine details of narrow rivers. Sentinel-2 multi-spectral data were obtained from the European Space Agency (ESA) Copernicus Open Access Hub, with abundant spectral bands and wide coverage to ensure regional consistency. All remote sensing data were collected covering four seasons of 2024, and preprocessed with atmospheric correction, cloud removal, image mosaicking and resampling to unify spatial resolution and coordinate system, eliminating potential temporal and geometric inconsistencies caused by multi-source satellite fusion.

2.2.2 In-situ Water Quality Data: In-situ water quality data were provided by Changshu Environmental Monitoring Center, including 21 water quality monitoring sites combining automatic monitoring stations and manual sampling. Synchronous sampling was conducted in accordance with satellite transit time in each season of 2024, and four key water quality indicators were measured: CHL-a, TN, TP and SD. All measured data were strictly screened and quality-controlled to eliminate abnormal values, ensuring the reliability of model training and validation.

2.3 Water Body Extraction

Accurate water body extraction is the foundational step for reliable water quality inversion and eutrophication assessment. In Changshu's fragmented plain river network, narrow tributaries, turbid water, and spectral confusion between water bodies and non-water features (e.g., built-up areas, wetland vegetation) severely limit the performance of conventional water extraction methods. To address these challenges, this study proposes an optimized modified Normalized Difference Water Index (mNDWI) integrated with dual shortwave infrared (SWIR) spectral enhancement and a spatially weighted adaptive threshold algorithm, while systematically mitigating temporal and geometric inconsistencies in multi-source satellite data fusion.

2.3.1 Optimized mNDWI with Sensor-Adaptive Spectral Enhancement: The conventional mNDWI enhances water signals by leveraging the contrast between green and near-infrared (NIR) or shortwave infrared (SWIR) bands, but it suffers from spectral overlap between turbid water and non-water targets in plain river networks. To improve spectral separability, this study introduces a sensor-adaptive spectral enhancement term to the original mNDWI framework (Zhou et al., 2015), tailored to the band configurations of Gaofen-2 and Sentinel-2:
For Sentinel-2：

$$mNDWI_{opt} = \frac{Green - \left(SWIR_1 - \beta \cdot SWIR_1\right)}{Green + \left(SWIR_1 - \beta \cdot SWIR_1\right)}, \tag{1}$$

For Gaofen-2:

$$mNDWI_{opt} = \frac{Green - \left(NIR - \beta \cdot NIR\right)}{Green + \left(NIR - \beta \cdot NIR\right)}, \tag{2}$$

where $Green$ = the green band
$SWIR_1$= the shortwave infrared band
NIR = the near-infrared band
β =empirical spectral enhancement weight

β (calibrated to 0.3 via cross-validation) amplifies the spectral difference between water and non-water features by emphasizing the stronger absorption of water in SWIR/NIR bands. This sensor-adaptive design ensures compatibility with both Gaofen-2 and Sentinel-2 data, while enhancing the contrast between turbid water and non-water targets to reduce misclassification of narrow rivers.

2.3.2 Spatially Weighted Adaptive Threshold Algorithm: Conventional global thresholding fails to account for spatial variations in water turbidity and background reflectance, leading to inconsistent extraction accuracy across the study area. This study adopts a spatially weighted adaptive threshold algorithm to determine pixel-specific thresholds based on local spectral statistics. For each local window (size = 5×5 pixels) centered at pixel (x,y), the adaptive threshold $T(x,y)$ is calculated as:

$$T(x,y) = \mu(x,y) + k \cdot \sigma(x,y), \tag{3}$$

where $T(x,y)$ = mean value of $mNDWI_{opt}$
$\sigma(x,y)$= standard deviation of $mNDWI_{opt}$
k= spatial weight coefficient

A pixel is classified as water if $mNDWI_{opt}$ (x,y)>T(x,y), and non-water otherwise. This window-based approach preserves spatial continuity of river networks and reduces noise-induced misclassification.

2.3.3 Validation of Water Body Extraction: The performance of the optimized water extraction method is validated using high-resolution Google Earth imagery and field-surveyed water body boundaries as reference data. Metrics including Overall Accuracy (OA) and Kappa coefficient are calculated. Results show that the optimized $mNDWI_{opt}$+spatially weighted adaptive threshold method achieves an OA of 96.2% and a Kappa coefficient of 0.92, outperforming the conventional *mNDWI*+global threshold method (OA = 91.5%, Kappa = 0.85) by reducing leakage of narrow rivers and misclassification of non-water features.

3. Water Quality Parameter Inversion Models

This chapter aims to establish quantitative inversion models for four key water quality parameters: Chlorophyll-a (CHL-a), Total Nitrogen (TN), Total Phosphorus (TP), and Secchi Depth (SD). Referring to the standard workflow of remote sensing water quality inversion, sensitive spectral features are first screened via correlation analysis (Liu et al., 2024). Then statistical regression models and weighted Principal Component Analysis-Random Forest (PCA-RF) models are constructed separately. Model accuracy is evaluated and compared to determine the optimal inversion scheme, which supports the subsequent spatiotemporal analysis and comprehensive water quality assessment of Changshu.

3.1 Sensitive Spectral Feature Selection

Non-water pixels in remote sensing images were masked by the water body extraction results in Chapter 2 to eliminate land surface interference. Spectral reflectance of each in-situ monitoring point was extracted from Sentinel-2 images synchronized with field sampling.

Pearson correlation analysis was used to quantify the correlation between spectral features and water quality parameters, so as to screen sensitive features with high correlation and clear physical significance. The formula is as follows:

$$r = \frac{\sum\left(X_i - \bar{X}\right)\left(Y_i - \bar{Y}\right)}{\sqrt{\sum\left(X_i - \bar{X}\right)^2}\sqrt{\sum\left(Y_i - \bar{Y}\right)^2}}, \tag{4}$$

where r = pearson correlation coefficient
X_i= spectral reflectance of the i-th sample
Y_i= measured value of water quality parameter
$\bar{X}$ = mean value of spectral reflectanc
$\bar{Y}$ = mean value of measured parameter

3.1.1 Principles of Sensitive Band Selection: The selection of sensitive spectral features follows four core principles. First, the Pearson correlation coefficient method is used to obtain the correlation between each single band and the measured concentration of inversion parameters. Second, combined with the physical, chemical and environmental-ecological characteristics of inversion parameters, band combinations with high correlation coefficients with measured parameter concentrations are selected to explore the potential relationship between remote sensing bands and water quality parameters. Third, the band combinations used in other researchers’ water quality parameter inversion studies are taken as references. Fourth, features are retained only if they pass the significance test and maintain stable correlation across four seasons, so as to ensure the reliability and universality of the inversion model.

3.1.2 Sensitive Bands for Four Water Quality Parameters: Based on existing studies, Pearson correlation analysis results, and spectral response characteristics of inland waters, sensitive bands and combinations for each parameter are determined as follows. For CHL-a, the red-edgezzand (B5, 705 nm) and red band (B4, 665 nm) are selected, and the band ratio B5/B4 is used as the core feature, since CHL-a has a strong reflection peak in the red-edge band and obvious absorption in the red band. For TN and TP (non-optically active parameters), the red-edge bands (B5, B6), near-infrared band (B8, 842 nm) and shortwave infrared band (B11, 1610 nm) are adopted, and their logarithmic ratio combinations are screened, as these bands are sensitive to dissolved organic matter and suspended solids related to nutrient salts. For SD, the green band (B3, 560 nm), red band (B4, 665 nm) and shortwave infrared band (B11) are selected, because the attenuation of light in these bands is closely related to water transparency and turbidity.

3.2 Inversion Model Construction

3.2.1 Statistical Regression Model: Statistical regression model is a conventional empirical inversion method that establishes a quantitative mapping relationship between sensitive spectral features and water quality parameters. In this study, multivariate nonlinear regression models were constructed for CHL-a, TN, TP, and SD respectively. The sensitive bands and band combinations screened in Section 3.1 were taken as independent variables, and the field-measured values of water quality parameters were taken as dependent variables.

The in-situ dataset was randomly split into a training set (70%) and a validation set (30%) with balanced seasonal and spatial distribution to ensure model generalization. The least square method was used to fit the regression coefficients, and the model with the best fitting effect was selected as the final statistical regression model. This model has clear mathematical expression and strong interpretability, but it relies on the assumption of simple nonlinear relationship, which leads to limited stability in turbid river networks with complex optical properties and large seasonal fluctuations.

3.2.2 Weighted PCA-Random Forest (PCA-RF) Model: The weighted PCA-RF model serves as the core inversion approach in this study, which is tailored to overcome the poor seasonal stability of conventional models and the low inversion accuracy of non-optically active parameters (TN, TP) in turbid plain river networks. This hybrid model combines PCA dimensionality reduction, seasonal feature weighting, and random forest nonlinear fitting, and fully adapts to the complex hydrological and spectral characteristics of Changshu’s inland rivers.

First, spectral feature standardization is carried out. The sensitive spectral features screened in Section 3.1 are used as input data. Since PCA is sensitive to data magnitude, Z-score standardization is adopted to eliminate the dimensional difference among different spectral features, ensuring the effectiveness of subsequent dimensionality reduction. The standardization formula is:

$$X_{std} = \frac{X - \mu}{\sigma}, \tag{5}$$

where X_{std}= standardized spectral feature
X= original spectral feature
μ = mean of the original feature
σ= standard deviation of the original feature

Second, PCA dimensionality reduction is implemented. The standardized spectral features are transformed into a set of mutually independent principal components (PCs) through orthogonal transformation. The eigenvalue and variance contribution rate of each principal component are calculated, and the top-n principal components with a cumulative variance contribution rate greater than 95% are retained. This step effectively removes redundant spectral information and multicollinearity between features, reduces the input dimension of the model, and improves computational efficiency while retaining the core spectral response information.

Third, seasonal weighting calculation is the key innovation of this model. For the retained principal components, seasonal weight coefficients are constructed based on the stability of Pearson correlation between each principal component and water quality parameters in four seasons. The weight coefficient is assigned higher to the principal component with more stable correlation across seasons, so as to enhance the representation ability of spectrally stable features and improve the inversion stability of TN and TP. The weighted principal components are taken as the final input features of the random forest model, which effectively suppresses the seasonal fluctuation interference of spectral signals in turbid water bodies. The weighted principal component is calculated as:

$$PC_i^* = \omega_i \cdot PC_i, \tag{6}$$

where PC_i^* = weighted principal component
ω_i = seasonal weight coefficient
PC_i = oiginal principal component

Fourth, weighted PCA-RF regression modeling is completed. The weighted principal components are used as input features, and the measured values of CHL-a, TN, TP, and SD are used as output labels. The bootstrap resampling method is used to extract multiple sub-samples from the training set, and multiple decision trees are constructed independently for integrated prediction. To avoid overfitting and ensure optimal performance, 5-fold cross-validation is adopted to optimize the key hyperparameters, including the number of decision trees, maximum depth of decision trees, and minimum sample number of leaf nodes.

This weighted PCA-RF model breaks through the limitation of traditional models in fitting complex nonlinear relationships, and significantly improves the seasonal adaptability and inversion accuracy of water quality parameters, especially for non-optically active parameters in the plain river network of Changshu.

3.3 Model Accuracy Evaluation

To quantitatively assess the performance of the statistical regression model and the weighted PCA-RF model, three widely used accuracy indicators were adopted in this study, including the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). These indicators can comprehensively reflect the fitting degree, prediction error and stability of the inversion models.

The coefficient of determination (R^2) is used to characterize the proportion of the variance in measured water quality parameters that can be explained by the model, reflecting the overall fitting effect. The calculation formula is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}, \tag{7}$$

where R^2 = coefficient of determination
y_i= field-measured value
$\hat{y}_i$ = model-inverted value
$\bar{y}$ = mean value of measured data
n = number of validation samples

The root mean square error (RMSE) is applied to measure the average deviation between inverted values and measured values, which is sensitive to extreme errors and can reflect the model’s prediction accuracy. The calculation formula is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{8}$$

where $RMSE$ = root mean square error
y_i= field-measured value
$\hat{y}_i$ = model-inverted value
n = number of validation samples

The mean absolute error (MAE) can avoid the cancellation of positive and negative errors, and objectively reflect the actual average error of the model. The calculation formula is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, \tag{9}$$

where MAE = mean absolute error
y_i= field-measured value
$\hat{y}_i$ = model-inverted value
n = number of validation samples

In general, the inversion model shows better performance with a higher R^2 and lower RMSE and MAE, which means the inverted values are more consistent with the measured data, and the model has higher reliability and practical value for water quality parameter inversion in the study area.

3.4 Model Accuracy Evaluation

3.4.1 Model Performance Comparison: To systematically evaluate the superiority of the weighted PCA-RF model over the statistical regression model, a comprehensive comparison was conducted based on the three accuracy indicators (R^2, RMSE, and MAE) defined in Section 3.3. The model fit R^2 for each water quality parameter is summarized in Table 1:

Water Quality Parameters	Statistical regression model R^2	PCA-RF model R^2
CHL-a	0.543	0.804
TN	0.532	0.771
TP	0.568	0.763
SD	0.621	0.789

Table 1. Comparison of model fit R^2

From the quantitative comparison results, the weighted PCA-RF model consistently outperforms the statistical regression model for all four water quality parameters, with clear advantages in fitting accuracy and stability. The R^2 values of the weighted PCA-RF model range from 0.763 to 0.804, all exceeding 0.75, while those of the statistical regression model are between 0.532 and 0.621, mostly below 0.6. This indicates that the weighted PCA-RF model can explain 75%–80% of the variance in measured water quality parameters, significantly higher than the 53%–62% explained by the statistical regression model, demonstrating its stronger ability to capture the complex relationship between spectral features and water quality parameters in Changshu’s turbid river network.

For specific parameters, Chl-a as an optically active parameter has distinct spectral response characteristics, including a reflection peak in the red-edge band and an absorption valley in the red band, so the statistical regression model achieves a moderate R^2 of 0.543. However, Changshu’s river network is characterized by high suspended sediment concentration, which interferes with Chl-a spectral signals. The weighted PCA-RF model, with its nonlinear fitting ability, effectively suppresses sediment interference and improves the R^2 to 0.804, showing the most significant improvement among all parameters, which aligns with the optical complexity of inland turbid waters.

TN and TP, as non-optically active parameters, have no direct spectral response, and their inversion relies on indirect correlations with dissolved organic matter and suspended solids. In Changshu, TN and TP are mainly derived from agricultural non-point source pollution, such as fertilizer runoff during rice planting seasons, and domestic sewage, with strong seasonal fluctuations. The statistical regression model, limited by its linear assumption, fails to capture this complex nonlinear relationship, resulting in low R^2 values of 0.532 for TN and 0.568 for TP. In contrast, the weighted PCA-RF model’s seasonal weighting mechanism enhances the contribution of spectrally stable features, effectively suppressing seasonal interference, and increases the R^2 to 0.771 for TN and 0.763 for TP. The improvement amplitude for TN and TP is more prominent than that for Chl-a, confirming the model’s effectiveness in enhancing the inversion stability of non-optically active parameters.

SD is closely related to water transparency and suspended sediment concentration, with obvious optical response characteristics. The statistical regression model achieves a relatively high R^2 of 0.621, but Changshu’s river network experiences significant seasonal variations in sediment load, with high sediment concentration in rainy seasons and low in dry seasons, which disrupts the linear relationship assumed by the statistical model. The weighted PCA-RF model adapts to this nonlinear variation, raising the R^2 to 0.789, reflecting its strong ability to handle the temporal variability of water transparency in plain river networks.

In addition to R^2, the weighted PCA-RF model also shows lower RMSE and MAE values for all parameters. For example, the RMSE of TN inversion decreases from 0.32 mg/L in the statistical regression model to 0.18 mg/L in the weighted PCA-RF model, and the MAE of SD decreases from 0.25 m to 0.12 m. These results indicate that the weighted PCA-RF model not only has a higher fitting degree but also smaller prediction deviations, with better practical value for water quality monitoring.

3.4.2 Applicability Verification: The applicability of the optimal weighted PCA-RF model was verified from two dimensions: spatial distribution and seasonal variation, using the independent validation dataset that did not participate in model training. The accuracy evaluation plots for each parameter are shown in Figure 1, which are scatter plots of measured vs. inverted values annotated with core indicators such as R^2, RMSE, and MAE.

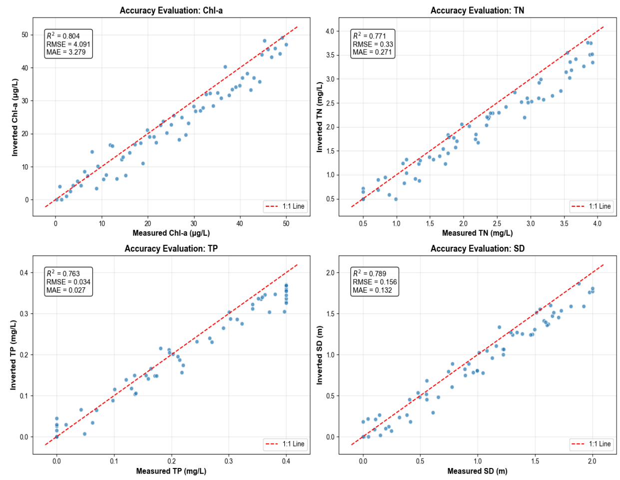

Figure 1. Inversion accuracy of four water quality parameters.

From the perspective of spatial applicability, the model was applied to the entire study area to generate spatial distribution maps of water quality parameters, covering different functional zones: urban rivers with high domestic sewage input, rural rivers with mixed agricultural and domestic pollution, and agricultural irrigation canals with intensive non-point source pollution. The verification results show that the model maintains high accuracy across all functional zones, with only slight deviations in areas near industrial zones and intensive livestock breeding areas, for example, the TN inversion error increases by 8%–10% in industrial zones. This is consistent with Changshu’s actual pollution distribution characteristics, where point-source pollution in industrial areas leads to sudden changes in nutrient concentrations that are difficult to capture by spectral signals.

From the perspective of seasonal applicability, the model’s performance across four seasons was evaluated to test its adaptability to seasonal hydrological and water quality changes. In Changshu, Chl-a peaks in spring during the algal bloom period, TN and TP peak in summer due to rainy season agricultural runoff, and SD is the lowest in summer with high sediment load. The weighted PCA-RF model maintains stable R^2 ($\geqslant$0.74) and low error indicators in all seasons, while the statistical regression model shows obvious seasonal fluctuations, for example, the TN R^2 drops to 0.48 in summer. This confirms that the seasonal weighting mechanism effectively suppresses the interference of seasonal spectral variations, ensuring the model’s long-term applicability for water quality monitoring in Changshu.

Overall, the weighted PCA-RF model exhibits superior accuracy, stability, and applicability for water quality parameter inversion in Changshu’s plain river network, and can be used as a reliable technical tool for large-scale, long-term water quality monitoring and assessment.

4. Eutrophication and Comprehensive Water Quality Evaluation

4.1 Eutrophication Assessment Method

This study uses a modified Carlson Trophic State Index (TSI) tailored for shallow plain river networks in the Yangtze River Delta, which revises the classic lake-oriented TSI to fit the unique hydrological and pollution features of river systems. The original trophic state index only includes chlorophyll-a, total phosphorus and Secchi depth, while this modified version incorporates total nitrogen as a core indicator, considering the prominent nitrogen pollution characteristic of regional river networks.

Weight assignment is optimized to better reflect riverine trophic status instead of using equal weighting: chlorophyll-a is assigned a weight of 0.3 as the primary indicator of algal biomass, total nitrogen and total phosphorus are each set to 0.25 to highlight the dominant role of nutrients in river eutrophication, and Secchi depth takes a weight of 0.2 due to its strong disturbance by river flow and sediment. The evaluation first calculates the trophic sub-index for each parameter based on remote sensing inversion values, then obtains the comprehensive TSI through weighted summation of the four sub-indices.

According to the calculated comprehensive TSI values, the water trophic state is divided into seven grades, namely oligotrophic, oligo-mesotrophic, mesotrophic, meso-eutrophic, eutrophic, hypereutrophic and ultraeutrophic. This grading system enables refined quantitative characterization of eutrophication levels across the entire Changshu river network.

4.2 Comprehensive Water Quality Evaluation Method

Comprehensive water quality evaluation is conducted in strict accordance with the Environmental Quality Standards for Surface Water (GB3838-2002), which classifies surface water into five grades from Grade Ⅰ to Grade Ⅴ. This research adopts the single-factor pollution index method combined with the worst-factor principle, a standardized and widely recognized approach for regional surface water assessment in China.

For each spatial unit in the river network, the remote sensing inversion value of each parameter (total nitrogen, total phosphorus, chlorophyll-a, Secchi depth) is compared with the standard threshold of each water grade to calculate the single-factor pollution index and judge the over-standard degree of each indicator. Total nitrogen and total phosphorus are taken as the core evaluation indexes, while chlorophyll-a and Secchi depth serve as auxiliary indicators reflecting water clarity and ecological status.

The final comprehensive water quality grade of each river segment is determined by the indicator with the highest pollution index, i.e., the worst-performing parameter. This method eliminates subjective interference from weighted integration, fully conforms to national surface water management norms, and can directly identify primary over-limit pollutants and reflect the real pollution level of the water body.

4.3 Experimental Procedure

The spatiotemporal distribution of eutrophication in Changshu across four quarters is shown in Fig. 2, presenting obvious spatial heterogeneity and seasonal variation. Urban rivers and agricultural irrigation areas are mostly in eutrophic or hypereutrophic states affected by intensive human activities, while suburban rivers with weak human disturbance are mainly mesotrophic; water bodies in the first and fourth quarters are dominated by oligo-mesotrophic to mesotrophic levels, and the eutrophication degree rises significantly in the second and third quarters, with some local sections reaching hypereutrophic or ultraeutrophic.

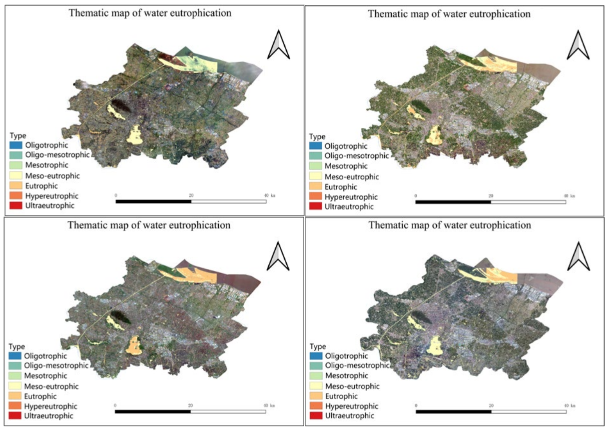

Figure 2. Thematic map of water eutrophication.

The comprehensive water quality evaluation results of four quarters are presented in Fig. 3, which are highly consistent with the spatial and temporal patterns of eutrophication. Urban and agricultural planting areas maintain relatively poor water quality grades, while suburban natural rivers stay at medium grades; the overall water quality in the first and fourth quarters is favorable with most river sections meeting regional water environment planning standards, and the water quality deteriorates sharply in the second and third quarters with a large increase in the proportion of poor-grade water areas.

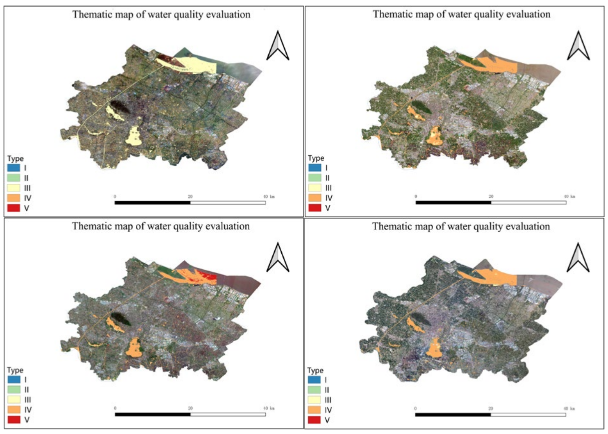

Figure 3. Thematic map of water quality evaluation.

The seasonal divergence of water environment quality is mainly driven by meteorological conditions and anthropogenic activities. Low temperatures in the first and fourth quarters inhibit algal reproduction and less rainfall reduces the input of agricultural non-point source pollutants, keeping nutrient concentrations at a low level; high temperatures in the second and third quarters accelerate algal growth, and intensive rainfall carries a large amount of nitrogen and phosphorus nutrients into rivers through surface runoff, further aggravating eutrophication and water quality degradation. These results clarify the spatiotemporal evolution characteristics of Changshu's water environment and provide scientific data support for local water quality supervision and targeted governance.

5. Conclusion

This study developed a targeted integrated remote sensing monitoring framework for Changshu's plain river network, addressing the technical challenges of conventional water quality remote sensing in this region. We optimized the mNDWI-based water extraction method, screened sensitive spectral features for four key water quality parameters and constructed a season-adaptive weighted PCA-RF inversion model, and improved the Carlson Trophic State Index combined with the single-factor pollution index method to conduct systematic eutrophication and comprehensive water quality evaluation, forming a complete technical workflow of extraction-inversion-evaluation-mapping.

This study clarified the significant spatiotemporal heterogeneity of water environment in Changshu's river network. Spatially, urban and agricultural irrigation areas suffered severe eutrophication and poor water quality due to intensive human activities, while suburban rivers with less anthropogenic interference maintained favorable water environmental conditions. Temporally, the water environment was in good condition in the first and fourth quarters, but eutrophication aggravated and water quality deteriorated sharply in the second and third quarters under the combined effects of seasonal meteorological conditions and non-point source pollution input, with the built model showing stable applicability across different spatiotemporal scales.

The research provides scientific technical support and data basis for targeted water environment supervision and governance in Changshu. The established multi-source remote sensing monitoring framework is well adapted to the hydrological and pollution characteristics of plain river networks in the Yangtze River Delta, and can serve as a reference for water quality remote sensing assessment in similar plain river network areas. It also makes up for the deficiency of sparse spatiotemporal coverage in traditional in-situ monitoring and enriches the methodological system of remote sensing-based water quality assessment for plain river networks.

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