APCS-MLR MODEL BASED SPATIOTEMPORAL CHARACTERISTICS AND SOURCE APPOINTMENT OF WATER POLLUTANTS IN NANYI LAKE, CHINA

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Abstract. The study of water quality variations and pollution sources provides a scientific foundation for pollution control. To explore the water quality and pollution sources in Nanyi Lake in the lower reaches of the Yangtze River, China, this study assessed the water quality of Nanyi Lake from 2013 to 2023 using the Trophic Level Index (TLI) and Comprehensive Pollution Index (CPI), elucidating the spatiotemporal distribution of pollutants in the lake. Based on this, the Absolute Principal Component Multiple Linear Regression (APCS-MLR) model was used to quantify the pollution sources. The results showed a mild pollution CPI (0.76). Seasonally, wet periods exhibit elevated permanganate index (COD_{Mn}) and chemical oxygen demand (COD_{Cr}) with reduced five-day biochemical oxygen demand (BOD_5), whereas dry seasons show TN, TP and ammonia nitrogen (NH_3-N) increases; summer features chlorophyll-a (Chl-a) accumulation. Spatially, pollutants peak in the eastern part of the lake. Source apportionment analysis indicated that agricultural non-point sources were the primary contributors to TN (72.54%) and NH_3-N (65.37%). Industrial point sources accounted for 44.32% of TP and 30.42% of Chl-a. Sediment deposition was identified as the dominant source of COD_{Mn} (82.75%), COD_{Cr} (41.03%), and BOD_5 (54.27%). Therefore, priority control measures must target agricultural runoff, sediment resuspension, and industrial emissions.
Keywords: *TLI, comprehensive pollution index, APCS-MLR model, pollution source analysis, Nanyi Lake*

Introduction

Lakes are essential components of terrestrial aquatic ecosystems, serving critical ecological functions as freshwater reservoirs, flood regulators, and habitats for biodiversity (Yang and Chen, 2004; Teittinen et al., 2025). Globally, approximately 1.42 million natural lakes exceed 0.1 km^2 in area (Wu et al., 2024). According to the China Environmental Status Bulletin, approximately 25.4% of the 209 monitored lakes and reservoirs failed to meet Class III standards under the national China's Surface Water Environmental Quality Standards (GB 3838-2002) [1]. This degradation is primarily attributed to pollution from industrial effluents, municipal wastewater, and agricultural runoff (Chen et al., 2018). Furthermore, the multiple sources and transport pathways of these pollutants, coupled with their potential synergistic effects, complicate the management of lakes (Li et al., 2024). Therefore, quantitative water quality analysis integrated with comprehensive pollution source assessments is essential to identify major pollutants and their contributions (Jiang et al., 2025).

[1] https://www.mee.gov.cn/

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Water quality evaluation is a critical prerequisite for effective water management and governance (Han et al., 2019). Initially, water quality assessments were based on sensory attributes such as color, odor, and turbidity (Li et al., 2021). With advances in science and technology, chemical and biological indicators have been incorporated into water quality assessment frameworks, significantly enhancing the accuracy of these evaluations (Chidiac et al., 2023). The single-factor water quality index method is straightforward in calculation and convenient to apply; however, it is heavily influenced by the most impaired indicator among those selected, leading to discrepancies between the evaluated results and actual water quality conditions (Uddin et al., 2021). In contrast, the comprehensive pollution index method, a widely adopted approach for water quality assessment, aggregates individual pollutant indicators to derive an overall index, thus providing widely recognized benchmarks and a management basis for environmental pollution (Su et al., 2022). The Trophic Level Index (TLI), based on chlorophyll-a (Chl-a), provides both qualitative and quantitative analyses of lake trophic status. The TLI reduces the bias caused by rapidly fluctuating or heavily weighted indicators (e.g., transparency) when evaluating eutrophication (Yunev et al., 2007).

The formulation of effective lake water quality management strategies relies critically on the identification of potential pollution sources and quantification of their contributions (Deng et al., 2025; Li et al., 2025). Multivariate statistical techniques, such as principal component/factor analysis (PCA/FA), provide a means to objectively identify key indicators, reduce redundancy in monitoring datasets, and support qualitative analysis of pollution sources across diverse water bodies (Gao et al., 2025). Among the receptor models commonly used for quantitative source apportionment are Positive Matrix Factorization (PMF), Unmix, and Absolute Principal Component Scores-Multiple Linear Regression (APCS-MLR) (Nkinahamira et al., 2024). These models do not require prior information on emissions or environmental conditions and are adaptable to various scenarios (Ren et al., 2023). In particular, the APCS-MLR model demonstrates strong stability and computational efficiency, with a relatively low sensitivity to missing data or outliers (Chen et al., 2022). Its applicability in quantifying pollution sources across rivers, lakes, and groundwater systems has been widely documented (Shi et al., 2022; Cai et al., 2025; Zhao et al., 2025). Qin et al. applied APCS-MLR to a highly regulated river in Northeast China and identified industrial wastewater as the primary pollution source during the dry season, with its impact diminishing in the rainy season (Qin et al., 2020). Similarly, Chen et al. used the APCS-MLR model to assess river water quality in the Northern Anhui Plain, attributing water quality degradation to industrial effluents, urban sewage, agricultural and domestic wastewater, geological processes and meteorological influences (Chen et al., 2022). Shen et al. employed PCA-APCS-MLR to investigate pollutant sources in stream networks across three urban polders in Jiaxing City (Shen et al., 2021). Despite these advances, lake water quality is often governed by complex interactions among environmental factors, such as seasonality, climate, and topography, and anthropogenic activities, including hydraulic regulation and pollution control measures (Wang and Mohd, 2025). Conventional analytical methods frequently fall short of accurately identifying key pollution sources or apportioning their contributions under such multifaceted conditions. Therefore, this study employed the APCS-MLR model to quantitatively assess river pollution sources through systematic statistical analysis, with the aim of establishing a robust framework for identifying pollution sources in lake systems.

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Nanyi Lake, situated in the southeast of Anhui Province at the junction of Anhui, Zhejiang, and Jiangsu provinces, is the largest natural lake in southern Anhui and a significant component of the Yangtze River. The lake and its surrounding wetlands are key water resources for local communities and provide critical habitats for migratory birds, such as wild geese and swans. However, the Nanyi Lake Basin has experienced increasing ecosystem degradation in recent years, driven by long-term environmental pressures from rapid agricultural, industrial, and urban development (Li et al., 2023a). The water ecological health of the Nanyi Lake Basin is related to the protection of the Yangtze River and the high-quality development of the Yangtze River Delta. Considering the importance of water source protection, Nanyi Lake was officially included in the first batch of lake protection lists in Anhui Province in 2018[2]. In recent years, the lake has exhibited gradient variations in water quality, with increasing concentrations of certain water quality indicators, particularly under the influence of high temperatures, heavy rainfall, and algal blooms. Nevertheless, a comprehensive regulatory framework and early warning system for water quality monitoring in Nanyi Lake has not yet been fully established, limiting the understanding of the causes and mechanisms of water quality deterioration. Therefore, a systematic water quality assessment and an in-depth investigation of potential pollution sources in the Nanyi Lake Basin are urgently needed.

Against this background, this study examined the variation patterns and driving mechanisms of water quality in Nanyi Lake. The CPI and TLI were used to assess the overall water quality and trophic conditions. In addition, an Absolute Principal Component Scores-Multiple Linear Regression (APCS-MLR) model was constructed to identify the key drivers of water quality variation and quantitatively apportion pollution sources. In contrast to previous studies, this study emphasizes the fluctuation patterns of water quality and the quantitative analysis of pollutants in Nanyi Lake, thereby addressing current research gaps and offering insights into the seasonal dynamics, anthropogenic influences, and environmental factors contributing to lake degradation. The main objectives of this study are as follows:(1) to characterize the water quality of Nanyi Lake from 2013 to 2023; (2) to analyze the spatiotemporal distribution of water pollutants; (3) to identify key drivers of water quality variation and quantify the contributions of different pollution sources in the lake basin; and (4) to propose targeted and practicable measures for water quality improvement from a basin-scale environmental management perspective. The significance of this study lies in the development of a rapid and cost-effective water quality assessment framework to support more informed and effective decision-making by local government agencies and water suppliers in developing countries. Furthermore, it offers a reference case for the environmental management of lake systems similar to Nanyi Lake.

Materials and methods

Study area

Nanyi Lake (30°57’-31°15′N, 118°43’-119°13′E), located in Xuancheng City, Anhui Province, China, covers a catchment area of 3,840 km² and constitutes an important component of the Yangtze River ecosystem (*Fig. 1*) (Ding et al., 2023). This basin has a subtropical humid monsoon climate with mild temperatures and ample rainfall. The

[2] https://slt.ah.gov.cn/xwzx/tzgg/29464801.html

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multi-year average temperature is 15.9 °C, and the average annual precipitation is 1,250 mm[3]. The lakebed is generally gentle in topography, with the East Lake depression lying lower than that of the West Lake. The average elevation of the lakebed is 8.2 m, descending to 6.0-7.0 m in the central area, while the shoreline extends approximately 140 km. These ecosystems play a significant role in supporting regional ecological integrity and socioeconomic development (Ariken et al., 2020). However, in recent years, Nanyi Lake has faced significant pressure from industrial and agricultural non-point-source pollution. The industrial pollution mainly comes from the wastewater discharge of the surrounding water related enterprises, in which the heavy metals (such as Mn, Sb, Fe) exceed the standard in the surface water, especially in the purse seine aquaculture area and living area, and their concentrations exceed the class III limit in the environmental quality standard for surface water[4]. Industrial wastewater and pollutants collected by rivers into the lake are enriched in the lake bay, resulting in a heavy metal content in sediments that is generally higher than the background value, with a high potential ecological risk (Tang et al., 2024).

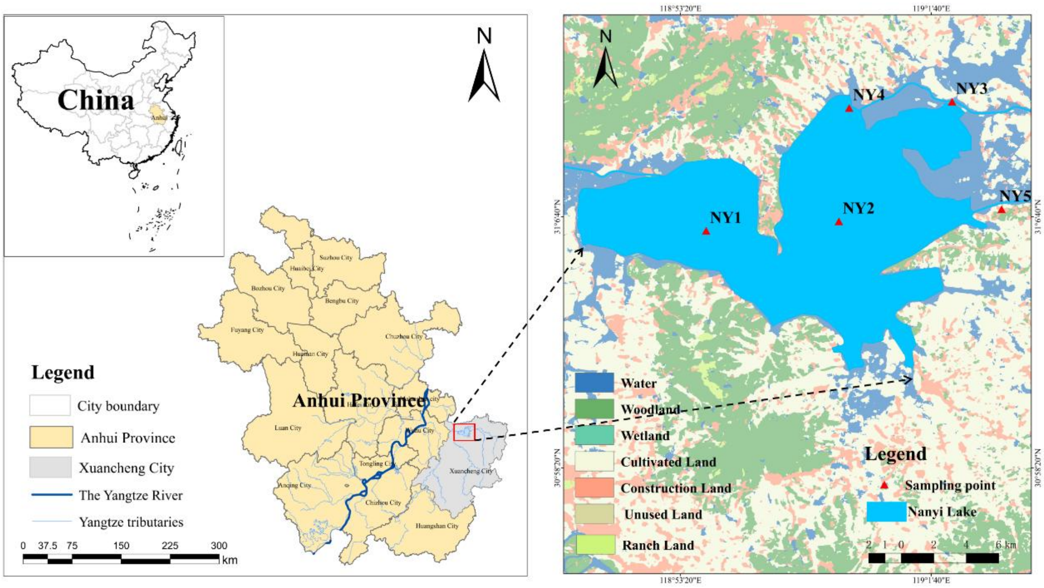

Figure 1. *Location of the study area and spatial distribution of sampling sites in Nanyi Lake*

Water samples collection and measurement

Water samples were collected monthly from five sampling points (NY1-NY5) from 2013 to 2023. The latitude and longitude of the sampling points are shown in *Table 1*. The water quality parameters analyzed in the laboratory included chlorophyll-a (Chl-a), total phosphorus (TP), chemical oxygen demand (COD_{Cr}), ammonia nitrogen (NH_3-N), total nitrogen (TN), permanganate index (COD_{Mn}), and five-day biochemical oxygen demand (BOD_5). During the sampling period, the location was first confirmed on-site using the Global Positioning System (GPS), and two water samples were collected. Each

[3] https://data.cma.cn/

[4] https://sthjt.ah.gov.cn/

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water sample was stored in a 1-liter container in polyethylene bottles pre-disinfected with 70% alcohol. During the sample collection process, the 1 L polyethylene bottle was rinsed three times with the original lake water. The samples were placed in a constant temperature chamber at 4 °C and sent to the laboratory for analysis. The water quality parameters of the collected samples were determined in the laboratory. The detection methods and standard indicators used in this study are listed in *Table 2*.

Table 1. *Monitoring methods and indicator standards used in the present study*

Sampling sites	Longitude	Latitude
NY1	118°54′11.16″ E	31°06'12.24" N
NY2	118°58'35.76" E	31°06'30.96" N
NY3	119°02'21.48" E	31°10'29.28" N
NY4	119°04'00.12" E	31°06'55.08" N
NY5	118°58'56.28" E	31°10'16.68" N

Table 2. *Monitoring methods and indicator standards used in the present study*

Indicator	Detection limit (mg/ L)	Monitoring method or standard
Total nitrogen (TN)	1.0	Alkaline potassium persulfate digestion - ultraviolet spectrophotometry (Zhang et al., 2025)
Total phosphorus (TP)	0.05	Potassium persulfate digestion - ammonium molybdate ultraviolet spectrophotometry (Chen et al., 2006)
Chemical oxygen demand (COD_{Cr})	20.0	Potassium dichromate process (Quintana et al., 2018)
Permanganate index (COD_{Mn})	6.0	Acid potassium permanganate method (Hue et al., 2017)
Ammonia nitrogen (NH_3-N)	1.0	Nessler reagent spectrophotometry (Du et al., 2024)
Five-day biochemical oxygen demand (BOD_5)	4.0	Dilution and inoculation method (Du et al., 2024)
Chlorophyll-a (Chl-a)	/	Extraction with acetone-ultraviolet Spectrophotometry (Lababpour and Lee, 2006)

Data analysis methods

Comprehensive pollution index

The pollution index was calculated as the ratio of each measured water quality parameter to its corresponding standard, and the comprehensive pollution index was derived by averaging these values with equal weights (Rajkumar et al., 2022). The comprehensive pollution index was calculated using the following formulas:

$$P_i = \frac{C_i}{S_i} \quad \text{(Eq.1)}$$

$$P = \frac{1}{n}\sum_{i=1}^{n} P_i \quad \text{(Eq.2)}$$

$$K_i = \frac{P_i}{\sum_{i=1}^{n} P_i} \times 100\% \quad \text{(Eq.3)}$$

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where, C_i is the measured concentration of the i^{th} indicator, measured in mg·L^{-1}; S_i is the concentration of index i specified in the water quality standard, measured in mg·L^{-1}; P_i is the pollution index of the i^{th} indicator; n is the number of water quality indicators, which is 6 in this article; K_i is the pollution sharing rate, expressed in %. The evaluation grading was based on the criteria shown in *Table 3*.

Table 3. *Assessment standards of the comprehensive pollution index (Mekonnen and Tekeba, 2023)*

Comprehensive Pollution Index	Water Quality Status
P≤0.40	Clean water quality
0.40 < P≤1.00	Light pollution water quality
1.00 < P≤2.00	Moderately polluted water quality
P > 2.00	Heavily polluted water quality

The trophic level index (TLI) method

Eutrophication in lakes is driven by various environmental factors, with nutrients such as nitrogen, phosphorus, and carbon being the primary pollutants (Carlson, 1977). Chl-a is a key indicator of eutrophication and is essential for assessing the overall trophic status of water bodies (Cudowski, 2015). The calculation formula is shown below, with the grading criteria listed in *Table 4*.

$$TLI(\sum) = \sum_{j=1}^{m} W_j \times TLI(j) \qquad \text{(Eq.4)}$$

where m is the number of main indicators participating in the evaluation, W_j is the relevant weight of the nutritional status index for the j^{th} indicator, *and TLI (j)* is the nutritional status index of the j^{th} indicator.

Table 4. *Evaluation criteria for TLI*

TLI	Trophic States
TLI < 30	Oligotrophic
30 ≤ TLI < 50	Mesotrophic
50 ≤ TLI < 60	Lightly eutrophic
60 ≤ TLI < 70	Moderately eutrophic
TLI ≥ 70	Hypertrophic

As Chl-a serves as the benchmark parameter in this evaluation method, the normalized correlation weight for the j^{th} indicator is calculated using the following formula:

$$W_j = \frac{{r_{ij}}^2}{\sum_{j=1}^{m} {r_{ij}}^2} \qquad \text{(Eq.5)}$$

where r_{ij} is the correlation coefficient between the j^{th} indicator and Chl-a. The correlations between Chl-a and r_{ij} and r_{ij}^2 are shown in *Table 5*.

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Table 5. *Correlation between rij, rij², and Chl-a*

Parameter	Chl-a	TN	TP	COD_{Cr}	COD_{Mn}
rij	1	0.84	0.82	0.83	0.83
rij^2	1	0.7056	0.6724	0.6889	0.6889

The nutrient level index of each index was calculated using the following equations:

$$TLI(TN) = 10 \times (5.453 + 1.694\, ln\, c_{TN}) \quad \text{(Eq.6)}$$

$$TLI(TP) = 10 \times (9.436 + 1.624\, ln\, c_{TP}) \quad \text{(Eq.7)}$$

$$TLI(COD) = 10 \times (0.109 + 2.661\, ln\, c_{COD}) \quad \text{(Eq.8)}$$

$$TLI(Chl - a) = 10 \times (2.5 + 1.0861\, ln\, c_{Chl-a}) \quad \text{(Eq.9)}$$

$$TLI(COD_{Mn}) = 10 \times (0.109 + ln\, C\, OD_{Mn}) \quad \text{(Eq.10)}$$

PCA/FA method

PCA/FA reconstructs complex datasets by generating principal components (PCs) through linear combinations of latent correlated variables (Ghosh and Panigrahi, 2024). Subsequently, a maximum variance rotation was applied to polarize the variable loadings on these components, forming new varimax factors (VFs) that provided a more effective interpretation of the data structure (Yang et al., 2024b). The strength of variable loadings is defined based on their value ranges: 0.3 to 0.5 indicates low loading, 0.5 to 0.75 denotes moderate loading, and 0.75 to 1 signifies strong loading (Liu et al., 2003). When multiple variables exhibit strong loadings on the same VF, it typically implies that they are influenced by a common underlying source. Prior to PCA/FA, the suitability of the dataset was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. A KMO value greater than 0.5 and a Bartlett's test p-value less than 0.05 indicate that the data are appropriate for factor analysis (Shrestha and Kazama, 2007).

APCS-MLR model

Because the dataset was normalized, the sample factor scores generated by PCA/FA could not be used to directly calculate the contribution of factors. It must be converted to an absolute principal component score (APCS) to estimate the original contribution of each component to the pollutant levels. The calculation formula is as follows.

$$APCS_{fk} = A_{fk} - A_{0f} \quad \text{(Eq.11)}$$

$$A_{0f} = \sum_{i=1} w_{if} Z_{0i} \quad \text{(Eq.12)}$$

$$Z_{0i} = \frac{0 - \bar{c}_i}{\sigma_i} \quad \text{(Eq.13)}$$

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where $APCS_{fk}$ is the absolute principal component score of k samples, A_{fk} is the score value of the f principal component of k samples by PCA/FA, C_i is the arithmetic mean of the pollution i factor, measured in mg·L^{-1}, *and* σ_i is the standard deviation of the pollution factor i. The principal component score of f is 0 for A_{0f}; Z_{0i} is the standardized value when the concentration of pollution factor i is set to 0.

To derive the regression equation, multiple linear regression was performed using the measured pollutant concentrations as dependent variables and the APCS values as independent variables. The calculation formula is as follows.

$$C_{ik} = \sum_{f=1} a_{fi} APCS_{fik} + b_i \quad \text{(Eq.14)}$$

where, C_{ik} is the concentration of pollutant factor i in sample k, measured in mg·L^{-1}; A_{fi} is the regression coefficient of pollution source f to pollution factor i; $APCS_{fik}$ is the absolute principal component score of pollutant factor f for sample i; b_i is a constant term in the multiple linear regression equation of the pollution factor i, which is generally considered to be the contribution of unidentified sources.

The average contribution rate of pollution source f to pollution factor i can be calculated using the following equation (Gao et al., 2025):

$$P_{fi} = \frac{|a_{fi}\overline{APCS}_{fi}|}{\sum_{f=1}|a_{fi}\overline{APCS}_{fi}|+|b_i|} \quad \text{(Eq.15)}$$

where P_{fi} is the average contribution rate of pollution source f to pollution factor i, C_i is the average contribution rate of unknown sources to pollution factor i, *and* $APCS_{fi}$ is the mean absolute principal component fraction of pollution factor i.

Statistical analyses

Data processing was performed using Excel 2024 and IBM SPSS Statistics version 27.0. The sampling point and spatiotemporal distribution maps were drawn using ArcGIS 10.2, and the other maps were drawn using Origin 2022.

Results and discussion

Water quality status in Nanyi Lake

Temporal distribution characteristics of water quality

To examine the seasonal variations in water quality, the monthly averages of the physicochemical parameters of water were calculated from 2013 to 2023, and the results are shown in *Figure 2*.

Pollutant concentrations are strongly correlated with the timing of precipitation events (Cánovas et al., 2012; Khoi and Thang, 2017). In Nanyi Lake, water levels are highest from May to August, lowest from December to February, and remain at normal levels during the rest of the year (Shan et al., 2018). Consistent with the high-water-level period, the COD_{Mn} and COD_{Cr} concentrations increased from May to August. In contrast, BOD_5 data showed considerable scatter from 2013 to 2023, indicating high variability, with overall lower concentrations observed during the wet season. TN and NH_3-N displayed similar seasonal trends, generally characterized by an initial increase, followed by a decline, and then a subsequent rise, with pollutant levels increasing during the dry season.

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The monthly average TP concentrations peaked in February, September, and November, aligning with the dry season of Nanyi Lake. Meanwhile, Chl-a concentrations were significantly higher in summer, which can be attributed to elevated water temperatures that promote phytoplankton growth and reproduction (Wei et al., 2025).

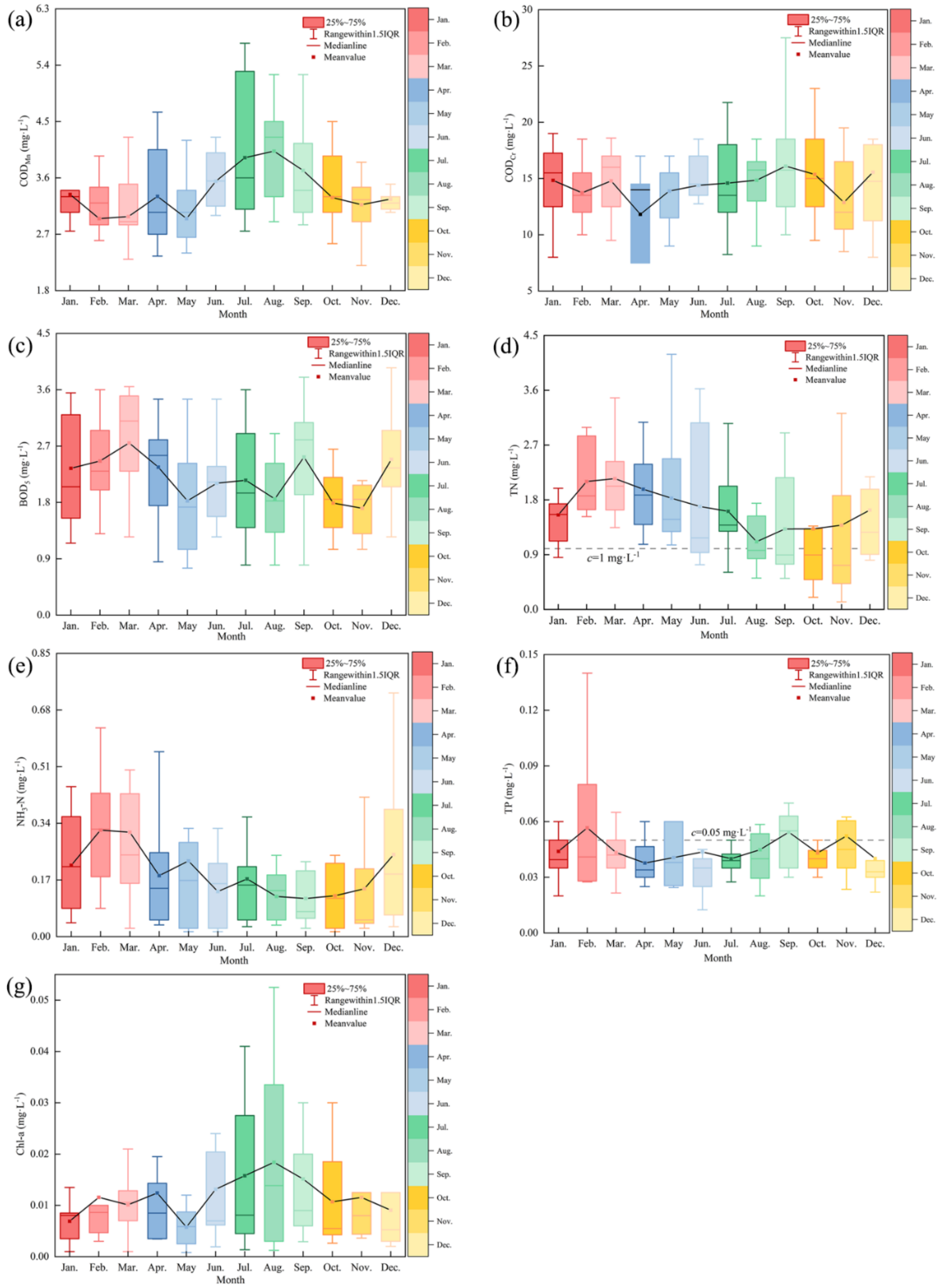

Figure 2. *The monthly means of main water quality indices in Nanyi Lake from 2013 to 2023*

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Spatial distribution characteristics of water quality

ArcGIS 10.2 was used to perform inverse distance weighting (IDW) interpolation on average water quality data from 2013 to 2023 to estimate pollutant concentrations in Nanyi Lake. As shown in *Fig. 3*, the concentrations of various water quality indicators were higher along the banks of the eastern part of the lake than in other areas.

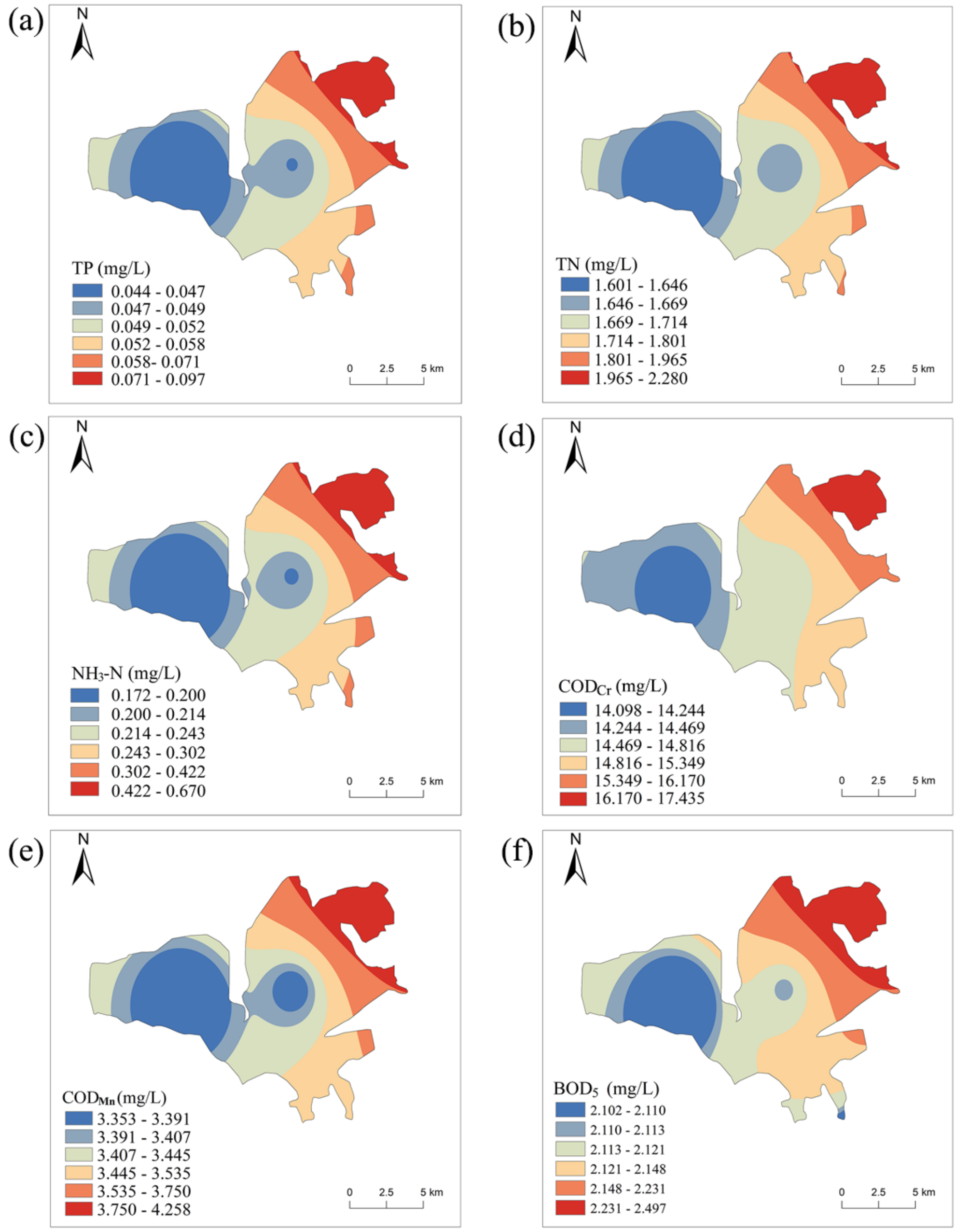

Figure 3. *The spatial distribution of main water quality indices of Nanyi Lake from 2013 to 2023*

Table 6 shows a strong correlation between TP, TN, and NH_3-N concentrations in the inflow rivers and those along the east bank of the lake. These findings suggest that inflow rivers significantly influence the nitrogen and phosphorus levels in the lake.

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Table 6. *The average values of main water quality indices at different monitoring points in Nanyi Lake and its inflow rivers from 2013 to 2023*

Sampling point	TP	TN	NH_3-N	Chl-a	COD_{Cr}	BOD_5	COD_{Mn}
NY 1	0.044	1.607	0.174	0.011	14.099	2.189	3.35
NY 2	0.048	1.678	0.204	0.012	14.704	2.197	3.366
NY 3	0.133	3.66	1.021	-	18.413	2.487	4.34
NY 4	0.098	2.28	0.671	-	17.436	1.994	3.435
NY 5	0.071	1.393	0.256	-	11.316	1.103	2.686

COD_{Cr} concentrations were relatively high in the central eastern region of the lake. The TP and TN levels were elevated near the east and south banks, whereas the COD_{Mn} and NH_3-N levels were higher along the northeast shore. Overall, poor water quality near the east bank may be linked to aquaculture activities and riverine pollution (Li et al., 2023b).

CPI

According to equation 1 and 2, the mean pollution index of the sampling points in the Nanyi Lake area from 2013 to 2023 was shown in *Table 7*. The average CPI of the Nanyi Lake area from 2013 to 2023 was 0.76, indicating that the water quality was classified as light pollution.

Table 7. *The pollution index of Nanyi Lake*

	TP	TN	COD_{Cr}	NH_3-N	BOD_5	COD_{Mn}
2013	0.92	0.81	0.39	1.33	0.73	0.59
2014	0.83	0.73	0.27	1.64	0.67	0.52
2015	0.90	0.74	0.29	2.30	0.58	0.58
2016	0.87	0.74	0.33	3.25	0.59	0.51
2017	1.21	0.79	0.12	2.15	0.54	0.55
2018	1.30	0.86	0.18	1.19	0.53	0.58
2019	0.99	0.57	0.17	1.39	0.44	0.58
2020	0.80	0.58	0.06	1.21	0.45	0.55
2021	0.66	0.63	0.07	1.20	0.33	0.52
2022	0.74	0.76	0.13	1.20	0.46	0.61
2023	0.86	0.67	0.10	1.07	0.49	0.61
Average pollution index	0.92	1.63	0.72	0.19	0.53	0.56
CPI	0.76					

According to *Equation 3*, the pollution contribution of the six water quality indicators was calculated based on the comprehensive pollution index (*Fig. 4*).

The single pollution index of TP was 0.92, and the pollution-sharing rate was 20.2%. The TN single pollution index was 1.63, and the pollution-sharing rate was 35.9%. The single pollution index of COD_{Cr} was 0.72, and the pollution-sharing rate was 15.8%. The pollution-sharing rates of NH_3-N, BOD_5, and COD_{Mn} were 4.2%, 11.6%, and 12.4%, respectively. It can be seen that the distribution characteristics of different pollutants are

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TN>TP> COD_{Cr} > COD_{Mn} >BOD_5>NH_3-N, and TN and TP account for 56.3% of the total pollution load, indicating that TN and TP are the main pollution sources in the six indicators involved.

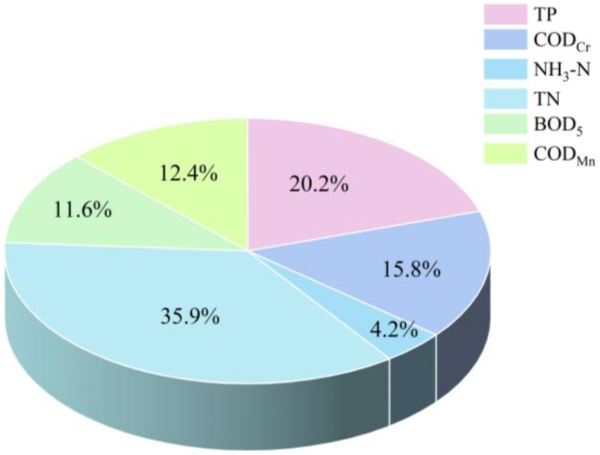

Figure 4. *The pollution contribution rate of Nanyi Lake*

TLI

According to *Equations 4 to 10*, the application of the TLI method revealed that Nanyi Lake had indices ranging from 52.79 to 75.13 between 2013 and 2023. Specifically, all years exhibited light eutrophication, except 2014 and 2021, which showed mesotrophic conditions (*Fig. 5*).

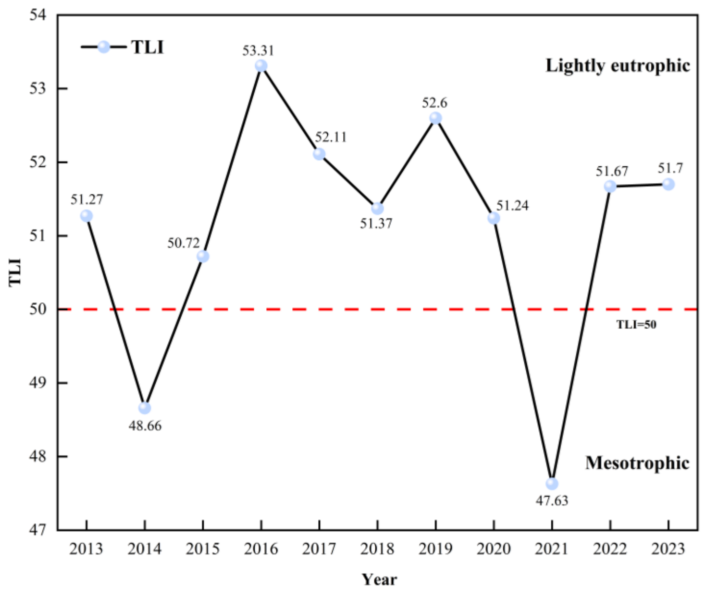

Figure 5. *The trend of TLI value for Nanyi Lake from 2013 to 2023*

As shown in *Fig. 5*, the comprehensive trophic index of Nanyi Lake has increased annually since 2014.The upward trend was most pronounced between 2014 and 2016 but slowed from 2017 to 2020, coinciding with Xuancheng City's intensified treatment

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efforts for inflow rivers during this period. Nanyi Lake's trophic index declined from 2020 to 2021 in 2019, Xuancheng City introduced the "Nanyi Lake Water Pollution Control Work Plan" [5], further advancing pollution control efforts. From 2021 to 2022, the TLI of Nanyi Lake increased significantly. Survey data show that Xuancheng City received 1,700.7 mm of precipitation in 2021, a relatively wet year, while rainfall dropped by 22.7% to 1,315.1 mm in 2022[6], educed precipitation concentrates pollutants in the water, increasing nutrient availability for algae and intensifying eutrophication (Zhang et al., 2023).

Pollution source identification

Correlation analysis

A correlation matrix was used to assess relationships among the variables (Nong et al., 2024). This study analyzes monthly average data from 2013 to 2023 to examine correlations among seven key water quality indicators in Nanyi Lake. *Fig. 6* presents the Pearson correlation matrix for the water quality indicators, with coefficients ranging from -0.24 to 0.52.

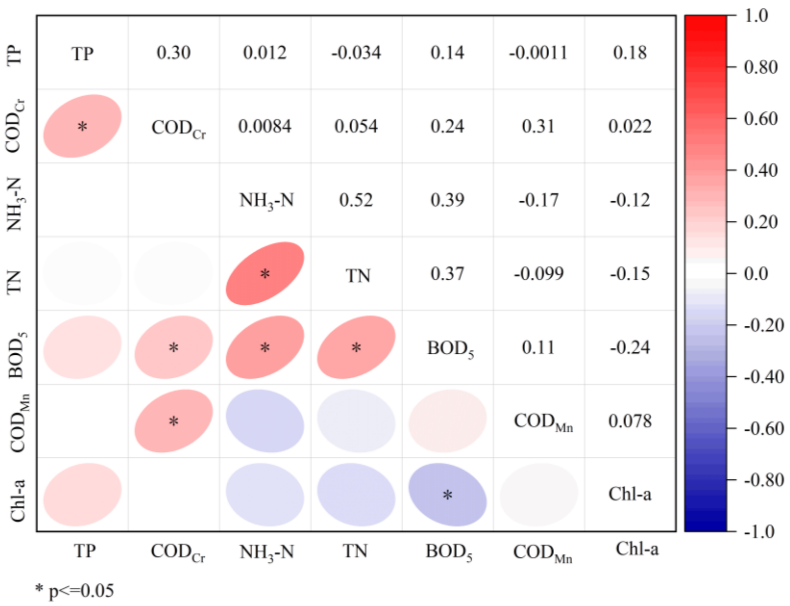

Figure 6. *The correlation coefficient matrix of water quality indicators*

The results revealed a significant correlation between TP and COD_{Cr}. Elevated COD_{Cr} levels generally indicate high organic matter content in water. During the decomposition of such organic material, dissolved oxygen is consumed, leading to anaerobic conditions that facilitate the release of phosphorus from sediments (Socha et al., 2018). Similarly, the correlation between TN and NH_3-N implies a shared pollution origin and comparable spatiotemporal variation patterns, which aligns with the earlier analysis of water quality distribution characteristics. BOD_5 showed significant correlations with COD_{Cr}, NH_3-N,

[5] https://sthjj.xuancheng.gov.cn

[6] https://data.cma.cn/

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and TN, underscoring a connection between organic and nitrogenous pollutants and reflecting the interdependence of organic matter decomposition and nitrogen transformation processes (Mindová et al., 2025). In contrast, a significant negative correlation was observed between Chl-a and BOD_5, suggesting mutual inhibition. On one hand, algal photosynthesis raises dissolved oxygen concentrations, thereby stimulating microbial decomposition of organic matter and lowering BOD_5 (Ma et al., 2019). On the other hand, algae compete with heterotrophic microorganisms for nutrients, which can suppress metabolic activity and further reduce BOD_5 levels (Jin et al., 2020).

Identification of pollution sources with PCA/FA

KMO-Bartlett test was used to analyse the correlation between variables. Results showed a KMO value of 0.581 and a significant Bartlett sphericity test ($P < 0.01$). This indicated strong correlations suitable for PCA and factor analysis. The criterion of eigenvalues > 1 resulted in 3 components with a 65.95% cumulative variance (*Table 8*).

Table 8. *The rotating component matrix of water quality indicators of Nanyi Lake*

Water quality indicators	Load factor after rotation		
	F1	**F2**	**F3**
TP	0.146	0.208	0.802
COD_{Cr}	0.155	0.744	0.308
NH_3-N	0.813	-0.171	0.018
TN	0.785	-0.073	-0.074
BOD_5	0.7	0.401	-0.064
COD_{Mn}	-0.212	0.795	-0.125
Chl-a	-0.302	-0.119	0.682
Eigenvalue (%)	1.975	1.55	1.092
Variance contribution rate (%)	28.208	22.14	15.602
Cumulative variance contribution rate (%)	28.208	50.348	65.95

Factor analysis was used to extract three principal components, followed by orthogonal rotation to simplify the factor loadings. The rotated matrix, shown in *Fig. 7*, reveals clearer factor structures with loadings approaching 0 or 1.

Factor 1 (F1) has an eigenvalue of 1.975 and accounts for 27.859% of the total variance after rotation. It is predominantly loaded with TN, NH_3-N, and BOD_5, indicating nitrogen pollution as a major influencing factor. Nitrogen in lake water typically originates from domestic and agricultural non-point sources. In the Nanyi Lake Basin, agricultural non-point source pollution contributes to the accumulation of TN, NH_3-N, and BOD_5 through multiple pathways (Qiu et al., 2025). For instance, nitrogen fertilizers such as urea, applied on farmland, enter the lake via surface runoff, directly elevating TN concentrations, with approximately 30%-50% of this nitrogen existing in the form of NH_3-N (Wen et al., 2023). Aquaculture operations introduce untreated inputs (e.g., residual feed, metabolic waste, and pharmaceuticals), degrading water quality and increasing nitrogen concentrations. In addition, dissolved oxygen is consumed in the degradation, resulting the average BOD_5 increased compared with the background value (Yang et al., 2024a). Therefore, F1 is characterized as an agricultural non-point source.

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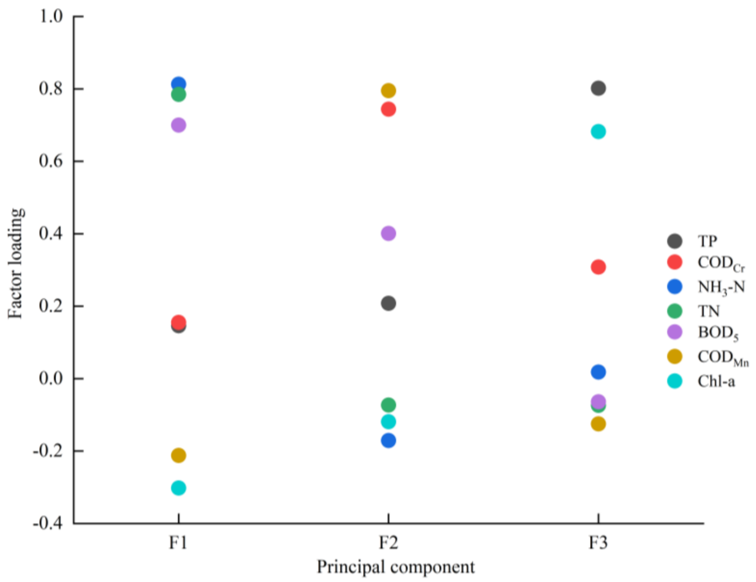

Figure 7. *Component loadings for 7 parameters after varimax rotation*

The eigenvalue of Factor 2 (F2) is 1.550, accounting for 20.5% of the variance after rotation. The main load variables are COD_{Mn} and COD_{Cr}, and BOD_5 load is moderate. The three indicators are comprehensive indicators reflecting the content of organic pollutants in water. As the largest natural freshwater lake in southern Anhui, the sediment deposition problem of Nanyi Lake is mainly concentrated in the estuary area (such as the estuary of the bridegroom River and the laolangchuan River)[7]. The sediment is mainly composed of clay, sediment and organic matter, which is enriched with nutrients such as nitrogen and phosphorus and heavy metal pollutants for a long time, forming an endogenous pollution pool (Tao et al., 2025). The research shows that the decomposition of organic matter in sediment under anaerobic conditions will release dissolved organic matter (DOM), which directly contributes to COD_{Mn} and COD_{Cr} in water (Chai et al., 2024). In addition, the degradation products of organic matter in the sediment (such as small molecular fatty acids) can significantly improve BOD_5, because it is easy to be quickly used by microorganisms to accelerate the process of oxygen consumption (Wang et al., 2025; Wen et al., 2025). The lakebed at the center of Nanyi Lake lies at 6.0-7.0 m, while the normal water level ranges from 8.5 to 9.0 m. Due to years without dredging, significant sediment accumulation has occurred. During dry periods, water depth in some areas drops below 1.0 m[8]. Wind and wave action readily resuspend sediments, leading to sharp increases in nitrogen and phosphorus concentrations and significantly affecting the lake's water quality and environment (Hu et al., 2024). Therefore, F2 can be defined as sediment deposition.

The Factor 3 (F3) eigenvalue is 1.092 and the variance contribution rate after rotation is 17.6%. TP and Chl-a serve as its primary loading factors. TP and Chl-a are the key indicators to evaluate the eutrophication status (Xiao et al., 2023). Industrial activities around Nanyi Lake are mainly concentrated in Xuanzhou District agricultural products

[7] https://www.xuanzhou.gov.cn/

[8] https://sthjj.xuancheng.gov.cn/

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(food) processing park and other areas. These industrial point sources may input nitrogen, phosphorus and other nutrients into Nanyi Lake through wastewater discharge, surface runoff and other channels (Li et al., 2023a). In addition, sewage outlets in the upstream areas of the Wuliangxi and Langchuan Rivers discharge pollutants from industrial and mining enterprises. Wastewater from electroplating, metal treatment, printing, dyeing, papermaking, and brewing industries enters the lake via sewage outlets, resulting in consistently high levels of total phosphorus and organic matter (Heisler et al., 2008; Li et al., 2023b). Moreover, industrial discharge may change the proportion of nitrogen and phosphorus in water and affect the structure of algal community and Chl-a is a key photosynthetic pigment in algae (Lu et al., 2024). With the increase of nutrient level, its concentration increases, thus promoting algal bloom (Islam et al., 2024). Therefore, F3 can be defined as an industrial point source.

Pollution source apportionment using APCS-MLR model

SPSS 27 was used to derive the coefficients of each absolute principal component and the constant term in the multiple linear regression equations (*Table 9*). According to equations 11 to 14, the reliability of the model was verified by calculating the water quality index values using regression equations and comparing the predicted results with the measured values (*Fig. 8*). The R^2 values, ranging from 0.55 to 0.78, indicate a good fit between the predicted and measured concentrations of water quality indicators in the reservoir area. The predicted-to-measured value ratio was close to 1, confirming the model's reliability and its suitability for analyzing pollution sources in Nanyi Lake (Xie et al., 2023).

Table 9. *The coefficients of MLR equation between APCS and water quality indices*

	TP	**COD_{Cr}**	**NH_3-N**	**TN**	**BOD_5**	**COD_{Mn}**	**Chl-a**
Constant	0.049	14.383	0.214	2.056	2.205	3.348	12.497
APCS1 coefficient	0.146	0.574	14.91	13.115	12.168	-3.91	-4.707
APCS2 coefficient	0.208	2.753	-3.127	-1.226	6.966	14.627	-1.847
APCS3 coefficient	0.802	1.14	0.333	-1.233	-1.114	-2.296	10.622

APCS: absolut principal component score

Using the APCS-MLR model and equation 15, the contribution rates of three pollution source types to key water quality indicators in Nanyi Lake were calculated (*Table 10 and Fig. 9*).

The source apportionment results demonstrate that agricultural non-point sources (APCS1) constitute the primary origin of nitrogen pollutants in the study area, contributing 72.54% and 65.37% to TN and NH_3-N, respectively. Organic pollutants, including COD_{Mn}, COD_{Cr}, and BOD5, are mainly derived from sediment deposition (APCS2), with contribution rates of 82.75%, 41.03%, and 54.27%, respectively. Meanwhile, TP and Chl-a are predominantly influenced by industrial point sources (APCS3), with the increase in TP concentration identified as the major driver of Chl-a variation (Han et al., 2025). The respective contribution rates of APCS3 to TP and Chl-a are 44.32% and 30.42%.

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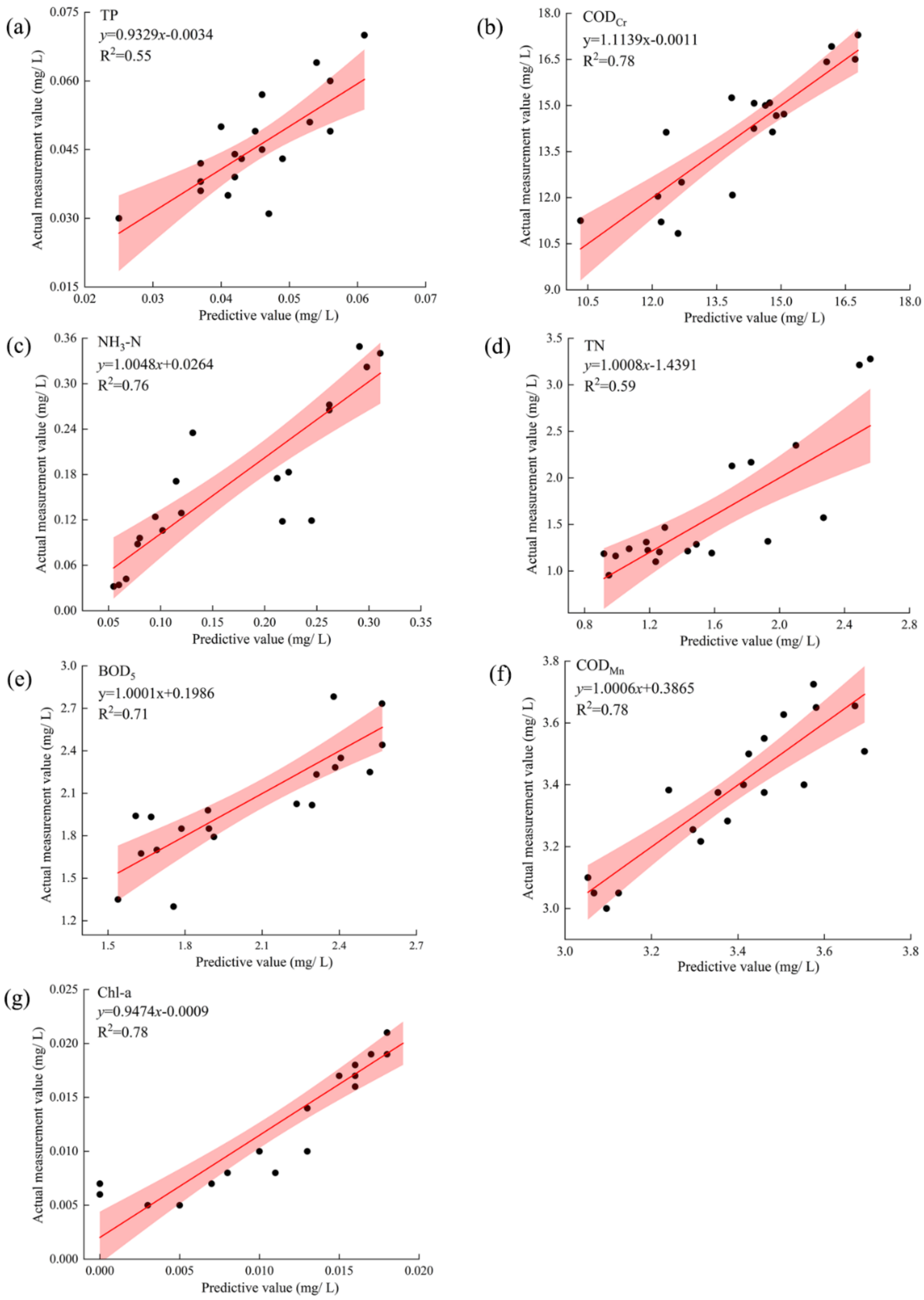

Figure 8. *The comparison of observed and predicted values of main water quality indices in Nanyi Lake*

On average, APCS1, APCS2, APCS3, and unidentifiable sources account for 31.7%, 41.1%, 13.0%, and 14.2% of the total water pollutants in Nanyi Lake, respectively. This indicates that sediment deposition (APCS2) serves as the most significant pollution source in the region, followed by agricultural non-point sources (APCS1), while industrial point sources (APCS3) exhibit the lowest average contribution. It is worth noting that the contribution from unknown sources even exceeds that of APCS3, which

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can be attributed to the fact that each pollutant indicator originates from multiple, widespread, and complex sources that are strongly influenced by anthropogenic disturbances (Cheng et al., 2016; Wang et al., 2022).

Table 10. *The contributions of different pollution sources to the main water quality indices in Nanyi Lake (%)*

Source of pollutants	TP	COD_{Cr}	NH_3-N	TN	BOD_5	COD_{Mn}	Chl-a
APCS1 contribution rate	12.02	3.54	65.37	72.54	39.25	9.16	20.08
APCS2 contribution rate	41.35	41.03	33.11	16.38	54.27	82.75	19.03
APCS3 contribution rate	44.32	4.72	0.98	4.58	2.41	3.61	30.42
Unidentified source	2.30	50.71	0.54	6.50	4.06	4.48	30.46

APCS: absolute principal component score

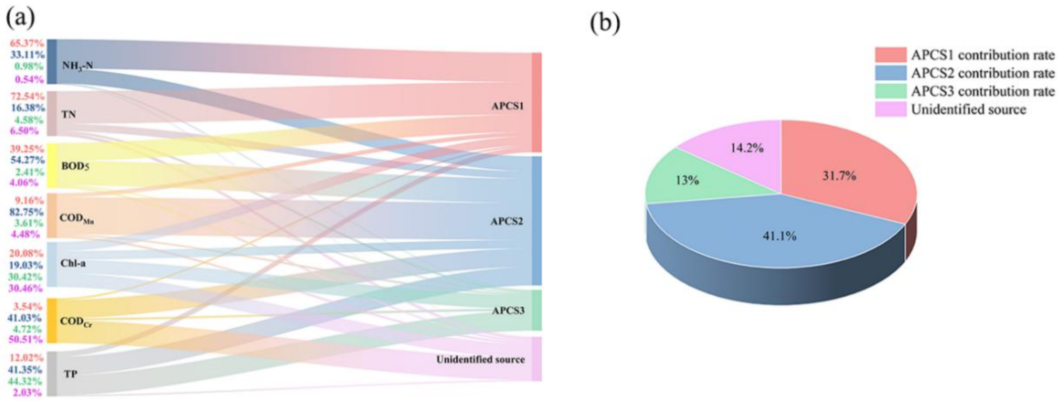

Figure 9. *The contribution ratio of various sources to each water quality index and the comprehensive contribution of various sources to water quality. APCS: absolute principal component score*

Conclusion

This study demonstrates that the water quality of Nanyi Lake is at a lightly polluted level, with TN and TP identified as the primary pollutants. The trophic state of the lake was mesotrophic in 2014 and 2021, and lightly eutrophic in all other years monitored. Analysis of spatiotemporal variations revealed that pollutant concentrations generally peaked during the wet season and decreased in the dry season. Furthermore, elevated pollutant levels were observed along the eastern shore, largely attributable to influences from inflowing rivers. Comprehensive analysis indicated that the main pollution sources in the Nanyi Lake Basin were agriculture, sediment deposition, and industry.TN and NH_3-N primarily originate from agriculture, contributing 72.54% and 65.37%, respectively. TP and Chl-a were mainly linked to industrial sources, at 44.32% and 30.42%. Sediment deposition was the dominant source of COD_{Mn}, COD_{Cr} and BOD_5, with contribution rates of 82.75%, 41.03%, and 54.27%, respectively. To improve the water quality of Nanyi Lake, targeted strategies should be implemented focusing on agricultural, industrial, and sediment management. Priority measures include enhancing pollution control in agricultural and aquaculture practices, upgrading sewage treatment infrastructure, strictly enforcing industrial effluent standards, and implementing targeted sediment dredging operations.

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REFERENCES

[1] Ariken, M., Zhang, F., Liu, K., Fang, C., Kung, H. (2020): Coupling coordination analysis of urbanization and eco-environment in Yanqi Basin based on multi-source remote sensing data. – Ecological Indicators 114: 106331.

[2] Cai, G., Zhang, J., Li, W., Zhang, J., Liu, Y., Xi, S., Li, G., Li, H., Chen, X., Song, F., Xie, F. (2025): Spatiotemporal variation and influencing factors of phosphorus in Asia's longest river based on receptor model and machine learning. – Ecological Indicators 171: 113217.

[3] Cánovas, C. R., Olías, M., Sarmiento, A. M., Nieto, J. M., Galván, L. (2012): Pollutant transport processes in the Odiel River (SW Spain) during rain events. – Water Resources Research 48: W06508.

[4] Carlson, R. E. (1977): A trophic state index for lakes. – Limnology and Oceanography 22: 361-369.

[5] Chai, S., Zhang, X., Xie, F., Zhou, X., Lü, C. (2024): Catchment-driven trend of dissolved organic matter characteristics in the Hailar River, China. – Applied Geochemistry 175: 106162.

[6] Chen, M., Daroub, S. H., Nadal, V. (2006): Comparison of two digestion methods for determining total phosphorus in farm canal water. – Communications In Soil Science and Plant Analysis 37: 2351-2363.

[7] Chen, J., Wang, J., Guo, J., Yu, J., Zeng, Y., Yang, H., Zhang, R. (2018): Eco-environment of reservoirs in China. – Progress in Physical Geography: Earth and Environment 42: 185-201.

[8] Chen, K., Liu, Q., Jiang, Q., Hou, X., Gao, W. (2022): Source apportionment of surface water pollution in North Anhui Plain, Eastern China, using APCS-MLR model combined with GIS approach and socioeconomic parameters. – Ecological Indicators 143: 109324.

[9] Cheng, W., Yang, Z., Zhong, C., Ji, J. (2016): Temporal-spatial variation and source apportionment of soil heavy metals in the representative river-alluviation depositional system. – Environmental Pollution 216: 18-26.

[10] Chidiac, S., El Najjar, P., Ouaini, N., El Rayess, Y., El Azzi, D. (2023): A comprehensive review of water quality indices (WQIs): history, models, attempts and perspectives. – Reviews in Environmental Science and Bio/Technology 22: 349-395.

[11] Cudowski, A. (2015): Dissolved reactive manganese as a new index determining the trophic status of limnic waters. – Ecological Indicators 48: 721-727.

[12] Deng, S., Tao, L., Li, Y., Lan, P., Wang, L., Cun, D., Chang, J. (2025): Lake pollution control and restoration: A critical review of strategies and measures for plateau lakes in Southwestern China. – Ecological Engineering 215: 107583.

[13] Ding, L., Qi, C., Zhang, W. (2023): Distribution characteristics of non-point source pollution of TP and identification of key source areas in Nanyi Lake (China) Basin: based on InVEST model and source list method. – Environmental Science and Pollution Research 30: 117464-117484.

[14] Du, J., Yang, X., Xu, P., Wan, X., Wang, P., Wang, D., Yang, Q., Wang, Q., Razzaq, A. (2024): Linking Water Quality Indicators in Stable Reservoir Ecosystems: Correlation Analysis and Ecohydrological Implications. – Water 16(24): 3600.

[15] Gao, J., Li, J., Tong, T., Chao, J., Dong, Z., Zhan, J. (2025): Water quality evaluation, pollution sources apportionment, and environment management strategies in plain reservoirs: A case study of Tianhe Lake, China. – Ecological Indicators 175: 113491.

[16] Ghosh, P., Panigrahi, A. K. (2024): Assessment of water quality and source apportionment of pollution in a tropical river in eastern India: A study utilizing multivariate statistical tools

and the APCS-MLR receptor model. – Environmental Monitoring and Assessment 196: 861.
[17] Han, H., Li, H., Zhang, K. (2019): Urban Water Ecosystem Health Evaluation Based on the Improved Fuzzy Matter-Element Extension Assessment Model: Case Study from Zhengzhou City, China. – Mathematical Problems in Engineering 2019(2): 1-14.
[18] Han, H., Yan, X., Li, X., Zhao, X., Qiu, J., Huang, Z., Yan, X., Xia, Y. (2025): Quantile regression reveals phosphorous overwhelms nitrogen in controlling high chlorophyll-a concentration in freshwater lakes. – Journal of Hydrology 654: 132845.
[19] Heisler, J., Glibert, P. M., Burkholder, J. M., Anderson, D. M., Cochlan, W., Dennison, W. C., Dortch, Q., Gobler, C. J., Heil, C. A., Humphries, E., Lewitus, A., Magnien, R., Marshall, H. G., Sellner, K., Stockwell, D. A., Stoecker, D. K., Suddleson, M. (2008): Eutrophication and harmful algal blooms: A scientific consensus. – Harmful Algae 8: 3-13.
[20] Hu, B., Liu, Y., Chen, Y., Yao, Y., Liu, H., Wang, Z. (2024): Water quality and pollution source apportionment responses to rainfall in steppe lake estuaries: A case study of Hulun Lake in northern China. – Ecological Indicators 168: 112791.
[21] Hue, D., Shiba, T., Maeda, Y., Takenaka, N. (2017): A 3-step chemiluminescence method for chemical oxygen demand measurement with dichromate oxidizing reagent. – Analytical Methods 9: 5797-5805.
[22] Islam, S. T., Bhat, S. U., Sabha, I., Sofi, M. S., Dar, S. A. (2024): Comprehensive Assessment of Trophic Status and Chlorophyll-a Dynamics in the Jhelum River Basin: Implications for River Ecosystem Management. – International Journal of Environmental Research 19: 48.
[23] Jiang, F., Wu, Q., Li, Q., Jiqin, K., Zeng, J., Gao, S., Yi, S., Liu, S., Liang, F. (2025): Integrated quantitative tracing for Karst groundwater contamination: A case study of landfill in Zunyi, Guizhou Province, China. – Environmental Pollution 368: 125731.
[24] Jin, X., Zhang, W., Li, S. (2020): Complex responses of suspended particulate matter in eutrophic river and its indicative function in river recovery process. – Ecological Indicators 115: 106397.
[25] Khoi, D. N., Thang, L. V. (2017): Climate change impacts on streamflow and non-point source pollutant loads in the 3S Rivers of the Mekong Basin. – Water and Environment Journal 31: 401-409.
[26] Lababpour, A., Lee, C. G. (2006): Simultaneous measurement of chlorophyll and astaxanthin in Haematococcus pluvialis cells by first-order derivative ultraviolet-visible spectrophotometry. – Journal of Bioscience and Bioengineering 101: 104-110.
[27] Li, L. J., Baohui, M., Rui, P. (2021): Water Quality Evaluation of Wenyu River Based on Single Factor Evaluation and Comprehensive Pollution Index Method. – Nature Environment and Pollution Technology 20(3): 1041-1046.
[28] Li, G., Li, X., Jiang, X., Zhang, Y., Li, H., Zhang, J., Cai, G., Luo, K., Xie, F. (2023a): Occurrence and source analysis of heavy metals and dissolved organic matter in Nanyi Lake, Anhui Province. – Environmental Monitoring and Assessment 195: 660.
[29] Li, Y., Xiao, H., Zhao, Y., Zhong, Y., Fu, G., Zhou, S., Xu, Y., Zhou, K. (2023b): Study on total phosphorus pollution load estimation and prevention and control countermeasures in Dongting Lake. – Energy Reports 9: 294-305.
[30] Li, N., Zhao, Z., Zhang, L., Zhang, H., Wang, G., Xie, X., Liu, K., Jia, Z., Cheng, X., Wen, J., Li, Y. (2024): Historical sources and ecological risk trends of typical toxic pollutants in sediments from Taihu Lake, Yangtze Delta, China. – Ecological Indicators 159: 111679.
[31] Li, H., Zhang, H., Duan, L., Liu, Q., Li, D., Huang, J., Fu, J., Zi, L., Xu, T. (2025): Spatiotemporal variations in water quality parameters and assessment of the current status and challenges of eutrophication in Lake Dian. – Ecological Indicators 177: 113821.
[32] Liu, C., Lin, K., Kuo, Y. (2003): Application of factor analysis in the assessment of groundwater quality in a blackfoot disease area in Taiwan. – Science of The Total Environment 313: 77-89.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1179111813

[33] Lu, J., Garzon-Garcia, A., Chuang, A., Burton, J., Jackson, C., Rogers, J., Newham, M., Saeck, E., Allan, M., Burford, M. A. (2024): Nutrient metrics to compare algal photosynthetic responses to point and non-point sources of nitrogen pollution. – Ecological Indicators 158: 111425.
[34] Ma, J., Wang, P., Ren, L., Wang, X., Paerl, H. W. (2019): Using alkaline phosphatase activity as a supplemental index to optimize predicting algal blooms in phosphorus-deficient lakes: A case study of Lake Taihu, China. – Ecological Indicators 103: 698-712.
[35] Mekonnen, Y. A., Tekeba, H. M. (2023): Analysis of water quality by comprehensive pollution index (CPI) and self-purification capacity of Shinta River, Ethiopia. – Sustainable Water Resources Management 10: 10.
[36] Mindová, M., Němec, M., Hou, X., Vockenhuber, C., Daňo, M. (2025): Distribution and variation of 129I in Danish water. – Marine Environmental Research 209: 107229.
[37] Nkinahamira, F., Feng, A., Zhang, L., Rong, H., Ndagijimana, P., Guo, D., Cui, B., Zhang, H. (2024): Machine learning approaches for monitoring environmental metal pollutants: Recent advances in source apportionment, detection, quantification, and risk assessment. – TrAC Trends in Analytical Chemistry 180: 117980.
[38] Nong, X., Luo, K., Lin, M., Chen, L., Long, D. (2024): Relationships between water quality of a long-distance inter-basin water diversion project and air pollution emissions along the canal: Distributions, lag effects, and nonlinear responses. – Environmental Pollution 361: 124813.
[39] Qin, G., Liu, J., Xu, S., Wang, T. (2020): Water quality assessment and pollution source apportionment in a highly regulated river of Northeast China. – Environmental Monitoring and Assessment 192: 446.
[40] Qiu, W., Du, Y., Liu, W., Liu, X., Deng, Y., Ma, T., Wang, Y. (2025): Multi-Phase mobilization and degradation pathway of natural organic matter within alluvial-lacustrine aquifer sediments. – Journal of Hydrology 659: 133310.
[41] Quintana, G. O., Fagnani, E., Candello, F. P., Guimaraes, J. R. (2018): The Dichromate Method versus the Photoelectrochemical Method: The Synergistic Influence of Turbidity and Chlorides on Chemical Oxygen Demand Analysis. – Journal of The Brazilian Chemical Society 29: 490-498.
[42] Rajkumar, H., Naik, P. K., Rishi, M. S. (2022): A comprehensive water quality index based on analytical hierarchy process. – Ecological Indicators 145: 109582.
[43] Ren, X., Zhang, H., Xie, G., Hu, Y., Tian, X., Gao, D., Guo, S., Li, A., Chen, S. (2023): New insights into pollution source analysis using receptor models in the upper Yangtze river basin: Effects of land use on source identification and apportionment. – Chemosphere 334: 138967.
[44] Shan, L., Zhang, L., Xiong, Z., Chen, X., Chen, S., Yang, W. (2018): Spatio-temporal evolution characteristics and prediction of dry-wet abrupt alternation during the summer monsoon in the middle and lower reaches of the Yangtze River Basin. – Meteorology and Atmospheric Physics 130: 427-440.
[45] Shen, D., Huang, S., Zhang, Y., Zhou, Y. (2021): The source apportionment of N and P pollution in the surface waters of lowland urban area based on EEM-PARAFAC and PCA-APCS-MLR. – Environmental Research 197: 111022.
[46] Shi, W., Li, T., Feng, Y., Su, H., Yang, Q. (2022): Source apportionment and risk assessment for available occurrence forms of heavy metals in Dongdahe Wetland sediments, southwest of China. – Science of The Total Environment 815: 152837.
[47] Shrestha, S., Kazama, F. (2007): Assessment of surface water quality using multivariate statistical techniques: A case study of the Fuji river basin, Japan. – Environmental Modelling & Software 22: 464-475.
[48] Socha, M., Bonislawska, M., Torz, A., Rybczyk, A., Nedzarek, A., Taski, A., Pender, R. (2018): Assessment of water quality in the Wisniowka River considering circulation of organic matter. – Iranian Journal of Fisheries Sciences 17: 690-712.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1179111813

[49] Su, K., Wang, Q., Li, L., Cao, R., Xi, Y. (2022): Water quality assessment of Lugu Lake based on Nemerow pollution index method. – Scientific Reports 12: 13613.
[50] Tang, S., Long, Y., Li, J., Wen, X., Chen, H., Zhang, Y., Chen, J. (2024): Current state, sources, and potential risk of heavy metals in sediments of typical inner lakes in the Dongting Lake Area. – Process Safety and Environmental Protection 190: 1290-1300.
[51] Tao, Y., Ma, S., Cao, M., Li, J., Wang, F., Gao, Z., Xu, Q., Guo, J., Sun, K., Wang, F. (2025): Recent advances on iron bound phosphorus in wetland sediments: characteristics, influencing factors, interactions with organic matter and emerging contaminants. – Environmental Pollution 383: 126826.
[52] Teittinen, A., Luoto, M., Muukkonen, P., Myyry, M., Reiman, M., Scherer-Lorenzen, M., Soininen, J. (2025): Cross-boundary connections of biodiversity and ecosystem functioning in boreal ecosystems. – Ecological Monographs 95: e70013.
[53] Uddin, M. G., Nash, S., Olbert, A. I. (2021): A review of water quality index models and their use for assessing surface water quality. – Ecological Indicators 122: 107218.
[54] Wang, X., Zhang, M., Liu, L., Wang, Z., Lin, K. (2022): Using EEM-PARAFAC to identify and trace the pollution sources of surface water with receptor models in Taihu Lake Basin, China. – Journal of Environmental Management 321: 115925.
[55] Wang, H., Mohd, N. S. (2025): Driving factors and management strategies for water quality improvement in Fuxian Lake, China: A case study on ecological restoration and sustainable management of plateau lakes. – Ecological Indicators 174: 113440.
[56] Wang, F., Sun, S., Xu, W., Fu, W., Shi, H., Zhao, M. (2025): Compound class carbon isotope characterization of organic matter sources, transport, and degradation in sediments of large river-influenced coastal oceans. – Geochimica et Cosmochimica Acta 400: 190-203.
[57] Wei, Z., Yu, Y., Yi, Y. (2025): Prediction of Future Chlorophyll-a Concentrations in Large Eutrophic Shallow Lakes Under Multiple Stressors. – Earth's Future 13(5): e2024EF005293.
[58] Wen, Y., Zhang, W., Shan, B. (2023): Amino acids as indicators of seasonal variations in organic matter degradation in surface sediments from a shallow lake. – Journal of Environmental Sciences 131: 1-10.
[59] Wen, S., Hu, A., Dini-Andreote, F., Han, L., Jiang, S., Jang, K., Wang, J. (2025): Molecular activity mediates the composition and assembly of dissolved organic matter in lake sediments. – Limnology and Oceanography 70: 1196-1209.
[60] Wu, J., Yang, B., Cheng, F., Zhao, F., Ma, S., Yuan, X., Zeng, H., Tang, C., Yang, K., Zhao, L. (2024): Decoding lake water dynamics to optimize watershed agriculture through isotopic analyses of memory effects and hydrological connectivity. – Ecological Indicators 169: 112826.
[61] Xiao, H., Luo, Y., Jiang, M., Su, R., Li, J., Xiang, R., Hu, R. (2023): Landscape patterns are the main regulator of pond water chlorophyll α concentrations in subtropical agricultural catchments of China. – Journal of Cleaner Production 425: 139013.
[62] Xie, D., Li, X., Zhou, T., Feng, Y. (2023): Estimating the contribution of environmental variables to water quality in the postrestoration littoral zones of Taihu Lake using the APCS-MLR model. – Science of The Total Environment 857: 159678.
[63] Yang, H., Chen, C. (2004): Emission inventory and sources of polycyclic aromatic hydrocarbons in the atmosphere at a suburban area in Taiwan. – Chemosphere 56: 879-887.
[64] Yang, X., Zhou, Y., Yang, X., Zhang, Y., Spencer, R. G. M., Brookes, J. D., Jeppesen, E., Zhang, H., Zhou, Q. (2024a): Optical measurements of dissolved organic matter as proxies for CODMn and BOD5 in plateau lakes. – Environmental Science and Ecotechnology 19: 100326.
[65] Yang, Y., Li, B., Li, C., Liu, P., Li, T., Luo, Y., Yang, L., Che, L., Li, M. (2024b): Spatiotemporal comprehensive evaluation of water quality based on enhanced variable fuzzy set theory: A case study of a landfill in karst area. – Journal of Cleaner Production 450: 141882.

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DOI: http://dx.doi.org/10.15666/aeer/2306_1179111813

[66] Yunev, O. A., Carstensen, J., Moncheva, S., Khaliulin, A., Ærtebjerg, G., Nixon, S. (2007): Nutrient and phytoplankton trends on the western Black Sea shelf in response to cultural eutrophication and climate changes. – Estuarine, Coastal and Shelf Science 74: 63-76.
[67] Zhang, F., Xue, B., Cai, Y., Xu, H., Zou, W. (2023): Utility of Trophic State Index in lakes and reservoirs in the Chinese Eastern Plains ecoregion: The key role of water depth. – Ecological Indicators 148: 110029.
[68] Zhang, Y. M., Zhang, S. W., Wang, Y., Kong, X. F., Shi, Q., Gao, Y., Gao, N., Fu, J. N., Chen, S. G., Liu, Y. (2025): Application of advanced oxidation method combined with sequential injection technology in in-situ monitoring of total nitrogen and phosphorus in water. – Journal of Environmental Chemical Engineering 13(5): 117855.
[69] Zhao, K., Gan, Y., Li, C., Guan, X., Wang, Z., Li, F., Liu, Y., Qi, F., Zhu, X. (2025): Regional pollution source apportionment and emission thresholds determination in Zunyi's major watersheds: Implications for environmental management. – Environmental Pollution 381: 126640.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2306_1179111813