

DOI: 10.11835/j.issn.2096-6717.2025.050



开放科学(资源服务)标识码 OSID:



基于Landsat-8数据的Chla时空分布反演及驱动因素分析——以太湖为例

张子薇^{1,2}, 郭先华¹, 王雅竹², 刘倩辰¹

(1. 重庆三峡学院 重庆市三峡库区水环境演变与污染防治重点实验室; 三峡库区环境生态重庆市野外科学观测站, 重庆 404100; 2. 中国科学院南京地理与湖泊研究所, 南京 210008)

摘要: 叶绿素a(Chla)主要来源于浮游植物, 是水体富营养化的关键指标, 反映了水质的生态状况, 也是衡量湖泊生态系统健康和初级生产力的重要参数。以太湖为研究区域, 利用Landsat 8 OLI卫星影像和实测数据, 建立半经验偏最小二乘(PLS)回归模型, 反演太湖过去10年(2015—2024)间Chla的时空分布。结果表明, 模型能有效捕捉太湖Chla浓度的空间分布和时序变化, 且不同年份的反演结果具有较好的预测准确性。进一步分析发现, Chla浓度的变化受自然地理和社会经济因素的双重影响, 在自然因素方面, 风速、温度、光照等气候条件以及磷浓度和水深等水体特征, 对Chla的时空分布具有显著影响; 在社会经济因素方面, 人口增长、工业化进程和农业活动等因素与太湖的富营养化程度呈线性相关关系。然而, 随着经济发展, 目前社会经济已超越环境库兹涅茨曲线(EKC)拐点, 环境质量与经济发展之间呈现负相关关系。

关键词: 叶绿素浓度; 遥感反演; 太湖; 水环境; 水质变化

中图分类号: X832 文献标志码: A 文章编号: 2096-6717(XXXX)XX-0001-16

Analysis of the spatiotemporal distribution inversion and driving factors affecting Chlorophyll-a concentration based on Landsat 8 data: A case study of Taihu Lake

ZHANG Ziwei^{1,2}, GUO Xianhua¹, WANG Yazhu², LIU Qianchen¹

(1. Chongqing Key Laboratory of Water Environment Evolution and Pollution Control in Three Gorges Reservoir Area; Three Gorges Reservoir Area Environment and Ecology of Chongqing Observation and Research Station, Chongqing Three Gorges University, Chongqing 404100, P. R. China; 2. Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing 210008, P. R. China)

Abstract: Chlorophyll-a (Chla), primarily sourced from phytoplankton, is a key indicator of water eutrophication, reflecting the ecological status of water quality. It is also an important parameter for assessing the health and primary productivity of lake ecosystems. This study focuses on Taihu Lake, using Landsat 8 OLI satellite imagery and field data to establish a semi-empirical Partial Least Squares (PLS) regression model, which was employed to retrieve the spatiotemporal distribution of Chla in Taihu Lake over the past decade (2015 – 2024). The results demonstrate that the model effectively captures the spatial distribution and temporal

Received: 2024-12-12

Foundation items: Science and Technology Planning Project of NIGLAS (No. NIGLAS2022GS07); National Sociology Foundation of China (No. 21BMZ141); Foundation of Intelligent Ecotourism Subject Group of Chongqing Three Gorges University (No. zhlv20221005);

Author brief: ZHANG Ziwei (1999-), main research interest: water environment, E-mail: ziweihappy@163.com.

WANG Yazhu (corresponding author), PhD candidate, E-mail: yzwang@niglas.ac.cn.

variations of Chla concentration in Taihu Lake, with good predictive accuracy across different years. Further analysis reveals that Chla concentration variation is influenced by both natural geographical and socio-economic factors. Regarding natural factors, climate conditions such as wind speed, temperature, and light, along with water characteristics including phosphorus concentration and water depth, significantly affect the spatiotemporal distribution of Chla. In socio-economic aspects, population growth, industrialization, and agricultural activities show linear correlations with the eutrophication degree of Taihu Lake. However, with economic development, the current socio-economic situation has surpassed the Environmental Kuznets Curve (EKC) inflection point, demonstrating a negative correlation between environmental quality and economic development.

Keywords: Chla concentration; remote sensing inversion; Taihu lake; water environment; changes in water quality

1 Introduction

Chlorophyll-a (Chla), mostly derived from phytoplankton, serves as a critical indicator of water eutrophication and serves as a fundamental parameter for evaluating eutrophication levels, biophysical conditions, and primary productivity within lakes. The rapid proliferation of algal blooms within phytoplankton communities provides a direct indicator of eutrophication in aquatic environments. As eutrophication involves significant alterations in nutrient loading for algae, this induces ecological imbalances in aquatic ecosystems. Excessive algal growth, combined with oxygen depletion in benthic zones, poses significant threats to aquatic biodiversity. As planktonic vegetation undergoes photosynthesis, this converts CO_2 and H_2O into oxygen^[1]. This process may modify the original ecological equilibrium of water bodies. Planktonic plants represent a vital component of aquatic ecosystems, fulfilling essential roles in their functional ecology^[2]. Consequently, the anthropogenically driven proliferation of cyanobacteria severely disrupts enclosed aquatic ecosystems, although this process has been shown to have negligible impacts on coastal ecosystems^[3]. Thus, Chla has been extensively adopted as a standardized indicator for lacustrine water quality assessment.

Traditional methods for detecting Chla and assessing water quality often face challenges in the large-scale characterization of the horizontal heterogeneity of aquatic ecosystems at large scales. These approaches yield limited surface-level data, thereby constraining rapid and large-scale detection capabilities. In comparison, remote sensing technology enables rapid detection and facilitates longitudinal

monitoring across extensive spatial domains. Remote sensing water quality monitoring uses the spectral reflectance characteristics of water bodies in conjunction with water quality parameters to establish inversion models, thereby permitting comprehensive regional water quality assessment through remote sensing imagery. This methodology demonstrates robust regional monitoring capabilities. As such, over the past six decades, remote sensing has emerged as a pivotal tool for global water quality monitoring, effectively mitigating the constraints inherent to conventional methodologies^[4-5]. Extensive scholarly research, both domestic and international, has been conducted on water quality and Chla quantification using remote sensing techniques. For instance, Hansen et al.^[6] examined the issue of Landsat revisit times for detecting short-term events in specific lakes within the Great Salt Lake surface water system, such as Great Salt Lake, Farmington Bay, and Utah Lake. GALL^[7] used data from the New Zealand Ocean, Coastal, and Estuary (NIWA-SCENZ) website, which provides access to remote sensing satellite data, to establish a monitoring and evaluation system for water quality in New Zealand's Otago Estuary and coastal waters. Yigit Avdan et al.^[8] assessed water quality in Borabey Dam, Turkey, using high-resolution RapidEye satellite data combined with in situ measurements taken at several-day intervals. Chegoonian et al.^[9] developed a support vector regression (SVR) model to estimate Chla concentrations in eutrophic Buffalo Pond Lake (BPL) located in Saskatchewan, Canada, validating the model with data from seven ice-free seasons. Wang et al.^[10] applied regression methods and physical models, utilizing hyperspectral satellite data and field

observations, to monitor key water quality parameters, such as turbidity (WT), total nitrogen (TN), total phosphorus (TP), and total organic carbon (TOC) in high-altitude rivers on the Qinghai – Tibet Plateau. The interaction between the concentration of optically active substances in water and the color of water is a key criterion affecting water quality^[11]. Currently, the main sources of Chla inversion data using remote sensing images include Landsat-5 series satellites^[12], Landsat-8 series satellites^[13], MODIS series satellites, Sentinel series satellites^[14], Gaofen-1 series satellites, MERIS image data^[15], Hyperion image data, SeaWiFs series satellites^[16], and unmanned aerial vehicle hyperspectral image data.

Taihu Lake, ranked as the third largest freshwater lake among China's five major freshwater lakes, functions as a critical hub for tourism, transportation, drinking water supply, and aquaculture in the Yangtze River Delta economic zone. Accelerated economic growth, urban sprawl, and anthropogenic pressures in the basin over the past two decades have induced a substantial influx of pollutants into the lake. Scientific evidence has identified nitrogen (N) and phosphorus (P) as pivotal limiting nutrients for algal proliferation^[17]. Furthermore, cumulative pollution has degraded water quality, elevated nutrient concentrations, exacerbated eutrophication, and induced cyanobacterial blooms. The water quality classification has also deteriorated from Class II to Class III, with localized areas even reaching Class IV and Class V standards. These exogenous pollutant-driven algal blooms have severely disrupted the ecological equilibrium, posing risks to public health. Over the years, anthropogenic pressures stemming from demographic expansion, industrial emissions, agricultural intensification, and regional economic transitions have collectively exacerbated hydroecological stressors in Taihu Lake. Given the lake's substantial surface area and periurban characteristics, organic pollutants constitute a predominant contributor to aquatic contamination. In this regard, hydrological constraints, including prolonged hydraulic retention and limited assimilative capacity, necessitate enhanced monitoring protocols to inform remediation strategies. In particular, the high temporal variability of algal-associated water quality parameters man-

dates systematic spatiotemporal monitoring for effective management.

Existing research has predominantly concentrated on analyzing water quality parameters and short-term Chla concentration fluctuations in Taihu Lake. For instance, Yang et al.^[18] systematically investigated heavy metal speciation in the aqueous and sedimentary phases of Taihu Lake, with a particular focus on the biogeochemical transformation of labile metal fractions in surficial sediments and their potential impacts on water quality. Concurrently, limnological studies^[19] using 1991 – 1992 datasets revealed dynamic water quality variations in Liangxi Bay and its western subregions. Zhang et al.^[20] further established an empirical algorithm for modeling Chla spatial distribution during 2006 – 2008, while subsequent research^[21] developed a Bayesian network-based simulation framework (1992 – 2020) to quantify Chla responses to meteorological and physicochemical variables. Spatiotemporal patterns of Chla and primary productivity in Meiliang Bay (1995 – 2003) were elucidated by Zhang et al.^[22] through vertical generalized production model (VGPM) applications. Yan et al.^[23] comprehensively analyzed three-decade (1990-2021) TP and TN trajectories, although Chla dynamics remained unaddressed. Current monitoring data demonstrate persistent eutrophication that exceeds regulatory thresholds, mainly characterized by escalating Chla concentrations. However, long-term, high-frequency Chla monitoring remains underdeveloped. Therefore, the present study constructs a semiempirical inversion model that integrates Landsat 8 imagery and in situ Chla measurements (2015 – 2024) to characterize decadal spatiotemporal Chla patterns, thereby providing critical insights into eutrophication mitigation in Taihu Lake.

2 Materials and Methods

2.1 Overview of the study area

The Taihu Lake Basin, centrally located in the Yangtze River Delta, contains China's third-largest freshwater lake^[24]. Geographically spanning 30°55'40"N-31°32'58"N and 119°52'32"N-120°36'10"E, the Basin predominantly occupies southern Jiangsu Province, extending across Jiangsu and Zhejiang provinces with a longitudinal reach of 393.2 km.

The lake itself covers 2 338.1 km² water surface area with 4.4×10^9 m³ storage capacity, serving as a multifunctional system for potable water supply (annual provision: 1.5 billion m³, serving 9.6 million residents), aquaculture, tourism, and flood regulation.

Climatologically, the basin exhibits a subtropical monsoon regime characterized by: Mean annual precipitation of 1000-1400 mm (peaking in July to August); Mean annual temperatures ranging from 14.9 °C to 16.2 °C; Seasonal patterns, including humid summers with concentrated rainfall and mild winters with persistent precipitation.

Geomorphologically, the eastern periphery features low-lying alluvial plains (<5 m elevation), contrasting with western uplands dominated by weathered granite hills (20 – 350 m elevation). This topographic heterogeneity supports well-developed fluvial networks that sustain regional ecological integrity and socioeconomic activities.

2.2 Data collection and research method

2.2.1 Water sample collection

This study mainly uses two types of data to analyze the spatiotemporal of Chla in Taihu Lake: satellite remote sensing data and data from an integrated water observation platform. Due to the vast area covered by Taihu Lake and considering the distribution characteristics of the lake water body and local topography, 30 sampling points (shown in Fig. 1) have been strategically arranged. Sampling was conducted during periods of calm lake surfaces and clear weather conditions. The corresponding relationship between the names and the numbers of sampling points is outlined in Table 1. Chla concentration was measured using spectrophotometry^[25]. In particular, a specific amount of water samples was filtered through a membrane filter to retain algae. Subsequently, the retained algae were ground, and the cell walls were ruptured to extract Chla using an acetone solution. Following centrifugation, the absorbance of the extraction solution was measured at wavelengths of 750, 664, 647, and 630 nanometers. Chla concentration was then calculated using the formula (1) and formula (2).

$$P_1 = 11.85(A_{664} - A_{750}) - 1.54(A_{647} - A_{750}) - 0.08(A_{630} - A_{750}) \quad (1)$$

$$C' = P_1 V_1 / V \quad (2)$$

In the formula, P_1 is the concentration of Chla in the sample; A_{630} , A_{647} , A_{664} , and A_{750} are the absorbance values of the sample at wavelengths of 630, 647, 664, and 750 nm, respectively; C' represents Chla concentration in the sample; V_1 is the constant volume of the sample; and V is the sampling volume.

In accordance with the “*Environmental Quality Standards for Surface Water*” (Table 1), during October 9 – 19, 2015, out of 30 sampling points, only 2 showed good water quality, falling under Class I water bodies. One sampling point recorded a Chla concentration between 10 and 15 µg/L, indicating Class II water quality. For 9 sampling points, the Chla concentration ranged between 15 and 25 µg/L, categorizing them as Class III water bodies. Additionally, 10 locations exhibited Chla concentrations between 25 and 40 µg/L, indicating Class IV water bodies. One point fell within the 25 – 40 µg/L range, classifying it as a Class V water body. Furthermore, Chla concentrations exceeding 50 µg/L were observed at the 7 remaining sampling points, signaling poor Class V water quality.

Similarly, during the sampling period from September 3 to 6, 2016, only 2 sampling points demonstrated good water quality, classified as Class I water bodies. Chla concentrations ranging between 10 and 15 µg/L were recorded at 7 sampling points, indicating Class II water quality. For 3 sampling points, the Chla concentration fell between 15 and 25 µg/L, placing them in Class III water bodies. One point exhibited a Chla concentration between 25 and 40 µg/L, indicating Class IV water quality. Chla concentrations between 25 and 40 µg/L were observed at two locations, classifying them as Class V water bodies. Finally, Chla concentrations exceeding 50 µg/L were observed at the remaining 15 sampling points, indicating poor Class V water quality.

2.2.2 Introduction to remote sensing data and data preprocessing

The Landsat 8 Operational Land Imager (OLI) data acquired on August 28, 2016 exhibited minimal cloud interference over Taihu Lake, with cloud cover affecting less than 5% of the study area. These satellite datasets were obtained from the United States Geological Survey (USGS) Landsat archive.

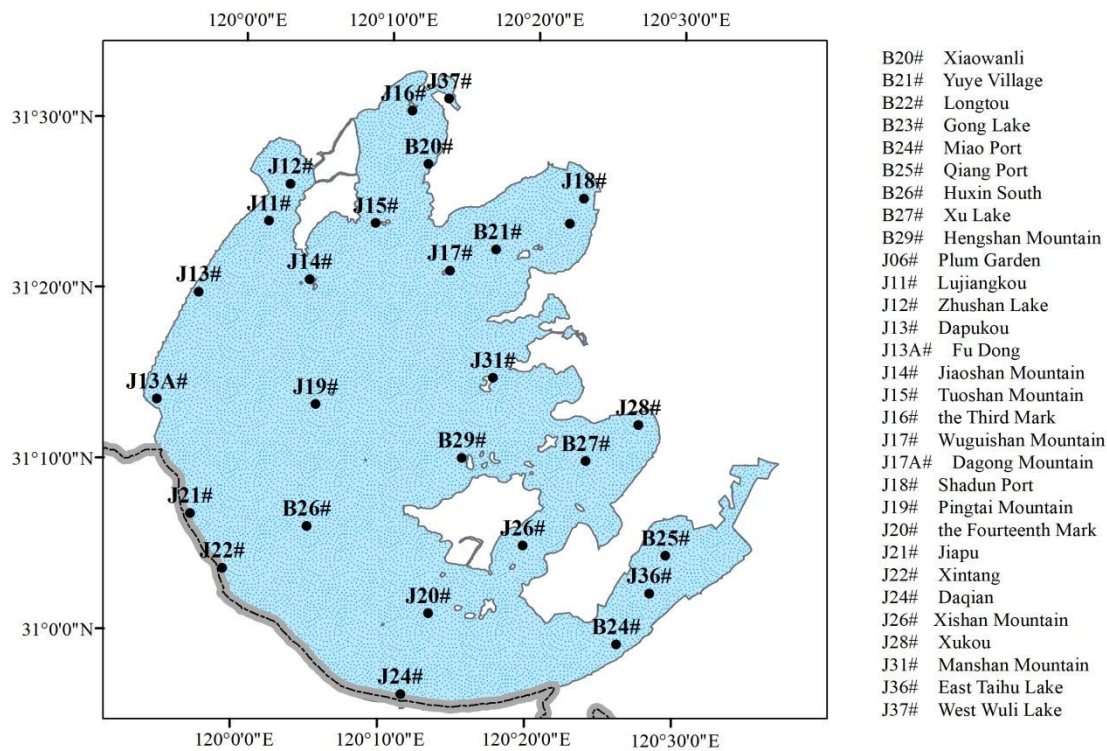


Fig. 1 Sampling point map of Taihu Lake

Table 1 Environmental quality standards for surface water

Water quality parameters	Chlorophyll-a
Classification	concentration/($\mu\text{g/L}$)
Class I	≤ 10
Class II	15
Class III	25
Class IV	40
Class V	50

Launched in February 2013, the Landsat 8 satellite operates two primary sensors: the OLI and the thermal infrared sensor (TIRS). The OLI sensor captures data across nine spectral bands at a 30-m spatial resolution, including a 15-m panchromatic band (Band 8) covering a 185-km swath width. Key spectral enhancements include the adjustment of Band 5 ($0.845\text{--}0.885\text{ }\mu\text{m}$) to avoid atmospheric water vapor absorption at $0.825\text{ }\mu\text{m}$ and the addition

of a coastal aerosol band (Band 1: $0.433\text{--}0.453\text{ }\mu\text{m}$) for improved aquatic monitoring.

Preprocessed Landsat 8 data, which were already geometrically corrected and coregistered, required radiometric calibration to convert raw digital numbers (DNs) to surface reflectance values. The radiometric calibration coefficients provided by the USGS were applied in the current study to eliminate sensor-specific radiometric distortions. Subsequent atmospheric correction was performed using the FLAASH module (Table 2) in ENVI 5.3, which incorporated sensor altitude (705 km), regional atmospheric profiles (Mid-Latitude Summer), and surface elevation data (average of 1.5 m). The final output comprised surface reflectance values for seven OLI bands (B1-B7), which were validated against concurrent MODIS reflectance products ($R^2 > 0.85$ in visible-NIR bands).

Table 2 FLAASH atmospheric correction model parameters (using image data from October 13, 2015 as an example)

Sensor type	Scene center location	Sensor altitude/km	Ground elevation/km	Pixel size/m	Atmosphere model
OLI	120.38°N/31.73°E	705.000	0.016	30.000	Tropical
Flight date	Initial visibility /km	Aerosol Retrieval	MODTRAN multiple scattering model	Flight time/ GMT (HH:MM:SS)	Aerosol model
2015-10-13	40.00	2-Band(K-T)	Scaled DISORT	02:31:11	Rural

2.2.3 Chla remote sensing inversion method

The semiempirical method is a scientific approach that addresses complex issues by combining empirically derived models with experimentally determined parameters. This methodology typically involves the analysis of measured water spectral data to identify optimal bands or band combinations, followed by the selection of appropriate mathematical techniques to establish quantitative relationships between remote sensing imagery and water quality parameters. Thus, by integrating physical principles with empirical observations, this approach enhances the accuracy of the ground feature representation. The advantage of this method lies in the fact that it incorporates empirical knowledge during model construction, thereby improving reliability and practicality when purely physical models prove insufficient.

Initially, neural networks in deep learning were employed in the modeling process. However, due to data scarcity at Taihu Lake sampling points and other factors, the root mean square error (RMSE) of the test set was notably high at 177.927 68, indicating poor model simulation performance. Additionally, this method only displays data processing results without illustrating the relationship between modeling parameters and spectral features. This restriction hinders the understanding of each band's response to spectral features, thereby limiting the applicability and dissemination of the research outcomes after using this method. Nevertheless, the strong correlation between various bands of Landsat 8 images prompted the consideration of the partial least squares (PLS) method in a multiple regression model for Chla modeling and inversion at Taihu Lake.

A multiple regression model calculates parameters suitable for measured data, evaluates their ability to fit regional information based on validation parameters, and makes further predictions. PLS regression (PLSR) integrates the principal component analysis of multiple linear regressions with canonical correlation analysis. Furthermore, PLSR extracts independent components from the set of independent variables to establish a relationship with the dependent variable. Compared to traditional multiple linear regression models, PLSR can handle severe multiple correlations between independent variables, include

all existing independent variables in the final model, perform regression modeling with fewer sample points than variables, and identify system information and nonrandom noise more effectively. Furthermore, the regression coefficients of each independent variable in the model are more interpretable.

In the current study, after preprocessing Landsat 8 remote sensing images, the reflectance values of each band were extracted from the sampling points. Next, correlation analysis between single bands and band combination spectral reflectance was performed, after which Chla concentration was measured using the Pearson method. The sensitive band, which had the highest correlation, served as the dependent variable, while the measured Chla concentration served as the independent variable. Subsequently, a PLSR model was constructed, and data were validated using different parameters, such as the coefficient of determination (R^2), prediction deviation ratio (PDR), and root mean square error (RMSE). An R^2 value closer to 1 signifies a stronger correlation between the predicted and measured values, indicating higher model accuracy.

$$R^2 = \frac{\sum_{i=1}^n (R'_i - \bar{R})^2}{\sum_{i=1}^n (R_i - \bar{R})^2} \quad (3)$$

RMSE is used to measure the deviation between predicted and measured values, and its expression formula is as follows:

$$E_{RMS} = \sqrt{\frac{\sum_{i=1}^n (R'_i - \bar{R})^2}{n}} \quad (4)$$

In the formula, n is the total number of data, R'_i is the estimated Chla concentration measured by the inversion model, R_i is the measured Chla concentration, and $\bar{R}$ is the average measured Chla value.

3 Results

3.1 Model construction results

The integrated model measured Chla concentrations from October 9 to 10, 2015, with FLAASH-corrected Landsat 8 band reflectance acquired on October 13, 2015. Concurrently, field measurements from September 3 to 6, 2016, were paired with preprocessed Landsat 8 reflectance data from August 28, 2016.

To identify spectral bands sensitive to Chla

variations, this study employed representative single-band reflectance values and dual-band ratio combinations as predictive variables. Specifically, band reflectance values from preprocessed images were extracted at georeferenced sampling coordinates and subjected to Pearson correlation analysis with synchronized Chla measurements. The results are shown in Table 3.

Table 3 Correlation analysis between Landsat 8 single band spectral reflectance and Chla concentrations

October 13, 2015		August 28, 2016	
Band	Correlation coefficient (<i>r</i>)	Band	Correlation coefficient (<i>r</i>)
B ₁	-0.22	B ₁	-0.601**
B ₂	-0.233	B ₂	-0.574**
B ₃	-0.128	B ₃	-0.577**
B ₄	-0.27	B ₄	-0.535**
B ₅	-0.22	B ₅	-0.559**
B ₆	0.299	B ₆	-0.532**
B ₇	0.273	B ₇	-0.532**

Note: ** Significant correlation at the 0.01 level (bilateral); * significant correlation at the 0.05 level (bilateral).

On October 13, 2015, the correlation coefficients between the Landsat 8 image band and the Chla concentrations measured on October 9 - 10 were small and not significant. However, on August 28, 2016, the correlation coefficients between the single-band Landsat 8 images and the measured Chla concentrations on September 3 - 6 were negative, with correlation coefficients (*r*) ranging between -0.532 and -0.601. Among them, Band 1 (B₁) exhibited the highest correlation coefficient (*r* = -0.601). Considering the relatively high correlation coefficients of Bands 1, 2, 3, and 5, we selected the Landsat 8 image band on August 28, 2016, for further investigation, in combination with dual-band studies. Subsequently, as shown in Table 4 we performed a combination analysis on the seven Landsat 8 image data bands (B₁-B₇) using various pairwise combinations, such as sum, difference, ratio, and sum difference ratio. This process resulted in 84 combination methods. The correlations between each band combination and Chla concentration were analyzed. Residuals indicating the difference between the observed and predicted values of the model were employed to identify and remove outliers. In particular, residual values exceeding a certain threshold were considered

outliers and were subsequently excluded from the analysis. After calculation, four sets of data with maximum residuals of 517.573 7, 203.639 4, 143.672 7, and -111.138 9, respectively, were removed. (Fig. 2)

The maximum correlation coefficient between the Landsat 8 image combination band on August 28, 2016, and the measured Chla concentration from September 3 to 6, 2016, is -0.648, indicating a strong correlation. The optimal band combination includes bands B₁, B₂, B₃, B₆, and B₇. Therefore, these bands were selected as sensitive bands to construct the model. To ensure robustness and accuracy, a ratio of 8:2 was used to divide the 44 sampling points into a modeling set (36 points) and a validation set (8 points). Then, a PLSR model was constructed as follows:

$$Y = 53.9292 - 0.0024B_1 - 0.0024B_2 - 0.005B_3 - 0.0056B_4 + 0.011B_5 + 0.0008B_6 + 0.0002B_7$$

In this model, *Y* represents the predicted Chla concentration, and B₁-B₇ represent the corresponding reflectance values of Landsat 8 bands.

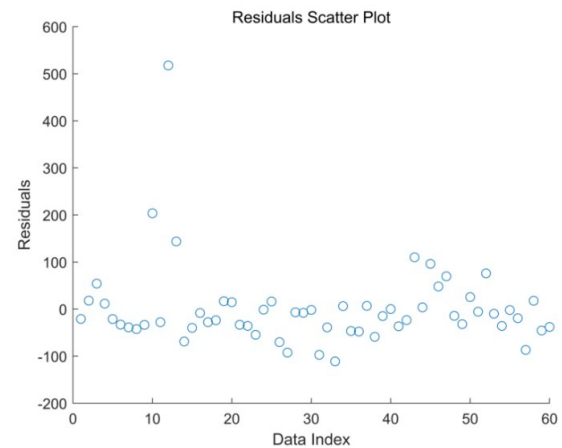


Fig. 2 Residuals scatter plot

3.2 Accuracy verification

3.2.1 Modeling accuracy

The PLS prediction model was applied to the spectral reflectance of pixels in each band of the modeling set. Then, the predicted value of Chla was calculated and then compared with the 44 data points in the modeling set. A prediction chart was created based on two sets of data. (Fig. 3) The *R*² and RMSE values of the PDR are 0.030 7 and 42.009 3, respectively, with the latter particularly showing a significant improvement compared to the RMSE

Table 4 Landsat 8 combination band correlation analysis

Band combination	Correlation coefficient	Band combination	Correlation coefficient	Band combination	Correlation coefficient	Band combination	Correlation coefficient
B ₁ +B ₂	-0.591**	B ₁ -B ₂	-0.186	B ₁ /B ₂	-0.029	(B ₁ +B ₂)/(B ₁ -B ₂)	-0.046
B ₁ +B ₃	-0.602**	B ₁ -B ₃	0.097	B ₁ /B ₃	-0.156	(B ₁ +B ₃)/(B ₁ -B ₃)	0.175
B ₁ +B ₄	-0.585**	B ₁ -B ₄	0.216	B ₁ /B ₄	0.116	(B ₁ +B ₄)/(B ₁ -B ₄)	-0.135
B ₁ +B ₅	-0.648**	B ₁ -B ₅	-0.113	B ₁ /B ₅	0.268	(B ₁ +B ₅)/(B ₁ -B ₅)	0.038
B ₁ +B ₆	-0.629**	B ₁ -B ₆	-0.433*	B ₁ /B ₆	0.301	(B ₁ +B ₆)/(B ₁ -B ₆)	-0.225
B ₁ +B ₇	-0.618**	B ₁ -B ₇	-0.509**	B ₁ /B ₇	0.267	(B ₁ +B ₇)/(B ₁ -B ₇)	-0.239
B ₂ +B ₃	-0.580**	B ₂ -B ₃	-0.574**	B ₂ /B ₃	-0.21	(B ₂ +B ₃)/(B ₂ -B ₃)	0.203
B ₂ +B ₄	-0.562**	B ₂ -B ₄	0.319	B ₂ /B ₄	0.187	(B ₂ +B ₄)/(B ₂ -B ₄)	-0.038
B ₂ +B ₅	-0.642**	B ₂ -B ₅	-0.064	B ₂ /B ₅	0.265	(B ₂ +B ₅)/(B ₂ -B ₅)	-0.028
B ₂ +B ₆	-0.625**	B ₂ -B ₆	-0.364	B ₂ /B ₆	0.282	(B ₂ +B ₆)/(B ₂ -B ₆)	-0.182
B ₂ +B ₇	-0.605**	B ₂ -B ₇	-0.455*	B ₂ /B ₇	0.258	(B ₂ +B ₇)/(B ₂ -B ₇)	-0.222
B ₃ +B ₄	-0.557**	B ₃ -B ₄	0.291	B ₃ /B ₄	0.33	(B ₃ +B ₄)/(B ₃ -B ₄)	-0.197
B ₃ +B ₅	-0.647**	B ₃ -B ₅	-0.144	B ₃ /B ₅	0.321	(B ₃ +B ₅)/(B ₃ -B ₅)	-0.07
B ₃ +B ₆	-0.640**	B ₃ -B ₆	-0.386*	B ₃ /B ₆	0.319	(B ₃ +B ₆)/(B ₃ -B ₆)	-0.225
B ₃ +B ₇	-0.615**	B ₃ -B ₇	-0.467*	B ₃ /B ₇	0.306	(B ₃ +B ₇)/(B ₃ -B ₇)	-0.257
B ₄ +B ₅	-0.613**	B ₄ -B ₅	-0.225	B ₄ /B ₅	0.16	(B ₄ +B ₅)/(B ₄ -B ₅)	0.035
B ₄ +B ₆	-0.605**	B ₄ -B ₆	-0.387*	B ₄ /B ₆	0.144	(B ₄ +B ₆)/(B ₄ -B ₆)	-0.124
B ₄ +B ₇	-0.579**	B ₄ -B ₇	-0.446*	B ₄ /B ₇	0.117	(B ₄ +B ₇)/(B ₄ -B ₇)	-0.139
B ₅ +B ₆	-0.599**	B ₅ -B ₆	-0.348	B ₅ /B ₆	0.027	(B ₅ +B ₆)/(B ₅ -B ₆)	-0.092
B ₅ +B ₇	-0.605**	B ₅ -B ₇	-0.400*	B ₅ /B ₇	-0.024	(B ₅ +B ₇)/(B ₅ -B ₇)	-0.028
B ₆ +B ₇	-0.537**	B ₆ -B ₇	-0.358	B ₆ /B ₇	-0.148	(B ₆ +B ₇)/(B ₆ -B ₇)	0.201

Note: ** Significant correlation at the 0.01 level (bilateral); * significant correlation at the 0.05 level (bilateral).

(177.927 68) of deep learning models. This result indicates that the model established using the least squares method has better predictive performance than that established using neural networks. Thus, the former is more suitable for predicting Chla concentration.

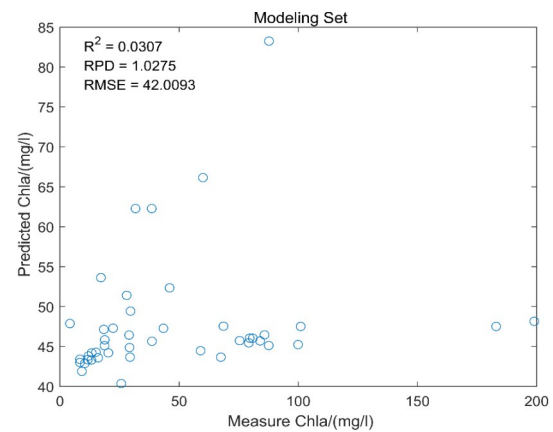
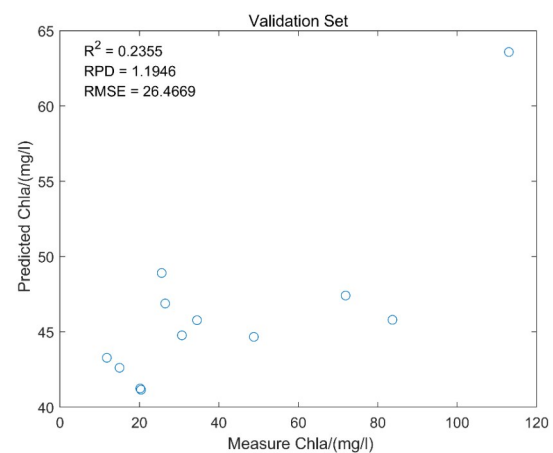
3.2.2 Verification accuracy

The PLS prediction model used 12 data points in the validation set to calculate the predicted Chla value, after which it was compared with the validation set. Next, the R^2 and RMSE of the RPD were calculated using two sets of data, as shown in the bottom-right corner. (Fig. 4) The correlation coefficient R^2 between the predicted and measured values in the validation set is 0.235 5, and the RMSE of the RPD is 26.4669, which shows further improvement compared to the modeling set, thus demonstrating better predictive performance. Thus, this method can be used for predicting Chla concentration.

3.3 Characteristics of Chla spatial distribution

3.3.1 Chla spatial interpolation results

Inverse distance weighting (IDW) is a commonly used spatial interpolation method, which assumes that closer points have greater similarity than distant

**Fig. 3 Modelling the scatter plot****Fig. 4 Verifying the scatter plot**

points, thereby transferring spatial relationships to attribute values. Its main advantages include simplicity and effectiveness in processing spatial data. Using the inverse distance weighting method, spatial interpolation was conducted on Chla concentrations measured from October 9 to 10, 2015 and September 3 to 6, 2016 (Fig. 5a, and Fig. 6a). The Chla concentrations measured in October 2015 and September 2016 range from 1.131 1 to 87.661 mg/L and from 0.167 9 to 373.776 mg/L, respectively. As can be seen, the Chla concentrations are dispersed and exist in various water body types. The interpolation result trends differ between October 2015 and September 2016. In October 2015, Chla concentrations gradually increased from south to north, with high values located in northern and western regions, such as Xiaowanli and Zhushan Lake. In October 2016, Chla concentrations varied across different regions, with high values found in multiple areas of Taihu Lake, including West Wuli Lake in the north, Manshan Mountain in the east, and Xukou in the southwest.

3.3.2 Results of Taihu Lake Chla remote sensing inversion

The PLS model was applied to Landsat 8 images taken from October 13, 2015 and August 28, 2016 to obtain Chla spatial distribution maps (Fig. 5b and Fig. 6b). The overall situation shows good water quality in both years, with suspected algal blooms occurring in the northwest of Taihu Lake in October 2015 disappearing by September 2016. Although water quality in 2016 improved compared to that in 2015, some areas, such as the southeastern edge of Taihu Lake, still maintain high water quality. Nevertheless, high Chla concentrations exceeding Class V water body standards appear in certain marginal areas as scattered points. Based on the obtained remote sensing images, while the number of Class III, IV, and V water bodies decreased significantly in 2016, Class I water bodies also decreased compared to 2015, whereas Class II water bodies increased.

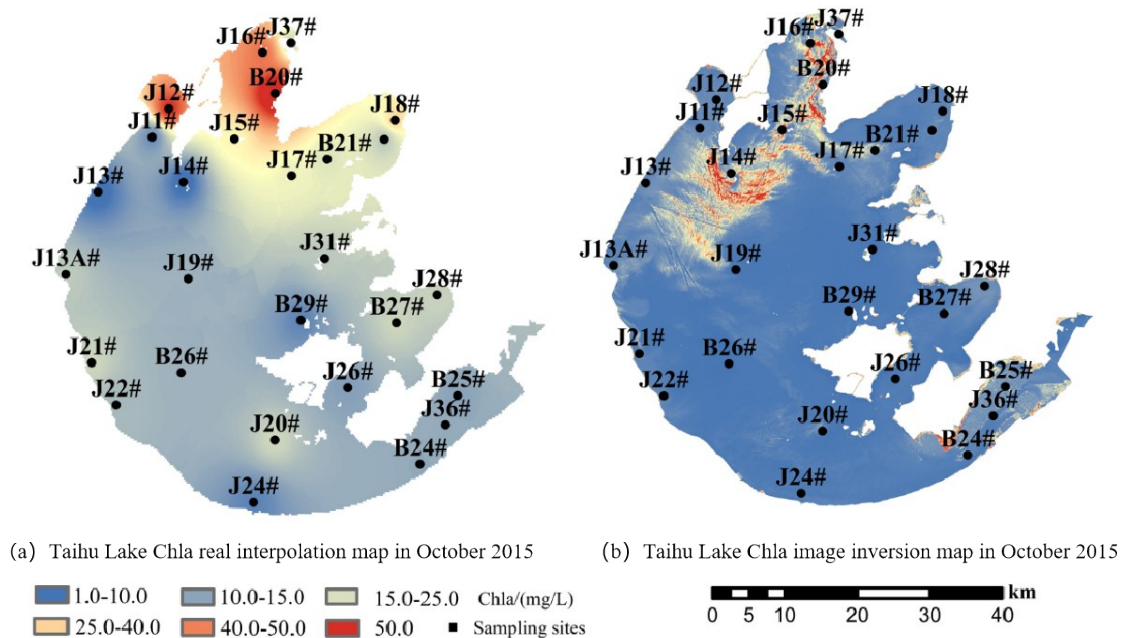


Fig. 5 Comparison of images of Taihu Lake in 2015

3.3.3 Method comparison

A comparison of the measured interpolation results of Chla in the Taihu Lake area with the remote sensing inversion results reveals that the spatial distribution results of Chla retrieved from remote sensing generally align with reality, albeit with some differences. However, certain aspects of the accuracy of

the inversion model still require improvement. Specifically, the estimation error within a certain range, based solely on the measured values of a single point in the interpolation results, can be relatively large. For instance, in 2016, the inversion map displayed singular points and small areas with star-shaped Chla concentrations. If the measured points fell within this

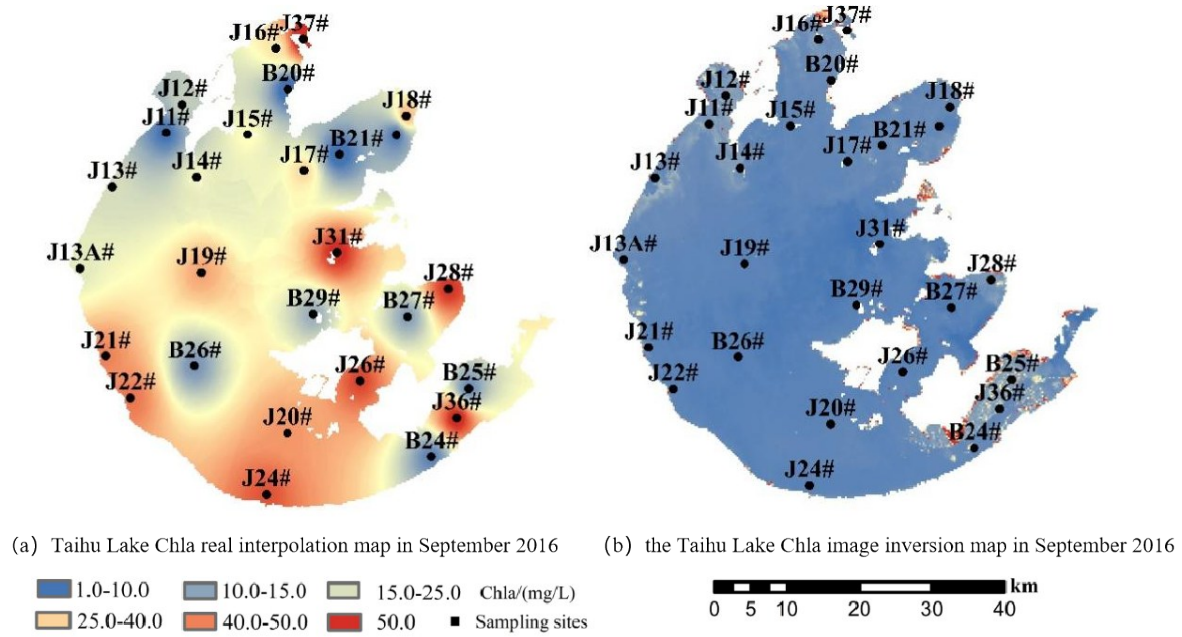


Fig. 6 Comparison of images of Taihu Lake in 2016

range, interpolation could lead to certain errors. Consequently, the interpolation results in 2016 exhibit significant deviations from the inversion results. This highlights a scenario of “point-to-point correspondence but less face-to-face correspondence.” Thus, further refinement is necessary to enhance the accuracy and reliability of the inversion model, ensuring better alignment with the actual spatial distribution patterns of Chla in the Taihu Lake region.

3.4 Spatiotemporal changes retrieved from the Taihu Lake Chla remote sensing method

3.4.1 Spatiotemporal changes retrieved from the Taihu Lake Chla remote sensing method

The PLS method demonstrates good prediction effectiveness in the inversion of Taihu Lake's Chla concentrations in October 2015 and September 2016, confirming its feasibility for use in this context. To further validate its effectiveness and investigate the spatiotemporal changes of Taihu Lake Chla, the Kangzhong method employed in this study was extended to inversion research covering other periods of Taihu Lake data collection.

The spatiotemporal distribution of Taihu Lake Chla over the eight-year period from 2017 to 2024 was inverted using this approach (Fig. 7). As the inversion model was initially established using data from September in 2016 and October in 2015, and the availability of such images varied from year to

year, the study selected Landsat 8 OLI remote sensing images from October and November of each year. Consistent preprocessing operations were conducted on each annual dataset to minimize errors and ensure comparability across different time periods.

3.4.2 Cause analysis of Chla concentration evolution in Taihu Lake

(1) Natural geographical factors As shown in

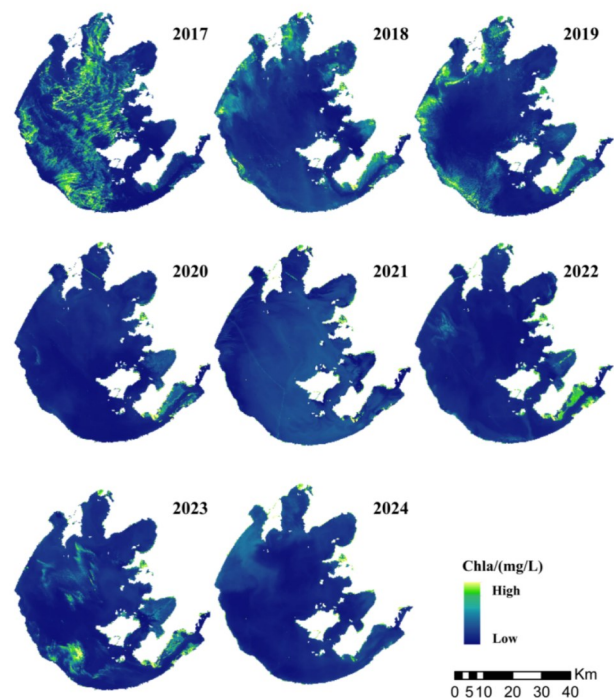


Fig. 7 Spatiotemporal changes in the Taihu Lake Chla image inversion from 2017 to 2024

Fig. 5(b) and Fig. 6(b), the remote sensing inversion illustrates that the Chla concentrations in the northwest and southeast parts of Taihu Lake are relatively high in 2015. Blue algae blooms are closely linked to wind speed; when wind speed is below 3.1 m/s, blue-green algae blooms are more likely to form^[26]. In recent years, the expansion of algal blooms spatiotemporally correlates with decreased wind speed. Thus, appropriate wind speed is vital in promoting the formation and expansion of blue-green algae blooms and is a significant factor influencing high Chla concentrations.

In the northwest part of Taihu Lake, several factors foster rapid algae multiplication, including low water levels, shallow water bodies, limited self-purification capacity, frequent sunny days, increased solar radiation, and rapid temperature rises. Southeast winds also cause algae to accumulate in the northwest of Taihu Lake, where wind and waves easily disturb sediment. Upon algae death, significant organic residue forms, which are degraded by microorganisms, thereby consuming substantial oxygen and leading to water hypoxia and deterioration.

The northwest region of Wujin District in Changzhou City is a significant agricultural area within Jiangsu Province. Pesticide residues have been identified as a critical concern affecting water quality not only in Wujin District but also across the entire Taihu Lake Basin. In 2016, high Chla concentrations were recorded in the eastern Taihu Lake area. By September 2016, autumn had arrived, and Chla concentrations in the area were masked by aquatic vegetation, primarily distributed in the original cage culture area and along the coast of Wuzhong District.

An analysis of retrieved images over the past eight years (2017-2024) reveals a significant downward trend in overall Chla concentration in Taihu Lake, with the lowest concentrations and better water quality observed in 2020 and 2024. The most severe algal blooms occurred in 2017, marking the worst blooms in history. Meanwhile, phosphorus plays a pivotal role in freshwater ecosystems^[27]. Monitoring data for 2019 reveal that 14 of the 22 main river channels entering the lake exceed the standards, primarily due to TP. Excessive external phosphorus input and unobservable internal phosphorus cycles

contribute to the lake's eutrophication. Furthermore, increased phosphorus concentration favors cyanobacteria dominance in algal communities, enhancing P release and sediment organic P transformation^[24].

Such increased eutrophication and cyanobacterial blooms accelerate the P cycle in Taihu Lake, with adverse effects. In 2017, a sudden increase in TP concentration and average temperature led to a rapid increase in *Microcystis* density in the lake, facilitating algal blooms. Relatively low wind speeds of 2.21 m/s promoted *Microcystis* aggregation. In 2018, algal bloom occurrences decreased slightly, but in 2019, Chla concentration increased, with the recorded algal bloom intensity second only to 2017. In that year, blue-green algae blooms predominantly occurred in the northwest bay and southwest regions.

The inverted images suggest an increase in Chla concentration in the eastern Taihu Lake area from 2017 to 2020, followed by a decrease from 2021 to 2022 before increasing again. The eastern Taihu Lake area comprises mainly aquatic plants, influenced by three factors: a basin-wide catastrophic flood in 2016; completion of breeding net demolition in Suzhou Wan in 2018; altering dominant vegetation from submerged to floating plants; and the harvesting of artificial flume grass from 2021 to 2022 in Wujiang District, thereby reducing aquatic vegetation biomass.

(2) Socioeconomic Factors Given that water quality is intricately linked to the discharge of water pollutants, this necessitates explorations into water pollution discharge driven by socioeconomic factors to come up with effective emissions reduction strategies^[28]. Within the socioeconomic system, final consumption propels producers. In turn, increased consumption levels subsequently promote production and escalate water pollution emissions. Any regional water quality deterioration can be traced back to the consumption demands of the region or related areas. Needless to say, a healthy ecological environment is paramount for achieving sustainable socioeconomic development.

The relationship between economic development and water Chla concentration was further elucidated in the current study by examining the correla-

tion between total population, regional gross product, per capita GDP, and water quality in the Taihu Lake Basin, focusing more on the consumer side. The environmental Kuznets curve (EKC) proposed by Ali and Sami^[29] is a notable concept in economic research. In a two-dimensional plane, the level of economic development is represented on the horizontal axis, while environmental quality factors, such as water quality, are represented on the vertical axis. The EKC is depicted as an inverted “U”-shaped quadratic curve. During the initial stage of economic development from 2003 to 2008, the total population of the Taihu Lake Basin increased annually from 41.31 million to 50.07 million, regional GDP rose from 182.66 million to 36824, and per capita GDP exhibited a trend of initial increase, subsequent decrease, and subsequent increase. Chla concentrations showed positive correlations with the total population, regional gross domestic product, and per capita GDP of the lake basin, in accordance with the linear regression analysis conducted with correlation coefficients. In the socioeconomic system, final consumption drives producers, and the increased consumption levels promote production and further elevate water pollution emissions^[30]. The analysis results reveal an overall negative correlation between economic development and water quality, with correlation coefficients of 0.702, 0.659, and 0.618, respectively, based on the linear regression analysis. In mid-2007, a severe cyanobacteria bloom erupted in Taihu Lake, resulting in water pollution in Wuxi’s tap water supply and severe shortages of domestic and drinking water, which significantly affected residents’ lives. Thus, “The Discharge Limits of Main Pollutants for Urban Sewage Treatment Plants and Key Industrial Industries in the Taihu Lake Region, Jiangsu Province” was revised significantly after the cyanobacteria incident. Toward the end of 2008, the Taihu Lake Water Pollution Prevention and Control Office was established by the Wuxi Municipal Party Committee and the Municipal Government to comprehensively supervise pollution prevention and control efforts.

From 2017 to 2022, the total population of the Taihu Lake Basin increased from 60.58 million to 68.25 million, with steady increases recorded annually (Fig. 8). Regional GDP also rose annually from

808.15 billion to 1 118.173 billion, and per capita GDP similarly increased. However, Chla concentrations showed negative correlations with the total population, regional GDP, and per capita GDP of the lake basin, with correlation coefficients of -0.535 , -0.271 and -0.584 , respectively, based on the linear regression analysis (Fig. 9 and Table 5). Along with economic development, water quality and environmental conditions are also progressively improving. Thus, environmental pollution in China is no longer worsening with economic growth, in alignment with EKC theory proposed by Grossman and Krueger.^[29]

Table 5 Correlation coefficients between Chla concentration and various economic indicators

Year	Correlation coefficient (r)		
	Population	GDP	GDP per capita
2016 – 2022	-0.535	-0.271	-0.584
2003 – 2008	0.702	0.659	0.618

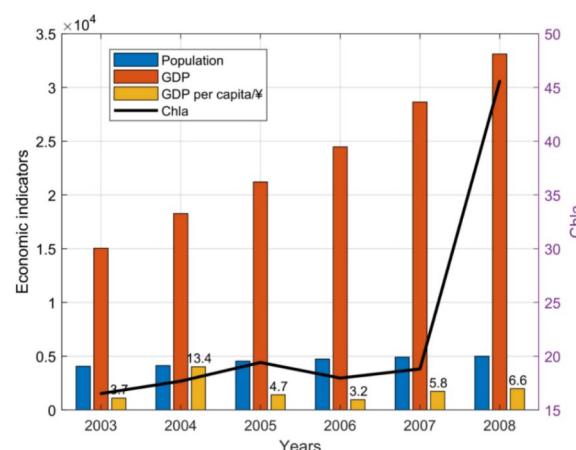


Fig. 8 Comparison of changes in economic indicators and Chla concentrations from 2003 to 2008

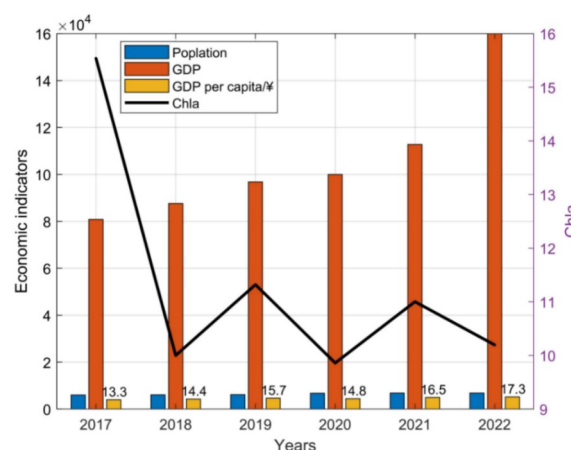


Fig. 9 Comparison of changes in economic indicators and Chla concentrations from 2017 to 2022

4 Discussion

4.1 Accuracy of the satellite remote sensing inversion of Chla concentrations

The accuracy of Chla inversion techniques via satellite remote sensing hinges on several factors, including the types of remote sensing image data bands utilized, which possess different center wavelengths and spectral response functions suited for various lake types, geographical locations, and water properties. While the current inversion model established for Taihu Lake can potentially be extended to other lakes, its inversion accuracy for such purposes remains uncertain. Researchers such as Tang and Huang^[31] have explored machine learning methods, such as backpropagation neural networks (BPNN) and support vector machines (SVM) to construct Chla concentration inversion models for specific lakes, such as Donghu Lake. Similarly, Peng and Chen^[32] utilized semiempirical analysis methods and the NDCI model to invert Chla concentration in Chaohu Lake based on GF-1 WFV impact. Meanwhile, Li et al.^[33] employed the empirical AO. emp algorithm and ocean color remote sensing to invert Chla concentration in specific high CDM water areas in the Arctic Ocean. Amid these proposed methods, a unified model for accurately inverting Chla concentrations in different lakes remains elusive. The applicability of Chla inversion concentration models varies across seasons and water environments, thus requiring further research to delineate the key factors influencing model construction.

In terms of the statistical analysis of Chla concentrations in lake water using remote sensing inversion, uncertainties remain particularly concerning the comprehensive values of surface and water columns. Assessing the chlorophyll maximum layer (SCM) and its primary contribution to water is pivotal, yet current research on its evaluation yields contradictory results. For example, the monitoring of surface object reflectivity by remote sensing satellites is constrained by the optical depth of the water column. Estimates are thus limited to surface algae populations, even though algae may also proliferate throughout the water column. Yu et al.^[34] introduced the columnar integrated algal biomass (CAB) to rep-

resent the total algal biomass of an entire lake, employing upper and lower methods as well as bivariate models to enhance CAB estimation ability in shallow water lakes. As such, exploring the relationship between algal concentration in the water column and surface, as well as intra-water column variability, is crucial. For this reason, the accuracy of Chla prediction using satellite remote sensing data necessitates further enhancement. Additional research is also required on the extraction and calculation methods of blue-green algae bloom information from mixed blue-green algae water pixels contained within satellite remote sensing data pixels.

4.2 Comparison of influencing factors

Climate, hydrology, wind speed, and phosphorus concentration are significant natural factors influencing the growth of blue-green algae because these affect the normal growth of algae and the occurrence of algal blooms to varying degrees. Xu et al.^[35] used MODIS data to explore the climate and hydrological factors of the five Great Lakes, revealing their dominant role in the changes in Chla within the lakes, with contribution rates ranging from 71.47% to 92.54%. Different lakes exhibit varying sensitivities to these natural factors; for example, blue-green algae blooms are more likely to occur under specific wind speed thresholds, while in Lake Superior, temperature fluctuations drive interannual Chla variations. In Lakes Huron and Michigan, runoff and sedimentation are the main contributing factors, while in Lake Erie, the influence of farmland predominates the Chla variations. Furthermore, Zhu et al.^[36] examined the regionally differentiated responses of Chla concentrations to reduced human activities during the COVID-19 lockdown in the San Francisco Bay area, further exploring the impact of environmental changes on aquatic ecosystems. The Taihu Lake Basin also demonstrates varying sensitivities to different natural factors at different times.

Previous studies have focused on natural factors, often overlooking the influence of humanistic and social factors, such as policy changes, population dynamics, and economic development. The present study, drawing from public statistical information provided by the Taihu Lake Basin Administration of the Ministry of Water Resources, inte-

grates total population data, GDP, and per capita GDP of the Taihu Lake area to explore the socioeconomic factors affecting changes in Chla concentrations in the lake. Analysis reveals that environmental changes in the region conform to the EKC, with various economic indicators initially exhibiting positive growth trends while water quality deteriorates annually. Correlation analysis indicates a peak in Chla concentration around 2008, with subsequent economic development correlating positively and negatively with improved water quality and Chla concentration, respectively, thus signifying the diminishing impact of economic development on the environment in the region.

In terms of policy, significant changes occurred with the State Council approving the implementation of the “11th Five-Year Plan for Water Pollution Prevention and Control” in 2008. This led to comprehensive ecological security assessments of Taihu Lake, Chaohu Lake, and the Three Gorges Reservoir Area, thereby initiating ecological security monitoring and laying the groundwork for comprehensive lake management. Additionally, a nationwide survey on the basic environmental conditions of centralized drinking water sources was organized, with over 15 000 sources inspected and rectification measures implemented in over 4600 protected areas, further safeguarding public drinking water safety. Notably, some environmental quality indicators in the country exhibited significant improvements, as exemplified by a decrease in the annual average concentration of the permanganate index in surface water, reaching Class III water quality standards for the first time. As shown by these developments, changes in policy are a crucial human factor influencing Chla concentration changes in Taihu Lake.

5 Conclusions

5.1 Significance of the present study

(1) To construct the proposed PLS model, this study focused on using Landsat 8 bands' reflectance data obtained from October 13, 2015, and August 28, 2016, alongside measured Chla concentrations from October 9 to 10, 2015, and September 3 to 6, 2016. The model demonstrated a decision coefficient of 0.030 7 and a prediction RMSE of 42.009 3 $\mu\text{g/L}$,

suggesting its efficacy in predicting Chla concentrations in Taihu Lake.

(2) Employing the PLSR model on Landsat 8 images obtained from October 13, 2015, and August 28, 2016, yielded inversion maps of Chla concentrations. Comparison with interpolation maps derived from measured sample points indicated superior clarity in depicting Chla distribution, notably showcasing water blooms in the Jiaoshan and Tuoshan areas in 2015.

(3) The widespread application of the PLS model has facilitated the study of spatiotemporal fluctuations in Chla concentrations within Taihu Lake over the past seven years. The inversion of Chla spatial distribution from 2017 to 2024 exhibits good agreement with existing data, revealing an overall declining trend in Chla concentration in the lake. In turn, such a finding indicates the effective implementation of cyanobacteria bloom control measures. However, the persistent threat of cyanobacteria blooms requires continued vigilance in terms of prevention, control, monitoring, and early warning systems. These measures provide crucial support for future Taihu Lake management and water quality assessment efforts.

(4) The analysis of the long-term correlation between Chla concentration and economic indicators spanning from 2003 to 2022 reveals a significant shift in China's economic development trajectory, surpassing the turning point of the EKC. This finding suggests a divergence from the historical trend of environmental deterioration accompanying economic growth.

(5) The development of Chla inversion models tailored to diverse timeframes and water bodies still faces inherent challenges, with model accuracy susceptible to various contextual factors. Consequently, addressing Chla concentration inversion complexities in inland Class II lakes remains an ongoing challenge, necessitating further research and refinement efforts.

5.2 Future research directions

(1) This study mainly focuses on remote sensing data from 2015 and 2016, with a limited frequency of image acquisition, resulting in a narrow coverage of spatiotemporal analysis. Future research should thus expand the time range to include data from multiple

years, especially during extreme climate events or large-scale cyanobacteria blooms. By increasing the temporal dimension of the data, a more comprehensive understanding of the trends in Chla concentrations, as well as the long-term impacts of different environmental factors on water quality, can be achieved.

(2) Although the PLSR model performed well in this study, there is still room for improvement. The complex water quality changes in Taihu Lake, especially in certain areas with unique water quality conditions, reveal limitations in the precision of the proposed model. Thus, future research could further improve model accuracy by incorporating more data samples, particularly from different seasons and water types. Additionally, more advanced remote sensing technologies, such as multisource remote sensing imagery, along with the combination of various modeling methods, could enhance the accuracy of Chla concentration estimation and improve the adaptability of the model proposed in this study, especially in regions with more complex water quality conditions.

(3) Although the study identified the spatiotemporal variability of Chla concentrations, the analysis of the driving factors behind cyanobacteria blooms was relatively simple. To address this, future research should conduct more in-depth investigations into the mechanisms driving cyanobacteria blooms, particularly the interactions between multiple driving factors, such as nutrient inputs, climate change, precipitation patterns, and hydrological factors. Doing so would not only help reveal the specific causes of bloom formation but also provide theoretical support for more accurate water quality management and predictions.

(4) The occurrence of cyanobacteria blooms and water quality changes involves knowledge and techniques from multiple disciplines. Thus, future research should consider cross-disciplinary collaboration and the integration of findings from different fields, such as ecology, meteorology, hydrology, and remote sensing, to analyze the causes and impacts of cyanobacteria blooms more comprehensively. This approach would lead to the development of more effective water quality management strate-

gies and would provide scientific support for related policy formulation.

References

- [1] DUAN H T, ZHANG Y Z, ZHANG B, et al. Assessment of chlorophyll-a concentration and trophic state for Lake Chagan using landsat TM and field spectral data [J]. *Environmental Monitoring and Assessment*, 2007, 129(1): 295-308.
- [2] CARSTENSEN J, KLAIS R, CLOERN J E. Phytoplankton blooms in estuarine and coastal waters: Seasonal patterns and key species [J]. *Estuarine, Coastal and Shelf Science*, 2015, 162: 98-109.
- [3] ZHANG F F, LI J S, SHEN Q, et al. Algorithms and schemes for chlorophyll *a* estimation by remote sensing and optical classification for turbid Lake Taihu, China [J]. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2015, 8(1): 350-364.
- [4] PIZANI F M C, MAILLARD P, FERREIRA A F F, et al. Estimation of water quality in a reservoir from Sentinel-2 MSI and Landsat-8 OLI sensors [J]. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 2020, V-3-2020: 401-408.
- [5] ZHOU Y, DONG J W, XIAO X M, et al. Open surface water mapping algorithms: A comparison of water-related spectral indices and sensors [J]. *Water*, 2017, 9(4): 256.
- [6] HANSEN C H, BURIAN S J, DENNISON P E, et al. Spatiotemporal variability of lake water quality in the context of remote sensing models [J]. *Remote Sensing*, 2017, 9(5): 409.
- [7] GALL M P. Satellite remote sensing of coastal water quality in New Zealand [J]. *New Zealand Journal of Marine and Freshwater Research*, 2022, 56(3): 585-616.
- [8] YIGIT AVDAN Z, KAPLAN G, GONCU S, et al. Monitoring the water quality of small water bodies using high-resolution remote sensing data [J]. *ISPRS International Journal of Geo-Information*, 2019, 8(12): 553.
- [9] CHEGOONIAN A M, PAHLEVAN N, ZOLFAGHARI K, et al. Comparative analysis of empirical and machine learning models for Chla Extraction using Sentinel-2 and Landsat OLI data: Opportunities, limitations, and challenges [J]. *Canadian Journal of Remote Sensing*, 2023, 49(1): 2215333.
- [10] WANG S Y, SHEN M, LIU W H, et al. Developing remote sensing methods for monitoring water quality of alpine rivers on the Tibetan Plateau [J]. *GIScience & Remote Sensing*, 2022, 59(1): 1384-1405.
- [11] CHEN X D, LIU L Y, ZHANG X, et al. An assessment of water color for inland water in China using a Landsat 8-Derived forel - Ule index and the google earth engine platform [J]. *IEEE Journal of Selected Topics in*

- Applied Earth Observations and Remote Sensing, 2021, 14: 5773-5785.
- [12] KWON Y S, BAEK S H, LIM Y K, et al. Monitoring coastal Chlorophyll-a concentrations in coastal areas using machine learning models [J]. Water, 2018, 10(8): 1020.
- [13] MAMUN M, FERDOUS J, AN K G. Empirical estimation of nutrient, organic matter and algal chlorophyll in a drinking water reservoir using landsat 5 TM data [J]. Remote Sensing, 2021, 13(12): 2256.
- [14] CHEN J, ZHU W N, TIAN Y Q, et al. Remote estimation of colored dissolved organic matter and chlorophyll-a in Lake Huron using Sentinel-2 measurements [J]. Journal of Applied Remote Sensing, 2017, 11(3): 1.
- [15] MISHRA S, MISHRA D R. Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-a concentration in turbid productive waters [J]. Remote Sensing of Environment, 2012, 117: 394-406.
- [16] HU C M, LEE Z P, FRANZ B. Chlorophyll *a* algorithms for oligotrophic oceans: A novel approach based on three-band reflectance difference [J]. Journal of Geophysical Research: Oceans, 2012, 117(C1): 2011JC007395.
- [17] GOPHEN M. Biomanipulation: retrospective and future development [J]. Hydrobiologia, 1990, 200(1): 1-11.
- [18] YANG W L, YANG L, ZHENG J X. Effect of metal pollution on the water quality in Taihu Lake [J]. GeoJournal, 1996, 40(1): 197-200.
- [19] CAI Q M, GAO X Y, CHEN Y W, et al. Dynamic variations of water quality in Taihu Lake and multivariate analysis of its influential factors [J]. Chinese Geographical Science, 1996, 6(4): 364-374.
- [20] ZHANG Y C, LIN S, QIAN X, et al. Temporal and spatial variability of chlorophyll *a* concentration in Lake Taihu using MODIS time-series data [J]. Hydrobiologia, 2011, 661(1): 235-250.
- [21] LIU J, HE Y C, DENG J M, et al. Analysis of influencing factors of Chlorophyll-a in Lake Taihu based on Bayesian network [J]. Huanjing Kexue, 2023, 44(5): 2592-2600.
- [22] ZHANG Y L, QIN B Q, LIU M L. Temporal - spatial variations of chlorophyll *a* and primary production in Meiliang Bay, Lake Taihu, China from 1995 to 2003 [J]. Journal of Plankton Research, 2007, 29(8): 707-719.
- [23] YAN X, XIA Y Q, TI C P, et al. Thirty years of experience in water pollution control in Taihu Lake: A review [J]. Science of The Total Environment, 2024, 914: 169821.
- [24] WU Z, LIU Y, LIANG Z Y, et al. Internal cycling, not external loading, decides the nutrient limitation in eutrophic lake: A dynamic model with temporal Bayesian hierarchical inference [J]. Water Research, 2017, 116: 231-240.
- [25] PYO J, PACHEPSKY Y, BAEK S S, et al. Optimizing semi-analytical algorithms for estimating chlorophyll-a and phycocyanin concentrations in inland waters in Korea [J]. Remote Sensing, 2017, 9(6): 542.
- [26] DENG J M, ZHANG W, QIN B Q, et al. Winter climate shapes spring phytoplankton development in non-ice-covered lakes: Subtropical Lake Taihu as an example [J]. Water Resources Research, 2020, 56(9): e2019WR026680.
- [27] CHUAI X M, DING W, CHEN X F, et al. Phosphorus release from cyanobacterial blooms in Meiliang Bay of Lake Taihu, China [J]. Ecological Engineering, 2011, 37(6): 842-849.
- [28] LIU D D, BAI L, LI X Y, et al. Spatial characteristics and driving forces of anthropogenic phosphorus emissions in the Yangtze River Economic Belt, China [J]. Resources, Conservation and Recycling, 2022, 176: 105937.
- [29] ALI H E, SAMI S M. Inequality, economic growth and natural resources rent: Evidence from the middle east and north Africa [M]//Contemporary Issues in Microeconomics. London: Palgrave Macmillan UK, 2016: 50-76.
- [30] HOU S Y, ZHAO X, LIU Y, et al. Spatial analysis connects excess water pollution discharge, industrial production, and consumption at the sectoral level [J]. NPJ Clean Water, 2022, 5: 4.
- [31] TANG X D, HUANG M T. Inversion of chlorophyll-a concentration in Donghu Lake based on machine learning algorithm [J]. Water, 2021, 13(9): 1179.
- [32] PENG J, CHEN B. Inversion of Chlorophyll-a concentrations in Chaohu Lake based on GF-1 WFV images [J]. IEEE Access, 2017, 12: 24791-24802.
- [33] LI J, MATSUOKA A, PANG X P, et al. Performance of algorithms for retrieving chlorophyll *a* concentrations in the Arctic Ocean: Impact on primary production estimates [J]. Remote Sensing, 2024, 16(5): 892.
- [34] YU Z Y, MA R H, HU M Q, et al. An improved algorithm for the column-integrated algal biomass retrieval in Lake Chaohu, a large eutrophic lake [J]. International Journal of Applied Earth Observation and Geoinformation, 2024, 127: 103670.
- [35] XU J F, LIU H Q, LIN J, et al. Long-term monitoring particulate composition change in the Great Lakes using MODIS data [J]. Water Research, 2022, 222: 118932.
- [36] ZHU W D, LI Y F, JIANG H, et al. Regionally differentiated responses of chlorophyll-a concentrations to reduced human activity during COVID-19 lockdown in the San Francisco Bay area [J]. Journal of Environmental Management, 2025, 373: 123801.