Seasonal changes of Chlorophyll-A concentration in Jiujiang city based on remote sensing

Wei Jiang [1], Fanping Kong[2]*, Xiaohui Ding [3], Elhadi Adam[4], Shiai Cui[5],Gan Luo[1]

[1] China Institute of Water Resources and Hydropower Research, Beijing, China-jiangwei@iwhr.com, luogan_jxsr@163.com
[2] Beijing Capital Air Environmental Science & Technology Co., Ltd., Beijing 100176, China-kongfanping@aircapital.cn
[3] School of Software and Internet of Things Engineering, Jiangxi University of Finance and Economics, 665 Yuping Road, Nanchang 330013, China, dingxiaohui@gdas.ac.cn
[4]School of Geography, Archaeology and Environmental Studies, University of The Witwatersrand, Jan Smut Ave, Johannesburg, Wit 2050-Elhadi.Adam@wits.ac.za
[5]Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing, China-cuisa@aircas.ac.com

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ABSTRACT:
The Chlorophyll-a (Chla) concentration is an important parameter characterizing the water quality of rivers and lakes. Satellite remote sensing provides new opportunities for the quantitative monitoring of Chla concentration in large-scale water bodies. In this study, Sentinel-2 satellite remote sensing data integrated on the Google Earth Engine (GEE) remote sensing big data platform are employed, along with hourly measured water quality site data, to establish a quantitative inversion model for Chla concentration water quality parameters in Jiujiang City within Jiangxi Province, China. The Chla concentration is estimated for each quarter from 2020 to 2022, and the spatial distribution is analyzed, revealing the changing trend of Chla concentration over the past three years. The key findings are as follows: (1) The quantitative inversion model for Chla concentration has been validated with measured data, achieving a model accuracy of 0.53; (2) The spatial inversion results of Chla concentration exhibit an increasing trend that is consistent with actual measurement site results; (3) Owing to the influence of human activities and the peak-low water level of rivers and lakes, Chla concentration shows a discernible seasonal variation pattern. This methodology offers a new perspective for analyzing the seasonal variation characteristics of Chla concentration in rivers and lakes, providing valuable insights for the sustainable management of river and lake water quality.

1. Introduction

With the rapid development of urbanization and industrialization, the protection and management of water environment has become widely attraction issue (Papenfus et al., 2020; Rodríguez-López et al., 2020). As one of the important freshwater resources, lakes' water quality is directly related to the health of the surrounding ecosystem and anthropogenic activity. Chlorophyll a (Chla), is an important indicator of algae and plant growth in water bodies, hence, is of great significance for lake water quality monitoring(Rodríguez-López et al., 2021; Wang et al., 2021). Jiujiang City is located in the central part of Jiangxi Province and has abundant water resources. However, with urban development and population growth, lake water quality is facing increasingly severe challenges(Tong et al., 2022). Therefore, an in-depth study of the seasonal variation patterns of Chla in Jiujiang City is of great significance for scientifically understanding the status of water ecosystems, guiding lake management, and formulating scientific environmental protection policies.

Many studies have used various technical methods for monitoring Chla concentration in fresh water. These methods include field sampling, laboratory analysis and satellite remote sensing have been providing information on spatiotemporal changes in lake ecosystems to a certain extent, but each method comes with its limitations (He et al., 2020; Pi et al., 2021; Wang and Chen, 2024). Field sampling and laboratory analysis have the advantage of high accuracy. However, these methods have difficulties in covering large areas of lakes due to the limited sampling sites(Jiang et al., 2023). At the same time, frequent sampling is restricted by time and labor costs, making it difficult to comprehensively monitor seasonal changes in Chla concentration. With the development of satellite remote sensing technology, especially the widespread application of high-resolution satellite data has been made in water quality monitoring at large scale (Jiang et al., 2020; Markogianni et al., 2020; Wang et al., 2022). Satellite remote sensing has the advantages of globality, regularity and large-scale, and can provide comprehensive Chla concentration information in lakes and rivers (Tong et al., 2022; Zhang et al., 2020). The feature band or feature band combination for the inversion model is highly correlated with the Chla concentration in water body. Specifically, the wavelength of the diagnostic band moves towards the long wave direction when the concentration increased from very low value to 100μg/L of Chla. However, current research on Chla concentration monitoring in Jiujiang City is still relatively limited. Existing studies mostly focus on the overall water quality conditions of lakes, with relatively insufficient research on seasonal changes. Therefore, it is necessary to conduct more systematic and in-depth research to comprehensively understand the seasonal change pattern of Chla concentration in Jiujiang City. Compared with previous studies, the season change pattern in Jiujiang city will be determined by combining with remote sensing data and water quality monitoring data, which will benefit to provide a more accurate scientific basis for lake management and protection.

This research take Jiujiang City as study area firstly. Then, Sentinel-2 satellite data from Google earth engine (GEE) remote sensing cloud computing platform and water quality monitoring data are integrated to establish a remote sensing sample library and develop a quantitative inversion model for Chla concentration. Finally, the inversion model is used to generate seasonal map of Chla concentration in Jiujiang City over the past three years (2020 to 2022) and the season change patterns of Chla can be explored to guide the lakes and rivers water quality protection in Jiujiang City.

* Corresponding author

2. Study Area and Datasets

2.1 Study Area

Jiujiang City, located in northern Jiangxi Province, spans 19,000 km^2, representing 11.3% of the province's total area. Abundant water resources characterize the city, featuring three major water systems: the Yangtze River, Xiuhe River, and Boyang River. The Yangtze River has a transit length of 151 km and an annual flow of 890 billion cubic meters. The Xiu River's main stream extends for 357 km, with an average annual runoff of 13.5 billion cubic meters. Jiujiang City encompasses 70% of Poyang Lake, covering nearly 2,000 km^2, and hosts the Zhelin Reservoir with a basin area of 9,340 km^2 and a total reservoir capacity of 7.92 billion cubic meters.

Dedicated to water environmental protection, the city has invested significantly in comprehensive water management. The research area boasts 34 online water quality monitoring stations to provide essential data for constructing a sample library for a remote sensing quantitative inversion model of water quality parameters. The study area and water quality station monitoring distribution map is shown in Figure 1.

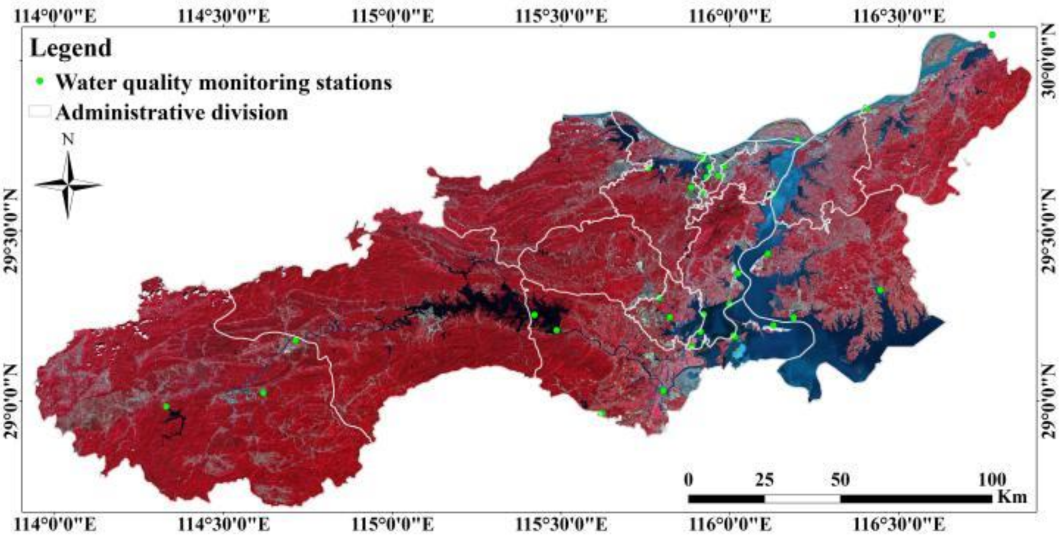


Figure 1. Study area and water quality station monitoring distribution

2.2 Datasets

This study utilizes imagery from the Sentinel-2 satellite, known for its ability to produce precise water quality parameter products with superior temporal and spatial resolutions. The surface reflectance products of Sentinel-2 collected from the GEE platform are employed to determine the Chlorophyll a concentration.

Based on 20 effective water quality station monitoring data in Jiujiang city and leveraging the Google Earth Engine (GEE) platform, a total of 248 original remote sensing image scenes from the Sentinel-2 image collection were selected, spanning from July 1, 2018, to November 17, 2022.

3. Methodology

3.1 Surface water extraction

An improved normalized Surface Water Index (SWI) is used to extract the surface water of lakes and rivers. The SWI index is calculated using the spectral reflectivity values (ρ_{band5}andρ_{band11}) from Band 5 and Band 11 of Sentinel-2, respectively. The formula is as follows:

$$SWI = \frac{\rho_{band5} - \rho_{band11}}{\rho_{band5} + \rho_{band11}} \qquad (1)$$

This method is complemented by the integration of the JRC global surface water dataset to accurately identify and extract water bodies on a large scale(Jiang et al., 2021).

3.2 Inversion model establishment

In order to reduce model uncertainty, data from satellite remote sensing and water quality monitoring stations at the same time were selected to establish the Chla concentration inversion model. Remote sensing reflectance values for each band corresponding to the water quality monitoring stations are extracted, forming the remote sensing inversion sample dataset. Out of 122 valid samples of Chla concentration, 2/3 of the data are employed for inversion model establishment, while the remaining 1/3 is used for model verification.

Pearson correlation analysis is applied to determine the relationship between feature band and the Chla concentration data. The band with the highest correlation is selected as the dependent variable. Polynomial, logarithmic, linear, and exponential fitting are performed on the sample database data to establish a relationship model between Chla concentration and reflectance values of satellite image. The coefficient of determination (R^2) serves as the evaluation index for the optimal inversion model, culminating in the establishment of the quantitative Chla concentration inversion model.

The overall technical route of this study is illustrated in Figure 2.

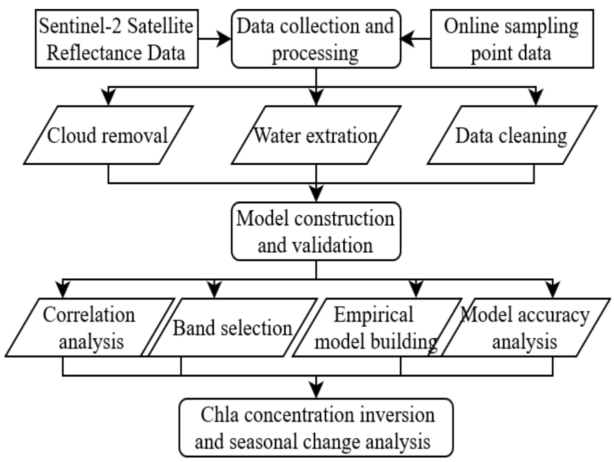


Figure 2. Technical flow chart

4. Results

4.1 The inversion model of Chla concentration

Since Chla exhibits absorption peaks around 440nm and 670nm, coupled with high reflectance in the near-infrared band, water bodies experiencing pronounced eutrophication tend to have elevated Chla concentrations. Through correlation analysis involving relevant bands and first-order differential bands of Sentinel-2 images, the selection process is identified as the B4 band near 670nm, the B8A near-infrared band around 864nm, and their respective first-order differential bands. These selected bands forming the Chla inversion model is as follows:

$$\mathrm{Chla} = -10000.361 * B3' + 1611.099 * B8A' - 174.998 * \frac{\mathrm{B4}}{\mathrm{B5}} + 71.649 * \left(\frac{B4}{B5}\right)^2 - 11.511 * \left(\frac{B6}{B4} - \frac{B6}{B5}\right) - 5407.452 * \left(B5' - \left(\frac{B4' + B6'}{2}\right)\right) + 1.447 * \exp(-3851 * B3') + 104.407 \quad (2)$$

The first-order differential band (B_i') for the i-th band is calculated using the following formula, effectively mitigating noise induced by water quality monitoring stations environments and improving the model's inversion accuracy. The formula is as follows:

$$B_i' = \frac{R_{rs}(\lambda_{i+1}) - R_{rs}(\lambda_{i-1})}{\lambda_{i+1} - \lambda_{i-1}} \quad (3)$$

Here, $R_{rs}(\lambda_{i+1})$ and $R_{rs}(\lambda_{i-1})$ are the spectral reflectivity of the (i+1)-th band and (i-1)-th band respectively, while λ_{i+1} and λ_{i-1} correspond to the wavelengths of the (i+1)-th band and (i-1)-th band, respectively. This formula serves to minimize the impact of noise arising from water quality monitoring station environments, thereby contributing to an improved the accuracy of the inversion model. The accuracy of the proposed model was assessed by comparing the predicted Chla concentration values with the corresponding measured values. The scatter plot fitting results are illustrated in Figure 3. As depicted in Figure 3, the Chla inversion model indicates a notably high accuracy, in which the value of R^2 can reach 0.53, with predicted Chla concentration values closely aligning with the measured values. Consequently, the inversion model by integrating Sentinel-2 remote sensing data and Chla concentration data is deemed feasible, which can be applied for generating Chla concentration map in Jiujiang with Google earth engine.

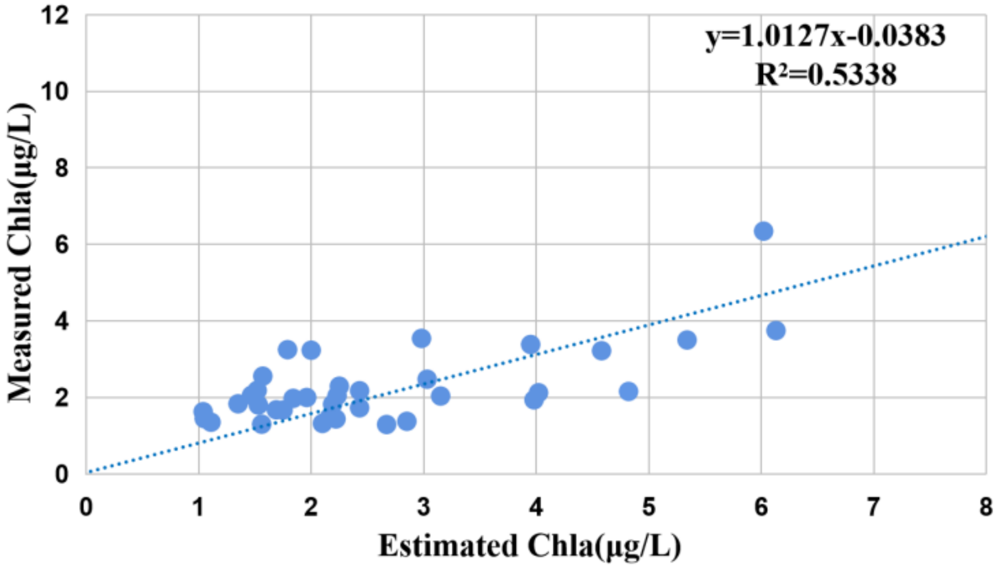


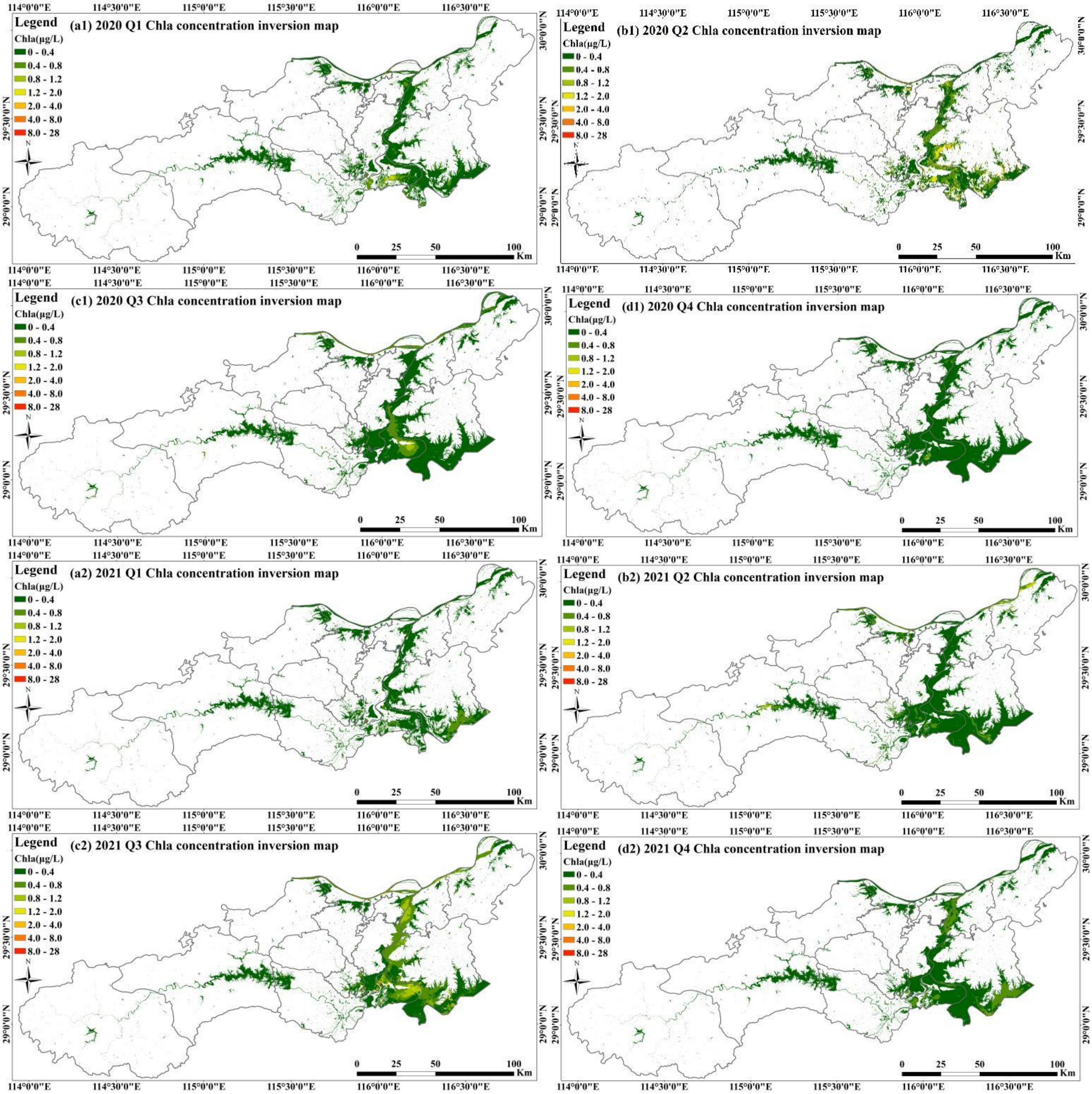
Figure 3. The scatter plot fitting results between estimated Chla and messured Chla

4.2 Spatial distributions and temporal changes of the Chla concentration inversion

To illustrate the seasonal variation characteristics of Chla concentration, calculations and synthesis were performed for each quarter from 2020 to 2022 on the GEE cloud platform. The spatial distribution results of the estimated Chla concentration are presented in Figure 4.

Chla concentration serves as a key indicator for characterizing phytoplankton biomass and plays a crucial role in assessing the eutrophication level of water bodies. Figure 4 reveals a discernible upward trend in Chla concentration within the water bodies of Jiujiang City over the past three years. Notably, areas with Chla concentration values exceeding 0.8 μg/L have witnessed a significant increase, with the highest values surpassing 2 μg/L primarily located in the northern and central regions of Poyang Lake, the eastern Lake District, and the western Great Lakes Pool. Among these, the most substantial increase in Chla concentration is observed in the water bodies of the Yangtze River and Poyang Lake, followed by the Ganjiang River, Saicheng Lake, and Xinmiao Lake. Meanwhile, the proliferation of phytoplankton biomass exacerbates water body eutrophication and deepens organic pollution.

Quarterly composite averages over the past three years indicate that the Chla concentration in the Poyang Lake water body tends to be higher in the first and fourth quarters compared to the second and third quarters. High-concentration areas are predominantly situated in the northern section of Poyang Lake, the western and eastern lake areas. Conversely, in the Jiujiang section of the Yangtze River, the average of Chla concentration is higher than that in the second and third quarters, with elevated concentrations mainly observed in Chaisang District in the western section of the Yangtze River and Pengze County in the eastern section. It should note that the high Chla concentration areas include Chihu and Bali Lake in the north of Jiujiang City, Xinmiao Lake in the central region, Zhelin Reservoir, Xiuhe River, and the Ganjiang River water body, with the peak Chla concentration occurs predominantly in the second quarter. In recent years, the Chla concentration in Poyang Lake has been continuously increasing, mainly due to the combined influence of human activities. Industrial emissions, agricultural cultivation, and the use of fertilizers in the surrounding areas have introduced large amounts of nutrients such as nitrogen and phosphorus into the lake, providing abundant nutrition for algae. Additionally, the discharge of sewage and industrial wastewater during the urbanization process has exacerbated eutrophication in the lake, leading to the Chla accumulation. Furthermore, the decrease in water level has resulted in shallower water and increased penetration depth of light, creating favorable conditions for algal growth and further promoting the increase of Chla (Jiang et al., 2023).



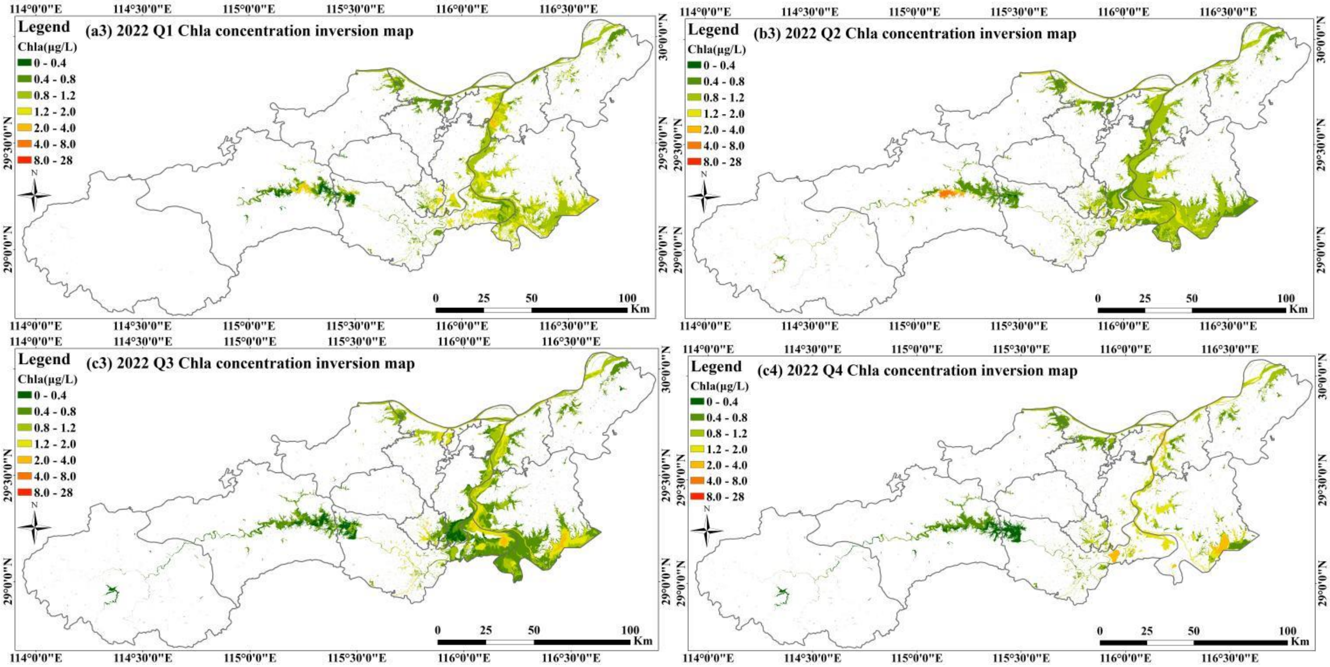


Figure 4. Spatial distributions of the Chla concentration. (a1)~(d1) , (a2)~(d2) and (a3)~(d3) are the four quarters (Q1,Q2,Q3 and Q4) Chla concentration inversion results in 2020, 2021 and 2022, respectively.

5. Conclusion

This study collects Sentinel-2 satellite remote sensing data and water quality station monitoring data to construct a Chla water quality parameter inversion model in Jiujiang City. The GEE remote sensing big data platform is utilized to achieve the quantitative inversion of quarterly Chla concentration form 2020 to 2022. The quantitative inversion model of Chla has been verified with measured data, demonstrating a high accuracy of 0.53. Spatial inversion results for Chla reveal an increasing concentration trend, particularly notable in the Poyang Lake area. Regions exhibiting relatively heavy pollution are concentrated in the Poyang Lake and water bodies near the Jiujiang urban area. Influenced by human activities and peak-low water, Chla concentration displays a discernible seasonal variation pattern. Human activities as an indispensable factor impact water quality, such as lakes situated near industrial zones affected by wastewater discharge.

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