Water Quality Monitoring Research Analysis Based on the Remote Sensing Technology

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Abstract. At present, supply and demand contradictions in water resources around the world are imminent and monitoring and governance of the water environment is urgent. This paper aims to combine space and aerospace remote sensing technology and water quality monitoring fields, fully consider the impact of current water body optical polarization on the accuracy of remote sensor optical signals, to identify the lower cost, more accurate measurement data, and easier to operate detection methods. The main analysis and study of three common water quality variables in water quality testing methods and the combination and synthesis of aerospace remote sensing data are proposed. In addition, this paper also selects the relevant water quality testing cases and the impact of optical polarization on the same type of parameter monitoring and performs a parameter analysis, estimating the financial cost that can be saved annually using remote sensing technology for water quality monitoring. Finally, the importance of the combination of space remote sensing data and aerial remote sensing data to improve the accuracy of water quality monitoring data is summarized, and the development prospect of the integration of air remote sensing and space remote sensing technology to overcome the impact of water multi-angle polarization on the accuracy of remote sensing data has prospected.

Keywords: RS, Monitoring, Water quality.

1. Introduction

Water is an essential resource in the natural environment, and social development and economic prosperity depend on the sustainable management of freshwater resources and ecosystems. However, today, water pollution caused by natural factors, such as tides and bacterial contamination, is increasing. At the same time, sewage emissions are also increasing year by year. This has led to a growing decline in clean fresh water available for human use, with 3.6 billion people worldwide suffering from water shortages [1]. Nowadays, supply and demand contradictions in water resources around the world are imminent and are critical for monitoring and governance of the water environment.

Traditional water quality testing is a multi-step process that includes sampling, transportation, storage, treatment, and measurement analysis. This method has some limitations, such as the need for a large amount of human effort, the high cost, the complexity of processes, and so on. The whole process takes longer and the accuracy is affected in many ways. To overcome these problems, the emergence of remote sensing technology provides a new source for environmental monitoring with increasingly high space and time resolutions. Remote sensing systems are mainly divided into boarding platforms and sensors, and boarding Platforms have remote sensation satellites, fixed-wing drones, and rotating-wing drones. The sensor is also divided into laser radar, multi-spectrometers, multiple lens cameras, etc., which can remotely obtain the water quality related multiple spectral data, obtaining data compared to traditional water quality detection is more convenient and comprehensive. Through drone measurement data, Zhu Xi and others established a water quality parameter model

based on total phosphorus, total nitrogen, ammonia, high mercury acid, and soluble oxidation in the lake and its surrounding waters, with a relative error rate of less than 30% [2]. This makes it easier and more accurate to obtain water quality monitoring data using remote sensing technology.

Therefore, this paper aims to combine Aeronautical remote sensing technology and the field of water quality monitoring to identify less costly, more accurate measurement data and more convenient detection methods to operate. This paper introduces the advantages and disadvantages of aeronautical and space remote sensing, introduces three common methods of detection of water quality variables for water quality testing, and proposes methods to combine and analyze data from aeronautic and aerospace remote Sensing. In addition, relevant water quality testing cases have been selected and parameter analysis has been carried out to estimate the financial costs that can be saved annually for water quality tests using remote sensing technology. Finally, this paper highlights the importance of combining space remote sensing data with aeronautical remote sensor data to improve the accuracy of water quality monitoring data.

2. The concept of remote sensing and its application

2.1. Remote sensing concept

(1) Space remote sensing technology

Space Remote Sensing refers to remote sensing technology systems that use various spacecraft as platforms. It is based on Earth-made satellites, including manned ships, spacecraft, and space stations. Space remote sensing is widely used in a range of fields such as ocean observation, meteorological observation, and early warning of disasters. Nowadays, most of the space remote sensing technology is used on remote-sensing satellites, Remote sensing satellites have the advantages of real-time updates, broad coverage, and quick response. However, the disadvantage of remote sensing satellites is that the cost is higher, the resolution is lower, the processing performance capacity is more demanding, and there are many influencing factors. Since the flight height of the remote sensing satellite makes the detection of images often obscured by clouds, the complexity and difficulty of the use of remote sensor satellites in the field of water quality detection is greater.

(2) Aeronautical remote sensing technology

Aerial remote sensing refers to a remote sensor technology system that senses the ground from aircraft, balloons, aerial boats, and other air platforms. At present, aviation remote sensing technology is more concentrated in drone technology, such as low-lying drones with multi-spectral equipment and drones equipped with push scanners. Drone remote sensing technology has the advantages of low cost, easy operation, short survey cycle, and high resolution. This enables it to avoid the negative impact of clouds and weather is suitable for large-scale terrain mapping and small-sized scans, and does not require complex ground treatment equipment. Domestic and international drone applications have been quite popular. In the field of water quality testing, Huang XinXi and others based on drone multi-spectral images through the OPT-MPP algorithm to establish a model of the suspension concentration and brightness, and the results found their combined error is less than 20%[3].

2.2. Principles of water quality detection based on remote sensing

The spectral characteristics of a water body are determined by the water's material composition and the condition of various elements within the water (Figure 1). The fundamental principle behind remote sensing for monitoring water quality is as follows: When sunlight irradiates the water, a portion of its energy gets absorbed by the atmosphere, while another portion penetrates the water surface and interacts with molecules within the water. As a result of the water's reflective properties, the light changes direction, allowing the backscattered light and the light reflected from the water's bottom to return to the water's surface. Eventually, these rays are captured by remote sensors positioned at the air-water interface. These collected data are then combined with the water body's spectral characteristics to facilitate water quality monitoring.

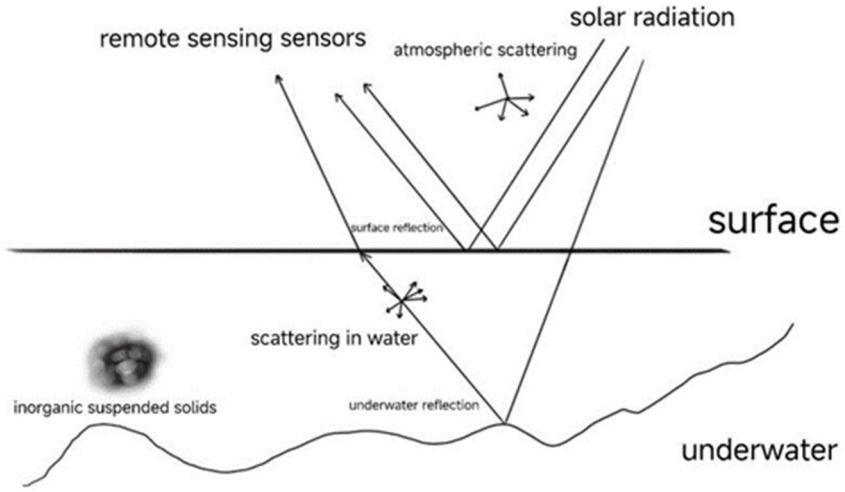


Figure 1. A Schematic diagram of water quality detection based on remote sensing

2.2.1. Remote sensing monitoring of water quality parameters in water bodies

Water bodies exhibiting pollution or specific substances often display distinct spectral characteristics compared to clean water bodies. Remote sensing serves as a valuable tool for monitoring water quality parameters by leveraging these spectral traits. Presently, remote sensing can effectively monitor various water quality parameters, including chlorophyll concentration, suspended matter, water transparency, and colored soluble organic matter [4]. Throughout the remote sensing monitoring process for lake water quality, phytoplankton algae, suspended materials, and dissolved organic matter significantly influence light reflection. The spectral curve of observed water experiences notable alterations, particularly near the blue or 676 nm range, especially when algae accumulate in the water. This results in a discernible peak within this band, allowing for the assessment of water body pollution levels [5]. Utilizing remote sensing technology to monitor water bodies essentially involves recording shifts in the spectral signatures of water quality and correlating these changes with water quality parameters. Based on the distinct light absorption and scattering characteristics exhibited by various substances within water bodies, remote sensing monitoring of water quality parameters can be categorized into photosensitive and non-photosensitive parameters [6].

2.2.2. Remote sensing monitoring of water transparency

Water transparency is the most intuitive parameter to describe the water quality and the main index of water eutrophication evaluation [7]. Remote sensing technology to detect water transparency is the characteristic of using water bodies to reflect electromagnetic radiation at different wavelengths, this characteristic results from the combination of material composition and physicochemical properties of water bodies. The reflectivity of a body of water changes as the incident wavelength changes, this is known as the spectral characterization of a body of water.

3. Practical applications and case studies

3.1. Aerospace remote sensing monitoring of lake water color anomalies - multi-angle polarization spectral properties of water bodies and their applications

In this study, a comprehensive approach was devised to monitor water color anomalies within inland lakes, primarily relying on the hue angle of the Forel-Ule index model, supplemented by other remote sensing metrics. These additional remote sensing indices encompass turbidity (TWI), planktonic algae index (FAI), and cyanobacteria and nutrient salt index (CMI). The research, conducted between 2013 and 2020, focuses on three lakes situated in the middle reaches of the Yangtze River Basin. Landsat-8 OLI images serve as the primary dataset for this analysis. The study aims to establish connections between watercolor anomalies and variations in water quality and

environmental conditions. Additionally, efforts are made to differentiate various water pollution states within regions exhibiting watercolor anomalies, with a particular emphasis on precise identification of algal blooms, high sediment loads, and eutrophication.

The difficulty of monitoring, in this case, lies in the precise identification of watercolor. Watercolor is a result of the interaction between sunlight and substances in the water, its remote sensing monitoring will be largely affected by the multi-angle polarization spectral characteristics of the water body of the clean water body of the spectral reflectance is low, the light has a strong absorption ability, the reflection is mainly in the visible light in the blue-green band in the general remote sensing image, the body of water is shown as a dark tone, in the infrared spectral performance is particularly obvious. However, passive remote sensing monitoring is mainly based on the differences in reflectance spectral characteristics of features for research. Due to the low spectral reflectance and inconspicuous characteristic spectra of water bodies, this leads to inaccurate results of remote sensing identification of water bodies and inversion of water quality parameters. Polarization is a fundamental property of various vectors through waves. Different features or different states of the same feature produce different polarization states, which are closely related to the wavelength, constituting the polarization spectrum. At present, detecting the polarization information of target features is also gradually becoming a new means of remote sensing target identification [8].

To investigate the impact of water's multi-angle polarization, Prof. Yan Lei's team at Peking University conducted measurements in 2010 using a visible/near-infrared spectrometer (spectral range: 350-2,500 nm) from the American company ASD. The study area chosen was Peking University's Wei-Ming Lake, which featured calm and clear conditions without ripples. Data collection occurred at noon under clear, cloudless weather. A Thomson prism with minor polarization spectrum fluctuations served as the polarizer for the experiment. As illustrated in Figure 2, the study captured horizontal polarization, vertical polarization, and unbiased reflection ratio spectra curves of water bodies at zenith angles of (a) 0° (vertical detection), (b) 30°, and (c) 45°.Figure 2(a) indicates that during vertical detection, unbiased curves depict the spectral characteristics of the water body. Reflectance remains consistently low across all bands, with a slight peak in reflectance in the green light band. Presently, most orbiting remote sensors employ vertical surface detection, leading to the dark appearance of water bodies in standard optical remote sensing images. This makes it challenging to utilize the water body's spectral features for remote sensing identification and water quality parameter retrieval. During vertical detection, both horizontal and vertical polarization readings of the water body approach zero, suggesting no polarization reflection in the water body's vertical direction, resulting in zero polarization. Changes in the detection angle correspondingly affect the Bopp curve. In Figure 2(b), the polarizability curves surpass unbiased reflectivity values only in the band range of 350-900 nm, while in Figure 2(c), polarization curves exceed unbiased reflectivity values across the entire band from 350 to 1350 nm. Overall, the polarization values during detection are tens of times greater than unbiased reflectivity values during vertical detection in specific bands. This suggests that using multi-angle polarization remote sensing data could theoretically transform the originally dark water body in intensity images into a bright feature in polarization images. This has the potential to enhance water body identification capabilities and inversion accuracy.

In addition, the research results of Prof. Yan Lei's team also pointed out that the characteristics and laws of multi-angle polarization spectra of water bodies measured by spectrometer on the ground are also applicable to the identification and inversion of water bodies by satellite-borne multi-angle polarization remote sensors. POLDER's multi-angle polarization data not only provide high-precision atmospheric parameters but also have advantages in the detection of low-reflectivity features, such as water bodies. This advantage broadens the application range of polarization remote sensing satellites and largely improves the remote sensing identification of water bodies and the inversion accuracy of water quality parameters [9].

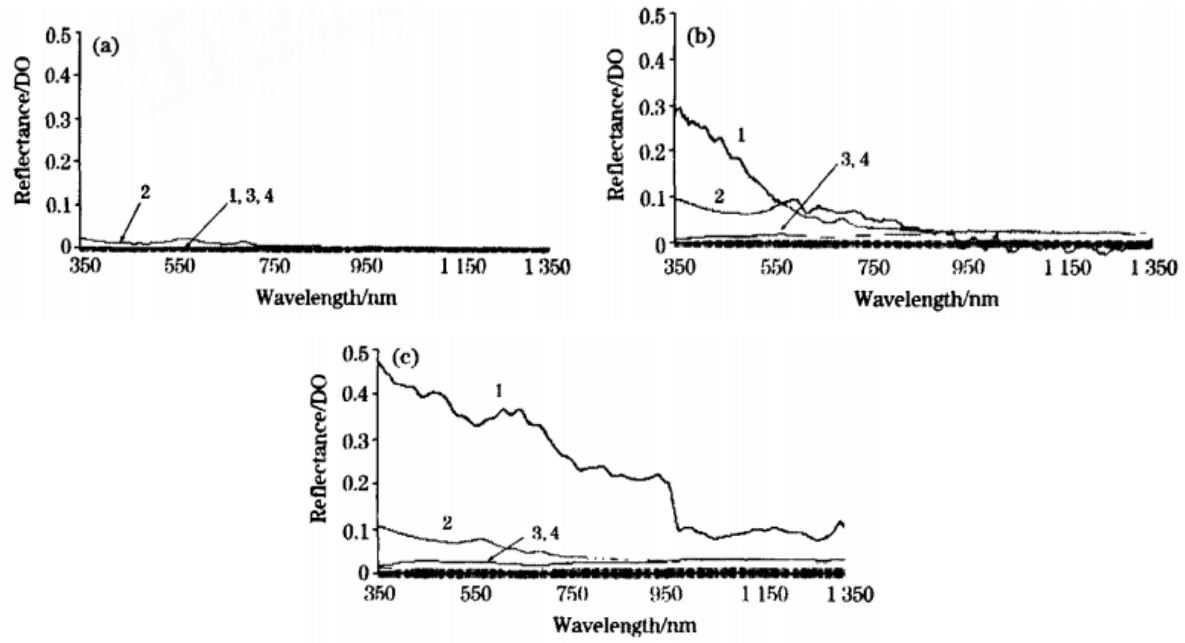


Figure 2. The water s polarization spectra at different viewing angles.

This research follows a similar case to that chosen by Prof. Yan Lei's team. In this study, Landsat-8 OLI observational data are utilized to detect watercolor anomalies, algal blooms, high sediment levels, and eutrophication. This is achieved by employing various remote sensing indices (TWI, FAI, CMI) and examining the factors associated with water environment anomalies. Multiple datasets, including water quality data, environmental data, and airborne remote sensing data, are integrated to investigate the factors influencing different types of watercolor anomalies in distinct areas. Figure 3(a) showcases Chang Lake, situated in the northeastern suburbs of Jingzhou City, the third largest freshwater lake in Hubei Province. Recent water quality measurements indicate a continual decline in water quality due to the discharge of both point-source and non-point-source pollutants, leading to increasing pollutant concentrations. Consequently, the lake's capacity to support its ecosystem has diminished. Figure 3(c) depicts Longguan Lake, a submerged freshwater lake at the border of Anhui and Hubei Provinces. Rapid population growth and extensive land development have significantly impacted local morphology and water quality. Inland lake water color is influenced by factors such as chlorophyll absorption, suspended solids, and colored organic matter (CDOM). Variations in watercolor are directly linked to the optical properties of constituent concentrations, providing insights into regional colored water quality characteristics. However, remote sensing of water quality or color in inland lakes is complicated due to the complex water environments. Additionally, the multi-angle polarization effect of the water body can impact the accuracy of experimental results in remote sensing of water quality or color. Three distinct watercolor anomalies (a), (b), and (c) are observable in RGB images derived from atmospheric correction data obtained from land remote sensing satellites. The framed portion of the RGB image of Changhu (enlarged in the upper right corner) displays a noticeable color difference, indicating aquatic vegetation (a). Algae communities and turbid water bodies, as seen in Figures (b) and (c), exhibit colors distinct from the natural hues of the water bodies.

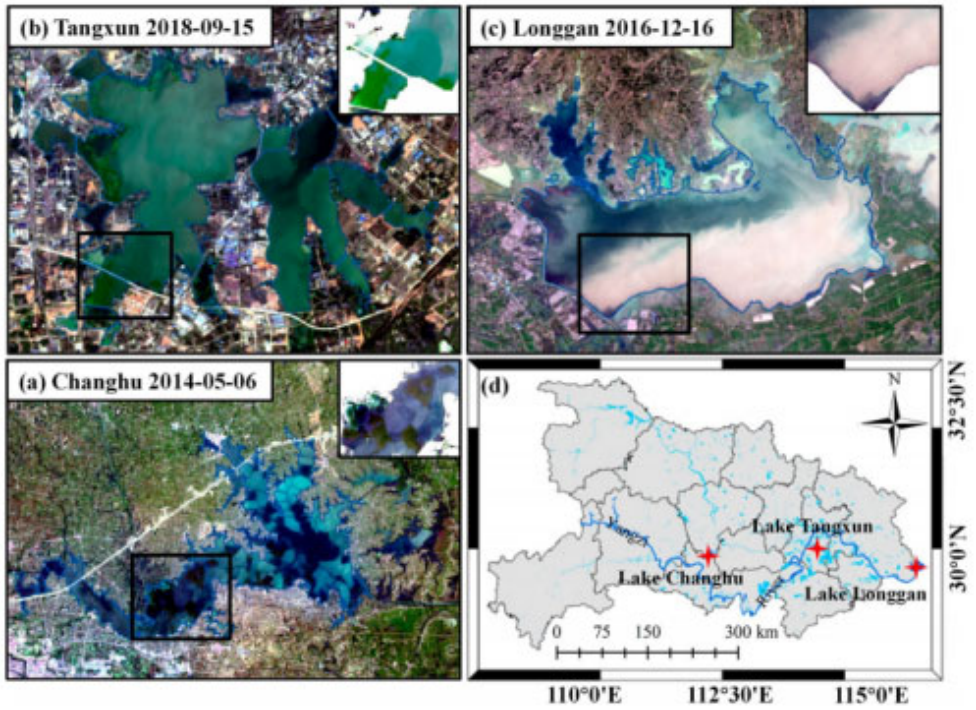


Figure 3. Research area map.

The Landsat OLI dataset utilized in this case boasts a spatial resolution of 30 meters and a strong signal-to-noise ratio. Remote sensing imagery is thoughtfully chosen through the Google Earth Engine (GEE) platform to minimize the impact of atmospheric factors like clouds, aerosols, and sunlight. For accurate atmospheric correction of Landsat 8 OLI data, the LaSRC (Landsat 8 Surface Reflectance Code), a program designed specifically for this purpose by USGS, is employed. LaSRC is widely acknowledged as the most precise atmospheric correction method available for Landsat 8 OLI data. Noteworthy enhancements to LaSRC include the incorporation of shortwave blue light and daily atmospheric environmental data. The Landsat-8 OLI SR dataset has earned recognition for its applicability over complex inland water bodies. It's important to note that Landsat 8 does not feature preprocessing techniques explicitly tailored to mitigate the effects of light polarization in the water column on remote sensing. Nevertheless, specialized remote sensing software can often be applied to Landsat 8 remote sensing data post-acquisition to minimize the impact of water column light polarization on images. The hue angle, measured in degrees, represents the rotation angle of polarized light relative to its direction of propagation. In Figure 4, shifts in hue angle can signify various phenomena, including nutrient excess and the timing of critical events like algal blooms. Remote sensing metrics allow the identification of areas with unusual watercolor characteristics, indicating algal blooms, aquatic vegetation, high sediment loads, and eutrophication. When light interacts with the surface of a body of water, it undergoes partial polarization due to scattering and water molecule absorption. The polarization state of reflected light may change depending on factors such as the angle of incident light, water surface properties, and observation angles. Consequently, varying observation angles can cause changes in the hue angle due to multi-angle light polarization effects. These variations can impact the analysis and interpretation of remotely sensed data, particularly in scenarios requiring precise light polarization measurements or specific applications. Hence, accounting for multi-angle observations is essential in the study and remote sensing analysis of light polarization in water bodies to ensure data accuracy and reliability. Furthermore, a promising avenue for addressing multi-angle polarization effects and enhancing water quality monitoring data accuracy involves the combined analysis of aerospace and airborne remote sensing data.

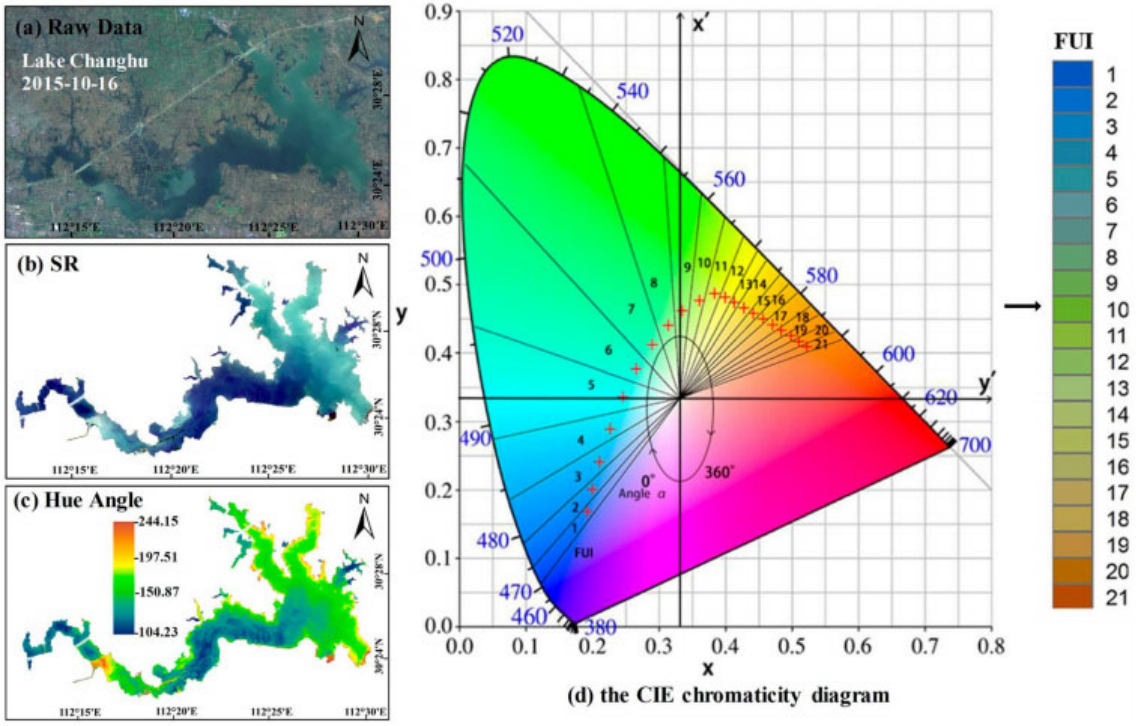


Figure 4. RGB plot of Landsat 8 lake hue angle raw data in the case of Long Lake.

Nowadays, in the field of remote sensing and monitoring of water quality, mature techniques do exist to overcome the effects of optical polarization of water bodies on remote sensing data. This includes the use of polarized remote sensing techniques such as polarized synthetic aperture radar (PolSAR) and multispectral polarimetric optical sensors to more accurately obtain optical properties of water bodies and water quality information. These techniques can help remote sensing professionals reduce the interference of optical polarization of the water body on the data, thus improving the accuracy and reliability of water quality monitoring. Different sensors and algorithms can be used for different monitoring needs to better address the challenges of water body optical polarization.

While these methods can help to reduce the effect of polarization of water body light on remote sensing data, they have some disadvantages and limitations. Polarized remote sensing data are expensive to acquire and have low spatial and temporal resolution. It is also susceptible to the influence of weather, resulting in lower accuracy.

Despite these limitations, polarized remote sensing techniques remain a valuable tool for providing more detailed information on water bodies in applications where accurate water quality monitoring is required. The use of these techniques needs to be weighed against cost, complexity, and application requirements to determine suitability.

3.2. Empirical algorithms and machine learning as drivers for improved remote sensing data analysis: the example of Secchi depth metrics

Secchi depth (SD) stands as a valuable metric for appraising eutrophication in lakes. Implementing an automated system, equipped with proficient image processing capabilities and tailored transparency inversion algorithms for lake-rich regions, yields abundant temporal and spatial data for efficient lake management. This is especially pertinent in improving the accuracy of remote sensing data in regions abundant with inland lakes, were water body optical properties impact data precision.

The case study highlights the utilization of the ACOLITE algorithm for atmospheric correction in conjunction with the Google Earth Engine (GEE) platform, aimed at producing specific remotely sensed reflectance outputs. Additionally, it showcases the performance of the lake elevation inversion algorithm for Yunnan Plateau lakes, one of China's five Great Lakes, often lacking in-situ data. Researchers conducted training and evaluation employing empirical algorithms like stepwise

regression, alongside machine learning techniques such as support vector machines and multilayer perception. This analysis incorporated data from four lakes with wide SD ranges, along with imagery from Landsat Operational Land Imager (Landsat) and aerial drone remote sensing (Figure 5).

The results underscore the notable improvement in retrieval accuracy achieved by models incorporating combinations of spectral bands and band ratios, in contrast to those reliant solely on single bands or band combinations. This research serves as a valuable point of reference for augmenting the precision of remote sensing monitoring data through the integration of empirical algorithmic analysis and machine learning [9].

With the rise of remote sensing satellites, the application of image data for evaluating lake water quality has garnered growing interest [10-13]. Google Earth Engine (GEE) boasts the capability to process and analyze remotely sensed imagery using Google's robust, clustered servers, effectively surmounting the constraints of traditional image processing methods [14,15]. Nonetheless, utilizing Landsat 8 surface reflectance data directly from GEE may introduce errors in aquatic remote sensing due to the non-specific nature of atmospheric correction algorithms for water-related radiation [16].

Therefore, a more efficient approach lies in combining unprocessed imagery from GEE with specialized atmospheric correction algorithms tailored for water environments, facilitating the accurate calculation of water quality in both marine and inland water bodies [17]. This synergistic use of GEE, coupled with atmospheric correction algorithms and lake water quality modeling, empowers the assessment of lake water quality based on remotely sensed data. These techniques yield crucial insights into the current status and fluctuations in lake water quality, serving as invaluable assets for monitoring water resource management and environmental preservation.

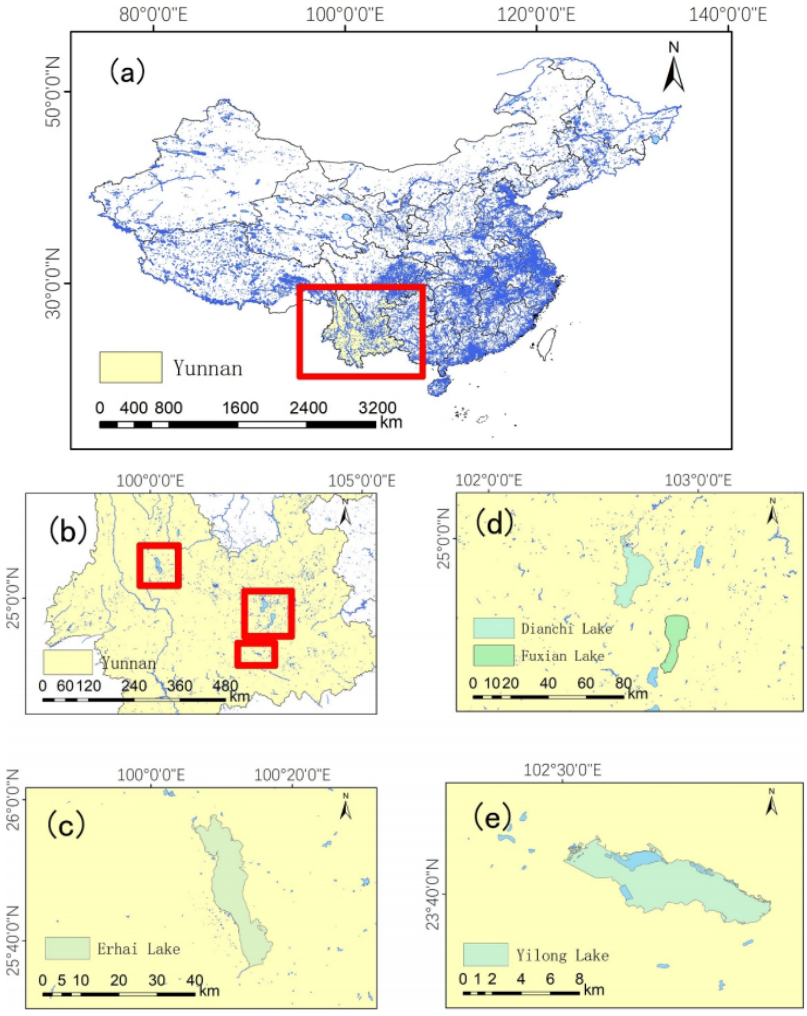


Figure 5. Objects of the study lake selected for this study

This study utilizes GEE combined with atmospheric correction algorithms for remote sensing data assessment of lake water quality typically involves the following major approaches.

(1) Data acquisition: Use the GEE platform to access satellite remote sensing data, such as the Landsat series or the Sentinel series, and select image data relevant to the lake area.

(2) Atmospheric correction: For selected image data, an atmospheric correction algorithm is applied to correct for atmospheric disturbances to obtain reflectance data. This can include commonly used atmospheric correction methods such as DOS (Dark Object Subtraction) or 6S (Second Simulation of the Satellite Signal in the Solar Spectrum).

(3) Lake region extraction: use image classification or regional interest extraction (ROI) tools to extract lake regions from the corrected image.

(4) Estimation of water quality indicators: Based on the extracted lake area, water quality indicators such as water turbidity, chlorophyll concentration, dissolved organic matter concentration, etc. are calculated. This usually requires modeling the correlation between reflectance with remote sensing data and field sampling data.

(5) Data validation and model calibration: Use ground sampling data or water quality monitoring data from other sources to validate the accuracy of remote sensing estimates and calibrate the estimation model to improve prediction accuracy.

(6) Spatial and temporal analysis: time-series remote sensing data are analyzed to monitor seasonal spatial and temporal changes in lake water quality.

(7) Visualization of results: Using GEE's visualization tools, the results of water quality estimation can be visualized as charts, maps, or animations to better understand and communicate the results.

(8) Accuracy assessment: Assessment of the accuracy of water quality estimates, including error analysis and uncertainty estimation, to understand the reliability of the results.

Empirical algorithms usually have a role to play in this.

- Absorption Spectrum Ratio Method: Based on the ratio of reflectance in the visible and near-infrared bands, this method is used to estimate the concentration of dissolved organic matter and chlorophyll-a in the water column.
- Color index method: using color indices such as NDVI (Normalized Difference Vegetation Index) to estimate water quality parameters in lakes.
- Spectral Characterization Method: Estimation of lake water quality parameters by analyzing spectral characteristics such as absorption peaks and troughs.

Machine learning plays an application in this.

- Supervised learning: known water quality monitoring data are used to train supervised learning models such as Support Vector Machines (SVM), Random Forest, or deep learning models such as Convolutional Neural Networks (CNN) to infer water quality parameters from remote sensing data.
- Unsupervised learning: remote sensing data are clustered using clustering methods, such as K-mean clustering, to identify areas of lakes with similar spectral characteristics, which are then further investigated for their water quality characteristics.
- Deep Learning: Deep learning techniques can be used for automated feature extraction and water quality parameter estimation, which typically require large amounts of data and computational resources.
- Time-series analysis: Time-series remote sensing data were analyzed using machine learning methods to monitor seasonal and spatial-temporal variations in water quality parameters.

Combining atmospheric correction algorithms with aerospace remote sensing and airborne remote sensing data can overcome the effect of multi-angle polarization of water bodies on remote sensing data to a certain extent, and also help to improve the accuracy of water quality detection data. The following are the correlation and significance between them.

- Reduces the effects of multi-angle light polarization: Multi-angle observations allow remotely sensed data to be acquired from different angles and therefore help to reduce the effects of light polarization in the water column. Aerial remote sensing usually provides multi-angle data that can be

used to better understand how the polarization state of light changes at different viewing angles.

- Atmospheric correction: Atmospheric correction is a critical step that removes atmospheric effects and ensures that the remote sensing data acquired more accurately reflects the surface characteristics of the water body. Both aerospace and airborne remote sensing data require atmospheric correction to obtain comparable reflectance information.
- Data fusion: Combining aerospace and airborne remote sensing data allows for a more comprehensive analysis of lake water quality. Aerial data provide high-resolution, multi-angle information, while aerospace data provide broader coverage. Data fusion can improve the accuracy of water quality estimates.
- Model Calibration: Combining information from multiple data sources can improve the calibration and validation of water quality models. By using multiple sources of data, water quality estimation models can be better calibrated and validated to improve their accuracy.
- Spatio-temporal analysis: Combining information from multiple data sources allows for a more comprehensive spatio-temporal analysis that monitors seasonal and spatio-temporal patterns of water quality change, contributing to a better understanding of the dynamics of the lake system.

Therefore, the combination of atmospheric correction algorithms, multi-angle optical polarization observations, and space and airborne remote sensing data can more accurately assess the optical properties and water quality of water bodies, which can help to overcome the effects of optical polarization and improve the accuracy and reliability of water quality detection data. This integrated approach is of great significance in water resources management and environmental monitoring.

4. Conclusion

According to the progress of research in this field, it is possible to combine aerospace remote sensing with airborne remote sensing data to provide more detailed, high-resolution data information. This will result in a multi-source dataset that will facilitate a more comprehensive spatial and temporal analysis. By monitoring seasonal and spatial-temporal variations in lake water quality, the dynamic processes of water systems can be better understood. By selecting sensors with multispectral and hyperspectral bands, combined with multi-angle observations and machine learning or statistical model calibration to adapt to specific water body types and environmental conditions, it is of great significance to overcome the multi-angle polarization spectral characteristics of water bodies and improve the accuracy of water quality detection data at present.

Currently, there is a costly and economically inefficient barrier to using solely altered remote sensing techniques, such as the large-scale use of polarized remote sensing with polarized synthetic aperture radar (PolSAR) and multispectral polarimetric optical sensors to improve the accuracy of remotely sensed data and, to some extent, to reduce the interference of the polarization of the water column with the data. Through data fusion (e.g., aerospace remote sensing combined with airborne remote sensing data), multi-angle observation combined with the rapidly developing methods of big data analysis, machine learning, and deep learning, the best economic efficiency can be achieved and the cost of scientific research can be reduced under resource constraints.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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