

Case Study on the Application of Airborne Remote Sensing in Algal Bloom Monitoring

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Abstract. Currently, algal blooms pose a significant threat to water ecosystems and human health worldwide. Timely and accurate monitoring and forecasting of algal blooms are essential for maintaining ecological balance in water bodies. Airborne remote sensing (ARS) has emerged as an efficient and rapid method for acquiring large-scale environmental information and has gained attention in the field of algal bloom monitoring. In this study, we analyze the applicability and effectiveness of airborne remote sensing in algal bloom monitoring through four representative cases: Lake Erie, Lake Pinto, Geum River, and Lake Taihu. The results demonstrate that airborne remote sensing offers high temporal and spatial resolution, allows for all-weather observation, and enables rapid response in algal bloom monitoring. However, airborne remote sensing also presents challenges such as high costs and susceptibility to weather conditions. Furthermore, this study proposes future directions for the development of airborne remote sensing. It aims to enhance our understanding of the potential applications of airborne remote sensing technology in algal bloom monitoring, providing valuable insights for further improvements in monitoring techniques and water environment protection.

Keywords: Algal bloom, Environmental monitoring, Airborne remote sensing.

1. Introduction

Algal bloom phenomena have significantly increased globally in the last few decades, not only in terms of scale and frequency but also in duration [1]. Algal blooms, which are the rapid growth and accumulation of large quantities of algae, are usually caused by the over-enrichment of nutrients such as nitrogen and phosphorus in the water. This phenomenon led to the eutrophication of water bodies and caused a series of environmental and ecological problems [2]. When algae die and decompose after blooms, microorganisms consume a large amount of dissolved oxygen during the decomposition process. This will lead to a lack of oxygen in water bodies, threatening the survival of fish and other aquatic life. Moreover, some algae (e.g., cyanobacteria) produce toxic substances that seriously threaten human health [3]. Therefore, it is essential to monitor and warn of algal blooms in a timely and accurate manner to maintain the ecological balance of the water body.

Traditional methods for monitoring algal blooms rely on ground sampling and laboratory analyses. However, these methods are time-consuming, costly, and cannot meet the needs of large-scale and real-time monitoring. With the continuous development and maturity of airborne remote sensing (ARS) technology, its application in algal bloom monitoring has gradually received widespread attention. Airborne remote sensing involves collecting data from sensors on the ground using drones and other tools [4]. Currently, many scholars have utilized airborne remote sensing image data to monitor marine environments [5, 6], especially for algal blooms [7, 8], including chlorophyll-a [9], phycocyanin concentration [10], and phytoplankton index. Airborne remote sensing has high spatial resolution and flexibility, allowing all-weather observation and rapid reorientation of observations when needed. Airborne remote sensing provides a new solution for monitoring algal blooms.

This paper analyzed four typical cases of airborne remote sensing applications in algal bloom monitoring. It also discusses the applicability and effectiveness of aerial remote sensing in different water environments. These four cases are located in various freshwater lakes worldwide, each with its unique geographic and ecological characteristics. However, they all share common challenges in environmental protection and water resource management. In each case, airborne remote sensing

technology and various analysis methods were used to monitor algal blooms. This paper analyzed the effectiveness of airborne remote sensing in monitoring algal blooms in various water environments. It also discussed the advantages and limitations of airborne remote sensing in algal bloom monitoring, as well as potential challenges and future development directions.

2. Case Description

2.1. Case 1: Lake Erie, USA

2.1.1 Background

This case describes Ohio's efforts to address the challenges posed by harmful algal blooms in Lake Erie, specific outbreaks of *Microcystis aeruginosa*, which produces hepatotoxins [11]. To manage and control the potential impacts of algal blooms on water quality and public health, Ohio enlisted the help of NASA's Glenn Research Centre to monitor the distribution of algal blooms using advanced remote sensing technology.

2.1.2 Data and Methods

NASA Glenn Research Center used the S-3 Viking and the DHC-6 Twin Otter as platforms for piggybacking hyperspectral sensors to study algorithms for detecting and distinguishing harmful algal blooms (HAB) from 2014-2017.

The aircraft typically fly designated areas at altitudes of 3,000 ft, 8,500 ft, or 24,000 ft, depending on location and weather. In July 2016, NASA GRC started using the HSI-2 sensor, whose specifications are detailed in Table 1. In August 2016, researchers began using the new HSI-3.0 imager, whose specifications are detailed in Table 2. In some cases, the HSI-2 is used in conjunction with the HSI-3.0. The increase in horizontal pixels of the sensor, as well as the wider field of view, allows imaging of a wider strip of land for a given flight. Additionally, the aircraft is equipped with an air-to-air spectroradiometer to measure downgoing radiation, which is particularly useful when operating under clouds. Fig. 1 shows images of algal blooms in the study area.

In this case, extensive analysis of hyperspectral imagery was undertaken to assess the impact of different spatial resolutions on harmful algal bloom monitoring effectiveness. First, remote sensing images at different spatial resolutions were simulated by image degradation simulation technique to explore the effect of resolution change on algal bloom recognition ability. Next, the case quantified the specific impact of image quality degradation on the recognizability of algal bloom patches. This was done using global sub-pixel standard deviation analysis to assess monitoring accuracy at different resolutions. Finally, the experts conducted a comparative and analytical assessment of the images at various resolutions through visual inspection. This allowed them to determine the level of difficulty in identifying algal bloom patches. The integration of these comprehensive methods provided a scientific foundation for determining the optimal spatial resolution for algal bloom monitoring. Moreover, it ensured the attainment of highly accurate and practical monitoring outcomes.

Table 1. HSI-2 Technical specification

Parameters	Data
Wavelength range	400-900 nm
Spectral sampling resolution	1 nm
Detection resolution	14 bit
Horizontal pixel	658
Field of View	524
Spectral resolution	2.5 nm

Table 2. HSI-3 Technical specification

Parameters	Data
Wavelength range	400-900 nm
Spectral sampling resolution	2 nm
Detection resolution	14 bit
Horizontal pixel	1032
Field of View	324
Spectral resolution	4 nm

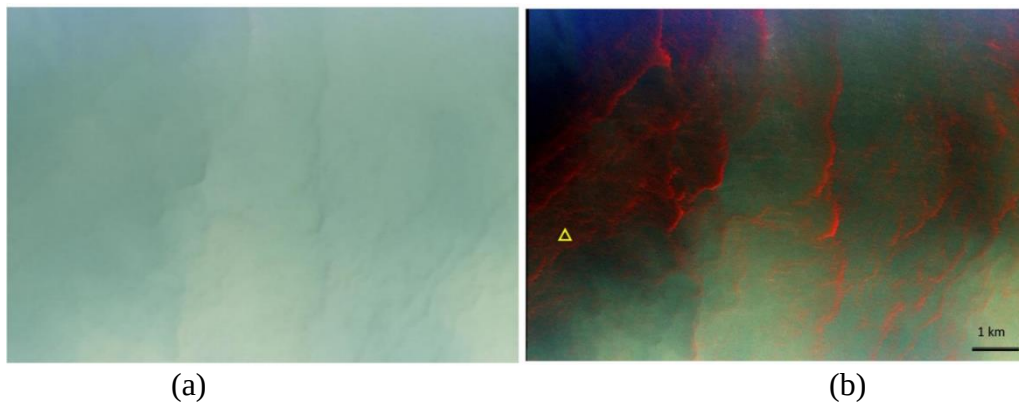


Figure 1. Images of algal bloom in the study area, taken on 19 September 2016 at 10:30 a.m. (a) True color image of algal bloom. (b) Color infrared image of algal bloom with reflectance in the 490 nm band in blue, 550 nm in green, and 709 nm in red [11]

2.2. Case 2: Pinto Lake, USA

2.2.1 Background

This case study is about Pinto Lake, a shallow natural lake in California, USA [12]. Pinto Lake is a typical shallow, natural lake. The lake is a suitable location for studying *Aphanizomenon* and *Microcystis* cyanobacterial blooms due to its unique geographic and ecological attributes. Kelly Lake was also included for qualitative validation, as shown in Fig. 2. While Kelly Lake differs from Pinto Lake in terms of geographic location and ecological characteristics, it provides an additional experimental basis for testing the stability and accuracy of the algorithms developed in the study under different environmental conditions.

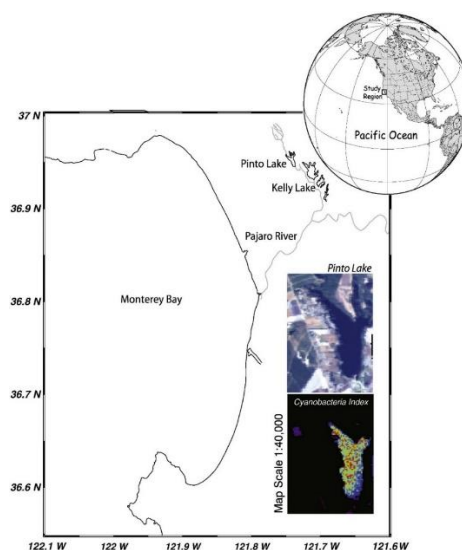


Figure 2. Geographic location of the study area, including Pinto Lake and Kelly Lake. The inset image provides AVIRIS imagery from 31 October 2013 depicting true color (top) and cyanobacteria index (bottom) [12]

2.2.2 Data and Methods

The data used in this case include field optical data and airborne remote sensing data. The field optical data were collected by using PANalytical FieldSpec spectrometers and Spectra Vista GER 1500 spectrometers for remotely sensed reflectance (Rrs) in the 400-800 nm wavelength range. They include different times when Aphanizomenon, Microcystis, and mixed and non-cyanobacterial communities were dominant. Airborne remote sensing data were acquired from NASA students through the Airborne Research Project (SARP) and HypIRI airborne campaigns for MASTER radiance metrics. The sensor has fine spatial resolution but a limited number of spectral bands. This case simulated remote sensing reflectance spectra using the Hydrolight 4.0 radiative transfer model. This was applied to calculate the end-element reflectance of the Aphanizomenon and Microcystis hydrographs to assess the sensitivity of the algorithms to intrinsic optical properties. Based on the observed data and Hydrolight simulations, the 654 nm, 714 nm, and 754 nm wavelengths of the MASTER band were used to estimate Cyanobacterial Index (CI) and Scattered-Line Height (SLH). A specific spectral shape algorithm called the Aphanizomenon-Microcystis Index (AMI) was used to distinguish between Aphanizomenon and Microcystis. The formula of these algorithms is shown in Table 3.

Fig. 3 illustrates the correlation between microcystin concentrations and three indices: CI, SLH, and AMI. A low AMI value indicates dominance of Microcystis aeruginosa, while a high AMI suggests the prevalence of Aphanizomenon. Intermediate values indicate a mixed community comprising both toxin-producing and non-toxic organisms. Notably, an increase in CI or SLH, coupled with a decrease in AMI, signifies a greater probability of toxic blooms.

Table 3. Algorithms developed or applied to spectral data. SS is a spectral shape

Algorithm	Formulas
	CI = -SS (681)
CI	$SS(681)= Rrs681 - Rrs665 - [Rrs709 - Rrs665] \times [(681\text{ nm}-665\text{ nm})/(709\text{ nm}-665\text{ nm})]$
SLH	$SLH = Rrs714 - Rrs654 - [Rrs754-Rrs654] \times [(714\text{ nm} - 654\text{ nm})/(754\text{ nm}-654\text{ nm})]$
AMI	$AMI = [640\text{ nm} - 510\text{ nm}] / [652\text{ nm} - 625\text{ nm}]$

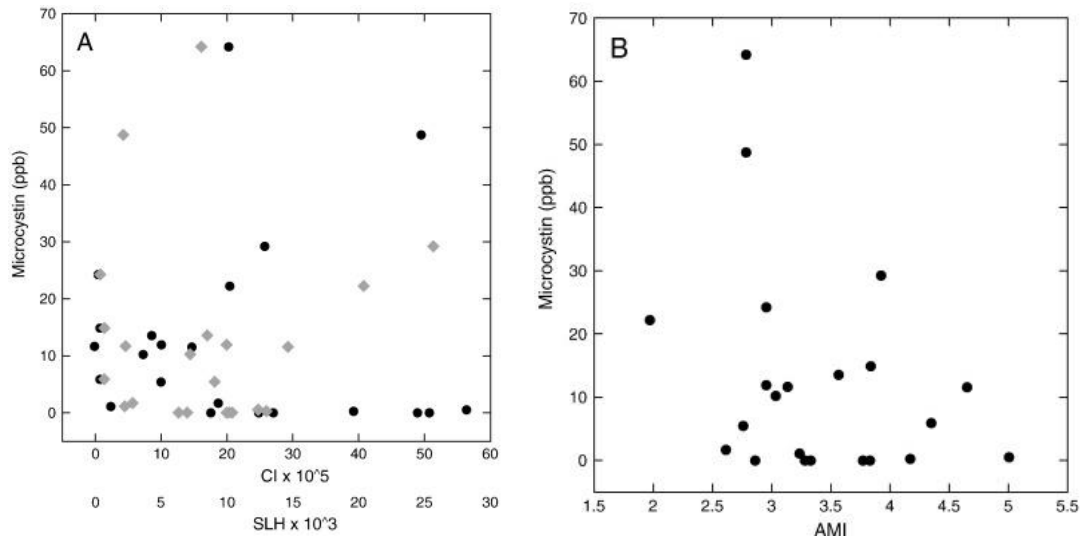


Figure 3. Scatter plots. (A) is the relationship between microcystin concentration and CI ($\times 10^5$; solid circles) and SLH ($\times 10^3$; grey diamonds); (B) showing microcystin concentrations versus AMI [12]

2.3. Case 3: Geum River, Korea

2.3.1 Background

The Geum River is a significant river and the third-largest water system in west-central Korea. It covers an area of 9,912 km² and is 360.70 km long, as shown in Fig. 4. It provides essential integrated water for Chungcheong and has nine water intake stations and several industrial parks [13]. Monitoring algal blooms is crucial as the area has a severe algal bloom problem every summer due to high rainfall from the monsoon climate.

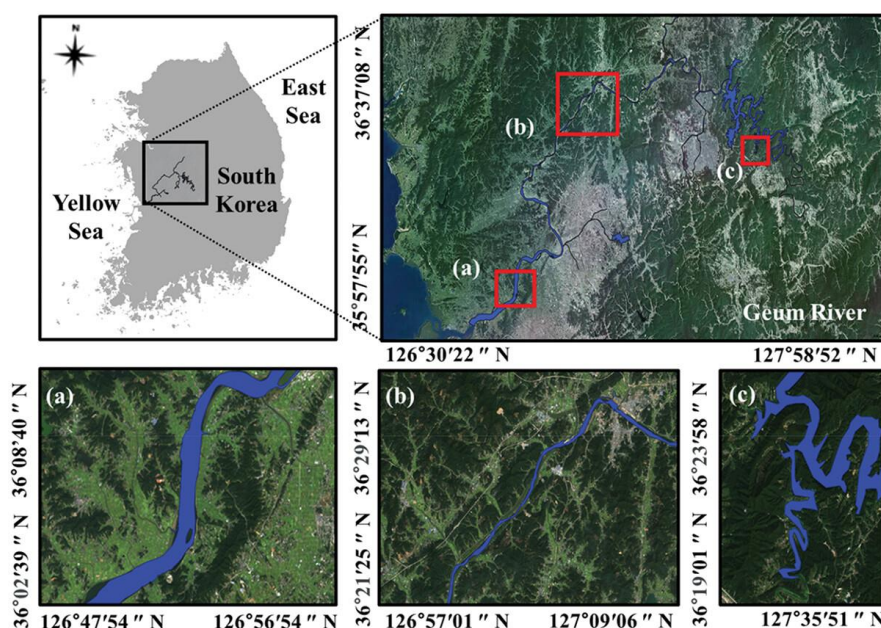


Figure 4. Location of the Geum River. (a) Lower Geum River, Republic of Korea (b) Middle (c) Upper [13]

2.3.2 Methods

Traditional methods for monitoring red tide are inadequate for capturing the spatial and temporal distribution characteristics of algal dynamics. To overcome this challenge, this case utilized airborne and satellite remote sensing data to capture the spatial and temporal features of algal dynamics. Three super-resolution (SR) analysis algorithms, double cubic interpolation, super-resolution convolutional neural network (SRCNN), and super-resolution generative adversarial network (SRGAN), are applied in this case to improve the estimation accuracy of water reflectance and to estimate chlorophyll-a concentration. Although deep learning techniques such as super-resolution analysis algorithms have been used in many applications in environmental monitoring, their application in red tide monitoring is still relatively rare. This case fills this gap.

2.4. Case 4: Taihu Lake, China

2.4.1 Background

Taihu Lake is a large freshwater lake located on the border of Jiangsu and Zhejiang Provinces in China [14]. It covers an area of approximately 2420 km². It has a subtropical monsoon climate characterized by cold winters, hot and humid summers, and abundant summer rainfall. The climate of Lake Taihu has created favorable conditions for the growth of cyanobacteria. In recent years, these blooms have become more frequent and pose a serious threat to the lake's ecosystem, as well as affecting the quality of life of nearby residents.

2.4.2 Data and Methods

This case used an N-series hyperspectral camera in conjunction with a DJI Warp and Weft multi-rotor drone for data acquisition. The acquired images have a high spatial resolution and cover a wide spectral range. The data was acquired in different seasons, including winter, spring, summer, and

autumn, with a total of 7 effective acquisitions and 18 sorties to ensure comprehensive data coverage. The preliminary and pre-processing of spectral data for data processing was carried out using Coral and Matlab2020a software platforms. Coral and Matlab software platforms were used to preprocess the spectral data.

It included the reconstruction of spectral data, single-point curve extraction, and discriminant analysis of cyanobacteria and water plants. The spectral curves of cyanobacterial concentrations in the visible to near-infrared bands were explored by analyzing the hyperspectral image data of different concentrations of cyanobacteria, as shown in Fig. 5. Finally, principal component analysis (PCA) was used to downscale the hyperspectral data and combined with the KNN classification algorithm to accurately distinguish cyanobacteria, aquatic plants, and other non-aquatic plants, as shown in Fig. 6.

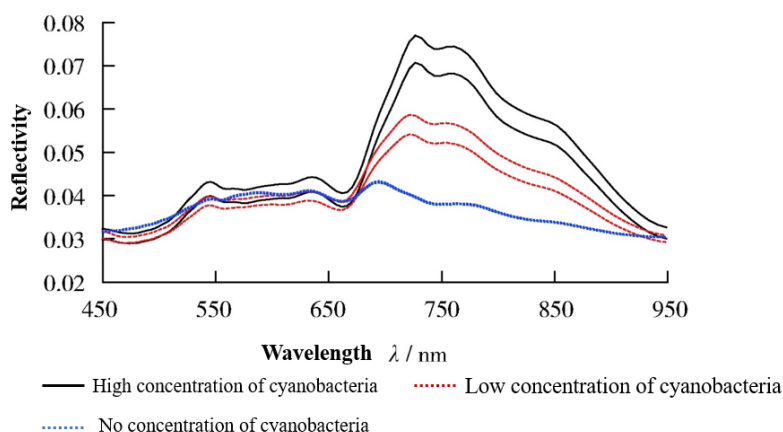


Figure 5. Spectral curves of cyanobacteria at different concentrations [14]

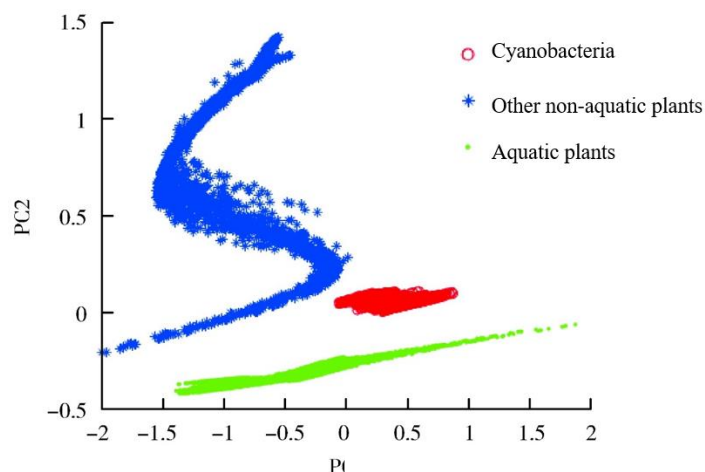


Figure 6. PCA distribution [14]

3. Analysis of Cases

The comparison of four cases of airborne remote sensing technology in algal bloom monitoring demonstrated the utilization of different techniques and analysis methods. Each approach was specifically tailored to address the unique algal bloom challenges in the respective area. These methods respectively reflected the advantages and limitations of airborne remote sensing in the field of algal bloom monitoring.

In Case 1, airborne remote sensing was utilized to monitor harmful algal blooms in Lake Erie, USA. The study found that a resolution of 25 m is optimal as it covers 75% of the feature size. If the resolution is lowered below 25 m, the potential within-pixel error can be reduced from 25% to 8%. These findings highlight the benefits of high-resolution airborne remote sensing in providing detailed and comprehensive water monitoring data, enabling more accurate and timely detection of algal

blooms. However, it is important to acknowledge that airborne remote sensing does have limitations, including the dependence on specific resolutions and the need for flexibility to adapt to varying conditions.

In Case 2, Pinto Lake, USA, based on CI, SLH, and AMI algorithms, monitored the seasonal variation in cyanobacterial toxin concentrations exceeding safety standards. The case study highlights the capability of airborne remote sensing systems to collect diverse data, including visible, infrared, hyperspectral, and other wavelengths of information. This rich dataset offers numerous characteristic parameters of the water body, enabling various methods for analyzing and identifying algal blooms. Airborne remote sensing can effectively assess the probability of surface bloom formation and differentiate between different types of cyanobacteria. Nevertheless, it is important to note that the applicability of algorithms may be constrained to particular water bodies and types of algae.

In Case 3, deep learning techniques such as super-resolution image algorithms were applied to accurately estimate the chlorophyll-a concentration in the Geum River, Korea. Airborne remote sensing data plays a crucial role in enhancing the spatial resolution of water body imagery and mitigating atmospheric interference, thereby leading to more precise estimations of chlorophyll-a concentration. However, it is important to acknowledge certain limitations. The algorithm necessitates a substantial volume of data for training and demands a high level of technical expertise, which can potentially increase the complexity and time required for data processing.

In Case 4, the study conducted in China's Taihu Lake revealed the distinctive spectral characteristics of cyanobacterial blooms, particularly in the visible to near-infrared bands. This discovery established an effective spectral indicator for monitoring cyanobacterial blooms. By analyzing hyperspectral data and utilizing principal component analysis to reduce data size, along with the KNN classification algorithm, accurate positioning and differentiation between cyanobacteria and non-aquatic plants, including water plants, can be achieved. When compared to satellite remote sensing, airborne remote sensing technology offers advantages such as lower operating costs and higher data collection efficiency. However, it is important to note that airborne remote sensing is susceptible to weather conditions, including strong winds, rain, snow, and other adverse weather factors, which may limit its applicability for data collection.

4. Summary

By comparing four sets of application cases of airborne remote sensing technology in algal bloom monitoring, several advantages of airborne remote sensing can be summarized as follows: Airborne remote sensing technology provides high spatial resolution and wide coverage, enabling more detailed and comprehensive water monitoring data. The airborne remote sensing system collects data in various wavelength bands, such as visible light, infrared, and hyperspectral, which provides a wealth of characteristic parameters of the water body and facilitates multifaceted analysis and identification of algal blooms. Airborne remote sensing enables accurate and timely monitoring of algal blooms. The combination of airborne remote sensing data and deep learning algorithms can accurately estimate the concentration of algal blooms. Moreover, in comparison to traditional satellite remote sensing, airborne remote sensing has lower operating costs and more efficient data acquisition capabilities. However, airborne remote sensing technology also faces limitations in practical applications. For example, adverse weather conditions can affect the efficiency of data collection by drones. Additionally, monitoring large areas using airborne remote sensing may have certain limitations.

In the future, the application of airborne remote sensing can be expanded to improve the monitoring range and efficiency in capturing dynamic changes in algal blooms in a more detailed manner. Advanced data fusion techniques and machine learning algorithms can be developed based on airborne remote sensing data to enable the automatic processing and analysis of large-scale data, thereby enhancing the efficiency and accuracy of algal bloom monitoring.

References

- [1] Yu Zhiming, Chen Nansheng. Trends and hotspots of red tide research at home and abroad. *Ocean and Lake*, 2019, 50 (03): 474-486.
- [2] Zhang T, Hu H, Ma X, et al. Long-Term Spatiotemporal Variation and Environmental Driving Forces Analyses of Algal Blooms in Taihu Lake Based on Multi-Source Satellite and Land Observations. *Water*, 2020, 12 (4): 1035-1035.
- [3] Boris V Gromov, Alexey A Vepritsky, Kira A Mamkaeva, et al. A survey of toxicity of cyanobacterial blooms in Lake Ladoga and adjacent water bodies. *Hydrobiologia*, 1996, 322 (1-3), 149-151.
- [4] Lin W C, Ho C F, Tsay H L, et al. Opto-mechanical Design of Airborne Remote Sensing Instrument. *Proceedings of SPIE - The International Society for Optical Engineering*, 2010, 7813.
- [5] Yuzhong L, Jie Z, Yongqi X, et al. Advance in marine technique and application research of airborne hyperspectral remote sensing in China. *State Oceanic Administration (China); Shanghai Institute of Technical Physics (China)*, 2003, 4897, 44-50.
- [6] Kim D J, Jung J, Kang K M, et al. Development of a Cost-Effective Airborne Remote Sensing System for Coastal Monitoring. *Sensors*, 2015, 15 (10), 25366-25384.
- [7] Alves B S R, Kozhikkodan B V, Pedro A V, et al. Remote sensing for mapping algal blooms in freshwater lakes: a review. *Environmental science and pollution research international*, 2023, 30 (8): 19602-19616.
- [8] Munsaf R K, Bahram S, Masoud M, et al. A Meta-Analysis on Harmful Algal Bloom (HAB) Detection and Monitoring: A Remote Sensing Perspective. *Remote Sensing*, 2021, 13 (21): 4347-4347.
- [9] El-Alem A, Chokmani K, Laurion I, et al. Ensemble-Based Systems to Monitor Algal Bloom with Remote Sensing. *IEEE Transactions on Geoscience and Remote Sensing*, 2019, 57 (10): 7955-7971.
- [10] Erkkilä A, Kalliola R. Patterns and dynamics of coastal waters in multi-temporal satellite images: support to water quality monitoring in the Archipelago Sea, Finland. *Estuarine, Coastal and Shelf Science*, 2003, 60 (2): 165-177.
- [11] Lekki J, Deutsch E, Sayers M, et al. Determining remote sensing spatial resolution requirements for the monitoring of harmful algal blooms in the Great Lakes. *Journal of Great Lakes Research*, 2019, 45 (3): 434-443.
- [12] Kudela M R, Palacios L S, Austerberry C D, et al. Application of hyperspectral remote sensing to cyanobacterial blooms in inland waters. *Remote Sensing of Environment*, 2015, 167: 196-205.
- [13] Hyuck D K, Min S H, Ather A, et al. Deep learning-based super-resolution for harmful algal bloom monitoring of inland water. *GIScience Remote Sensing*, 2023, 60 (1).
- [14] Ding Ming, Li Xuwen, Jiang Sheng, et al. A case study of the application of UAV hyperspectral remote sensing in the monitoring of cyanobacterial blooms in Taihu Lake. *Environmental Monitoring and Management Technology*, 2022, 34 (01): 49-51+71.