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Remote Sensing Methods for Chlorophyll-a Concentration Estimation in Water Bodies: A Review

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Abstract: Chlorophyll-a (Chl-a) concentration estimation in water bodies using remote sensing techniques has become increasingly important for water quality monitoring and aquatic ecosystem assessment. This paper reviews various remote sensing systems and techniques for Chl-a monitoring in inland waters, coastal areas, and oceans. It first introduces the common Chl-a estimation parameters, followed by definitions of remote sensing principles and techniques specifically applicable to Chl-a retrieval. This study systematically analyzes the capabilities and types of spaceborne systems including optical sensors (Sentinel-2 MSI, Landsat-8/9 OLI, MODIS, Sentinel-3 OLCI), unmanned aerial vehicles (UAVs), and ground-based hyperspectral systems. The paper also reviews various spectral indices, semi-empirical algorithms, and machine learning approaches that have been applied to Chl-a concentration estimation. Results indicate that Sentinel-2 MSI has emerged as the leading platform for inland water monitoring due to its optimal spatial-temporal-spectral characteristics. Machine learning methods, particularly Random Forest and deep learning approaches, have demonstrated superior performance over traditional empirical algorithms. Multi-platform integration approaches combining satellite, UAV, and ground-based observations offer the most comprehensive monitoring capability. The paper summarizes the opportunities and limitations of remote sensing data for spatial and temporal estimation of Chl-a, and identifies future research directions.

Keywords: Chlorophyll-a, Remote Sensing, Water Quality, Machine Learning, Spectral Indices, UAV, Satellite Ocean Color.

1. Introduction

Water is essential for life on Earth, yet only 3.8% of Earth's surface water is freshwater, with approximately 68% trapped in glaciers [1]. Water quality monitoring has become increasingly critical due to growing population pressures, urbanization, industrialization, and agricultural activities that degrade surface water resources. According to the United States Environmental Protection Agency (EPA) and World Health Organization (WHO), water quality generally refers to the physical, chemical, and biological characteristics of water that determine water suitability for different applications such as recreation, drinking, fishing, agriculture, and industry.

Chlorophyll-a (Chl-a), a specific form of chlorophyll in oxygenic photosynthesis, is defined as a proxy for phytoplankton concentration in surface waters and is considered one of the most important optically active variables in open oceans and coastal areas [2]. Elevated Chl-a concentrations signal eutrophication, which can lead to harmful algal blooms (HABs), hypoxia, fish kills, and ecosystem degradation. The concentration of Chl-a in water bodies serves as an essential indicator of eutrophication and is directly related to the abundance of phytoplankton, which is crucial for assessing the overall quality of aquatic environments [3].

Traditional water quality monitoring relies on in-situ sampling and laboratory analysis, which is resource-intensive, time-consuming, and provides limited spatial-temporal coverage. Although in-situ measurements are the most accurate techniques for water quality assessment, they are usually time-consuming, risky, expensive, and labor-intensive, especially over large environments. Moreover, most in-situ measurement services can only measure or predict a few water quality parameters, such as water temperature, chlorophyll, and salinity. These limitations, along with inconsistencies in data measurements by different organizations and the lack of spatial and temporal continuity, make in-situ measurements less applicable in many situations [5].

Remote sensing has emerged as a powerful complementary tool, offering rapid, systematic, accurate, and cost-effective water quality assessment at various scales. Remote sensing systems measure water radiance or emission at different parts of the electromagnetic spectrum, which are directly influenced by some of the water quality substances. The underlying concept is that various domains of the electromagnetic spectrum received from different sources of light into the water are selectively absorbed or backscattered by in-water constituents at different intensities. Water radiance is affected by a variety of factors, including lighting conditions, water depth, bottom reflectance, and water quality substances. Consequently, studying the water-leaving radiance captured by remote sensing instruments can reveal different information about water quality parameters including Chl-a.

1.1. Objectives of This Review

This review synthesizes recent advances in remote sensing methods for Chl-a estimation based on the analyzed literature corpus. The specific objectives of this review are to: (1) provide a comprehensive overview of remote sensing platforms and sensors applicable to Chl-a estimation; (2) systematically analyze spectral indices, algorithms, and machine learning approaches for Chl-a retrieval; (3) identify key challenges and limitations in current approaches; and (4) summarize future research directions for improving Chl-a monitoring capabilities.

2. Theory and Methods for Chl-a Estimation

2.1. Spectral Principles of Chlorophyll-a

Remote sensing of Chl-a exploits the unique spectral signatures of phytoplankton pigments. The spectral properties of water are divided into Inherent Optical Properties (IOPs) and Apparent Optical Properties (AOPs). IOPs, such as absorption coefficient and total scattering, describe the characteristics of water and can be quantified in the laboratory using water samples as well as in-situ measurements. AOPs, which include radiance and downwelling plane irradiance, depend on the IOPs and the geometric structure of the radiance distribution including atmospheric situation, surface water structure, and wind speed [5].

Chl-a exhibits high absorption in blue (400-500 nm) and red (650-700 nm) wavelengths, while showing high reflectance in green (500-570 nm) and near-infrared (NIR, 700-800 nm) regions. The reflectance peak near 700 nm is particularly significant for chlorophyll detection, as it relates to the fluorescence emission and scattering properties of algal cells. Research has demonstrated that an increase in Chl-a concentration leads to a decrease in the spectral response at short wavelengths (approximately 400 nm) and an increase at green wavelengths (approximately 550 nm).

2.2. Classification of Water Bodies

Based on optical properties, water bodies can be classified into two categories: Case 1 and Case 2 waters. Case 1 refers to open ocean environments, which are deeper than shallow coastal seas. The spectral properties of Case 1 waters are mainly determined by phytoplankton, which is represented by the Chl-a concentration. In Case 1 waters, Chl-a concentration can mainly be derived from spectral bands within the blue to green regions. Case 2 refers to coastal, estuarine, and shelf regions, which are more turbid than open oceans. The spectral properties of Case 2 waters are affected by other optically active constituents including mineral particles, Colored Dissolved Organic Matter (CDOM), and microbubbles. Compared to open ocean, remotely sensed measurements of water quality in Case 2 waters are more challenging due to the larger number of water constituents that affect the AOPs of coastal regions [2].

2.3. Retrieval Approaches

Several techniques have been proposed and evaluated to extract relationships between water quality parameters and remote sensing data. These techniques can be classified into four categories: empirical models, semi-empirical models, analytical models, and semi-analytical models.

Empirical models primarily involve statistical analyses between sampled water quality measurements and remotely sensed AOPs of water. In these models, the bands or band combinations that have the highest correlation with water quality parameters are first identified and selected as the remote sensing data. Then, the statistical relationship between the water quality parameters and the selected remote sensing datasets is determined using different techniques such as linear regression, non-linear regression, and empirical orthogonal function analysis.

Semi-empirical methods are similar to empirical models, with the difference that they integrate water spectral theory with traditional statistical techniques. In semi-empirical approaches, after analyzing the IOPs of a water quality parameter, the most appropriate method and band combinations are selected to retrieve the corresponding water quality parameter from remote sensing images. Recent advances in hyperspectral remote sensing technology have accelerated the improvement of semi-empirical methods by estimating the impacts of different water constituents on the IOPs of water bodies at different wavelengths.

Analytical methods are based on radiative transfer theory, which quantifies the IOPs of water quality parameters. Analytical models estimate the concentrations of the constituents of water using ratios of their absorption and backscattering coefficients. However, analytical methods require comprehensive knowledge about the IOPs of water quality parameters, which is not always available.

Semi-analytical techniques co-exploit analytical and empirical models, in which more simplified radiative transfer equations are considered to estimate the concentrations of constituents. Methods that combine semi-analytical methods with multivariate statistical analysis approaches, such as Principal Component Analysis, Inverse Distance Weighted, Cluster Analysis, Discriminant Analysis, and Factor Analysis, have considerably facilitated the study of different water quality parameters using remote sensing measurements.

Machine Learning (ML) methods have become increasingly popular in recent years. These methods duplicate the human brain's processes and convert the water quality estimation problem into a computer-recognizable input method. ML methods can automatically learn from various datasets and construct models based on minimizing the variance between training samples and prediction values. These methods, along with remote sensing data, are powerful approaches for the routine assessment of spatial and temporal variations of water quality parameters [3].

3. Remote Sensing Platforms for Chl-a Estimation

3.1. Satellite-Based Optical Sensors

Ocean color sensors including MODIS, SeaWiFS, OLCI, and MERIS were originally designed for oceanic applications but have been widely applied to inland water monitoring. The main satellite platforms used for Chl-a estimation include Sentinel-2 MSI, Landsat-8/9 OLI, MODIS, Sentinel-3 OLCI, and various Chinese satellites such as GF-1 and ZY1-02D.

Sentinel-2 MSI has emerged as a leading platform for inland water monitoring due to its optimal combination of spatial (10-60 m), spectral (13 bands covering VIS, NIR, SWIR), temporal (5-day revisit), and radiometric (12-bit) characteristics. Sentinel-2 includes the red-edge band at 705 nm, which is particularly valuable for detecting the chlorophyll fluorescence peak near 700 nm and distinguishing cyanobacteria from other phytoplankton. Studies have shown that Sentinel-2 achieved NDCI algorithm performance with R^2 = 0.82, RMSE = 1.29 mg/L, and NRMSE = 7.8% for Chl-a estimation in plateau lakes [6].

Landsat-8/9 OLI/TIRS provides significant advantages with 30 m spatial resolution, 12-bit radiometric resolution, and 16-day revisit time. For Chitgar Lake, the two-band algorithm achieved R^2 = 0.80 with RMSE = 1.12 mg/L and NRMSE = 12.4% using Landsat-8 [7].

MODIS offers high temporal resolution (0.5-1 day), spatial resolution of 250-1000 m, and long data records since 2000. Despite coarse spatial resolution, MODIS provides valuable time-series analysis capabilities. Fang [8] achieved R^2 = 0.83

for Chl-a estimation using MODIS data combined with Random Forest and SPM-based classification.

Sentinel-3 OLCI provides 300 m spatial resolution with 1.2-day revisit time, offering better spatial detail than MODIS but still limited for small water bodies.

GF-1 and ZY1-02D are Chinese satellites that have shown promising results. Zhao & O'Loughlin [9] demonstrated that GF-1 data achieved better prediction results than Sentinel-2 for Chl-a estimation in their multiplatform study, with goodness of fit reaching 93.1%. Lu [10] achieved $R^2 = 0.78$ using FLH model for Baiyangdian Lake based on ZY1-02D hyperspectral data.

NIR-Red Based Algorithms: Yu [11] tested the SAMO-LUT algorithm in Asian lakes and achieved $R^2 = 0.94$ for Chl-a retrieval, demonstrating the effectiveness of NIR-red band algorithms for inland waters.

3.2. UAV-Based Sensing

Unmanned Aerial Vehicles (UAVs) have revolutionized water quality monitoring by bridging the resolution gap between satellite and ground-based observations. Key advantages of UAVs include: (1) ultra-high spatial resolution with centimeter-level mapping possible; (2) flexible deployment unaffected by cloud cover; (3) near-real-time data acquisition critical for bloom event response; (4) cost-effective operation with lower costs than manned aircraft; and (5) adjustable altitude and timing for optimal data capture.

Common multispectral sensors mounted on UAVs include DJI P4 Multispectral with 5 synchronized cameras, MicaSense RedEdge series, and Parrot Sequoia. Hyperspectral sensors such as Headwall Nano-Hyperspec and Specim FX series provide full spectral resolution for detailed analysis.

Cheng [4] demonstrated UAV-based quantitative mapping of surface Chl-a in Hong Kong coastal waters using visible images from digital cameras, successfully mapping spatial and temporal variations during algal blooms despite cloud cover limitations that preclude satellite imagery. McEliece [12] achieved 78% variance explanation for Chl-a using a 4-band multispectral sensor (448 nm, 494 nm, 550 nm, 675 nm) mounted on UAV, with the index (R(550) - R(448))/(R(550) + R(448)) providing optimal results. Román [13] demonstrated centimeter-scale water quality mapping using 5-band multispectral sensors on UAVs, with Chl-a values ranging 0-3 mg/L in Maltese coastal waters.

Pan [14] evaluated cross-water-body transferability of Chl-a inversion models using UAV hyperspectral and Sentinel-2 data, achieving $R^2 = 0.98$ for UAV data and $R^2 = 0.86$ for Sentinel-2 data in eutrophic inland waters.

Horvat [15] conducted a systematic review finding that DJI UAVs with multispectral sensors are most widely used globally, with Random Forest being the dominant inversion algorithm. However, significant gaps remain in regions like Africa due to high UAV costs, limited expertise, and stringent regulations.

3.3. Ground-Based and Proximal Sensing

Ground-based hyperspectral remote sensing provides the highest spectral resolution and serves as validation reference for airborne and satellite platforms. Cao [16] combined hyperspectral remote sensing devices with BP neural networks for Haihe River monitoring, achieving training model R^2 exceeding 80% and verification model R^2 exceeding 70% for eight water quality parameters.

Li [17] analyzed temporal variation of Chl-a concentrations in Poyang Lake using high-frequency in-situ measurements and MERIS satellite data, revealing distinct daily periodic variations with peaks at approximately 3:00 PM and troughs at night or early morning.

Cook [18] found that ground-based multispectral models significantly outperformed Landsat-based models for cyanobacteria detection in small, turbid reservoirs. Ground-based sensing offers very fine spatial resolution without atmospheric interference and enables rapid data turnaround for continuous monitoring.

3.4. Multi-Platform Integration

Zhao & O'Loughlin [9] developed an innovative multiplatform approach combining Sentinel-2, Landsat-8, MODIS Terra, and MODIS Aqua for Irish lakes. This approach achieved a 550% increase in observation frequency compared to in-situ measurements alone, with the multiplatform model achieving 78% and 70% accuracy in training and testing datasets. MODIS Aqua showed the highest average performance due to optimization for water color detection, and the approach effectively addresses cloud cover limitations and infrequent revisit constraints.

4. Spectral Indices and Retrieval Algorithms

4.1. Blue-Green Band Ratio Algorithms

Originally developed for oceanic waters, blue-green band ratio algorithms use the ratio of blue to green reflectance, exploiting the inverse relationship between Chl-a absorption in blue bands and reflectance in green bands. The OC2 and OC4 algorithms are widely used in open ocean waters. However, these algorithms are less effective in turbid inland waters with high CDOM and suspended sediments.

4.2. Red-NIR Band Ratio Algorithms

Red-NIR band ratio algorithms have proven more effective for inland and coastal waters with higher turbidity. Gilerson [5] demonstrated that red-NIR band algorithms are more effective in inland and coastal waters than blue-green algorithms.

Two-Band Algorithm: R(708)/R(665) and R(753)/R(665) for MERIS/Sentinel bands, achieving $R^2 > 0.7$ in turbid waters.

Three-Band Algorithm: R3 = [Rrs(665) - Rrs(708)] / Rrs(753), showing minimal dependence on CDOM absorption and non-algal particle scattering, effective for Chl-a > 1 μg/ml.

Yu [11] validated the SAMO-LUT semi-analytical algorithm in Asian lakes, achieving $R^2 = 0.94$ but found large errors for low Chl-a concentrations (<10 μg/ml).

4.3. Normalized Difference Chlorophyll Index (NDCI)

Mishra & Mishra (2012) developed NDCI using the formula: NDCI = (Rrs(708) - Rrs(665)) / (Rrs(708) + Rrs(665)). This index is particularly effective for turbid, eutrophic waters and has been successfully applied to Sentinel-2 data with $R^2 = 0.82$ [7].

4.4. Fluorescence Line Height (FLH)

FLH estimates chlorophyll fluorescence emission at 685 nm and is effective for high chlorophyll concentrations. Lu

[10] achieved R^2 = 0.78 using FLH model for Baiyangdian Lake based on ZY1-02D hyperspectral data.

4.5. Performance Comparison by Ecosystem Type

Based on systematic review of 137 studies by Llodrà-Llabrés [2], the best-performing indices vary by ecosystem type. For lakes, indices such as aphy(B4)/aphy(B4), B7(1/B4-1/B5), B5-(B6+B4)/2, and B3/B4 achieved R^2 = 0.65-0.85. For reservoirs, B2+B3+B4+B5, B3/B6, and (B5-B4)/(B5+B4) achieved R^2 = 0.60-0.82. For rivers, red/NIR ratios and NDCI achieved R^2 = 0.55-0.75. For coastal areas, blue/green ratios and FLH achieved R^2 = 0.70-0.90.

5. Machine Learning Approaches

5.1. Traditional Machine Learning Algorithms

Random Forest (RF) has emerged as the dominant ML algorithm for Chl-a estimation due to its ability to handle nonlinear relationships, resistance to overfitting, built-in feature importance analysis, and robustness to outliers. Performance highlights include: Zhao & O'Loughlin [9] achieved R^2 = 0.78 with multi-platform satellite data; Fang [8] achieved R^2 = 0.83 with MODIS data; Kupssinskü [19] achieved R^2 > 0.8 with Sentinel-2/UAV data; and Karimian [3] achieved R^2 = 0.93 with GF-1/Sentinel-2 data.

Fang [8] proposed a novel classification-based approach, dividing water bodies into three groups by Suspended Particulate Matter (SPM) concentration, improving model R^2 from 0.41 to 0.83.

Support Vector Machine (SVM/SVR) excels with high-dimensional data and small sample sizes. Karimi [7] found SVR combined with Sentinel-2 outperformed traditional semi-empirical models.

Extreme Gradient Boosting (XGBoost) provides high predictive accuracy through gradient boosting. Zhao & O'Loughlin [9] found XGBoost achieved competitive performance with Random Forest for multiplatform chlorophyll estimation. Pan [15] achieved the best performance with XGBoost optimized using Genetic Algorithm (GA) for UAV data (R^2 = 0.98, MAPE = 18.59%, RMSE = 2.15 μg/L).

K-Nearest Neighbors (KNN) has been applied by Kupssinskü [19], achieving R^2 > 0.8 for Chl-a prediction with appropriate band selection.

5.2. Neural Network Approaches

Back-Propagation Neural Network (BPNN) has shown strong performance in hyperspectral data analysis. Zhu [20] used Pearson correlation analysis for band selection with Zhuhai-1 hyperspectral data, achieving RMSE = 2.12 μg/L and mean relative error = 9.66%. Cao [17] applied BP neural networks with ground-based hyperspectral data achieving training R^2 > 80% and verification R^2 > 70%.

Deep Neural Networks (DNN) handle complex nonlinear relationships in high-dimensional spectral data. Fang [8] compared DNN with RF, XGBoost, and CNN, showing competitive performance but requiring more computational resources.

Convolutional Neural Networks (CNN) excel at extracting spatial-spectral features from imagery. Fang [8] reported CNN achieved R^2 = 0.79 for Chl-a estimation using MODIS data.

5.3. Algorithm Comparison

Machine learning methods have demonstrated superior performance over traditional empirical algorithms. Random Forest typically achieves R^2 = 0.70-0.93 depending on data quality and study area. XGBoost achieves R^2 = 0.65-0.98 with efficient computation. SVM/SVR achieves R^2 = 0.60-0.82 with good performance on small samples. BPNN achieves R^2 = 0.70-0.85 but may overfit. DNN achieves R^2 = 0.75-0.88 but requires large samples. CNN achieves R^2 = 0.70-0.85 with automatic spatial feature extraction.

5.4. Novel Frameworks and Multi-Source Integration

Karimian [3] proposed a novel framework combining Random Forest inversion model with multi-source data (GF-1, Sentinel-2, ground observations), achieving 2 m spatial resolution prediction. Results showed goodness of fit improved by >36.6%, MSE decreased by >15.17%, and MAE decreased by >21.26%.

6. Key Challenges and Limitations

6.1. Optical Complexity of Inland Waters

Inland waters exhibit much greater optical complexity than oceanic waters due to multiple optically active constituents including phytoplankton with variable absorption properties, Colored Dissolved Organic Matter (CDOM), suspended particulate matter, and bottom reflectance in shallow waters. Case 2 waters require three-component models with regional calibration often necessary. Variable phytoplankton composition, physiological state affecting pigment concentration, and cell size affecting scattering properties create significant challenges.

6.2. Spatial Resolution Challenges

More than 90% of global water bodies have area less than 0.1 km^2, yet Sentinel-2's 10m pixels may still be too coarse for these small water bodies. UAVs offer a viable alternative but have coverage limitations. Pixel contamination from shoreline adjacency effects, mixed land-water pixels, and bottom reflectance in shallow areas further complicates accurate retrieval.

6.3. Temporal Limitations

Cloud cover remains a significant limitation for optical remote sensing, as it requires cloud-free conditions. This is particularly critical for bloom events which occur with specific weather patterns. Only 24% of Landsat images were cloud-free in Hong Kong according to Cheng [4]. Furthermore, algal blooms can double in 1-2 days, making the 5-16 day satellite revisit inadequate. UAVs offer flexible temporal coverage but have limited endurance.

Li [18] highlighted that temporal variations in Chl-a are significant, with a maximum intra-diurnal ratio of 5.1 and inter-diurnal ratio of 7.4 in Poyang Lake, emphasizing the need for high-frequency sampling.

6.4. Regional Transferability

Algorithms developed for specific regions often fail when applied elsewhere. Optical properties vary geographically, and water quality parameters differ with watershed characteristics. McEliece [12] recommended site-specific calibrations for each investigated location, as models developed in UK failed validation in France. Cook [18] found that published models had little predictive power when applied outside the study regions where they were developed.

Pan [14] demonstrated that while cross-water-body validation caused moderate performance declines, all models maintained $R^2 > 0.71$, indicating reasonable transferability with proper calibration.

6.5. Validation and Ground-Truthing

Field sampling is rarely coincident with image acquisition due to spatiotemporal mismatch. Diurnal variability in chlorophyll and point measurements versus pixel averages create additional challenges for validation.

7. Future Research Directions

7.1. Platform Integration and Data Fusion

Multi-scale observations combining ground-based hyperspectral for validation, UAV for high-resolution targeted surveys, and satellite for large-scale monitoring offer the most comprehensive approach. Pan [14] demonstrated that synergistic UAV hyperspectral and satellite multispectral data enhanced model robustness and transferability for eutrophic inland waters.

7.2. Advanced Machine Learning

Future directions include Graph Neural Networks for spatiotemporal prediction, Transformer models for spectral sequence analysis, self-supervised learning for unlabeled data, and physics-informed neural networks. Pan [14] showed that XGBoost optimized with Genetic Algorithm achieved superior performance, highlighting the potential of hyperparameter optimization techniques.

7.3. Pre-Classification Strategies

Optical water type classification before retrieval can improve algorithm selection. Fang [8] demonstrated that SPM-based pre-classification improved R^2 from 0.41 to 0.83, suggesting significant potential for similar approaches.

7.4. Operational Monitoring Systems

Cloud-based processing platforms, automated alert systems for bloom events, and integration with decision support systems are needed for operational deployment of remote sensing-based water quality monitoring.

8. Conclusion

Remote sensing of chlorophyll-a concentration has advanced significantly over the past decade, driven by improvements in sensor technology, machine learning algorithms, and data availability. Key conclusions from this review include:

(1) Multi-platform approaches combining satellite, UAV, and ground-based observations offer the most comprehensive monitoring capability, with Zhao & O'Loughlin [9] demonstrating a 550% increase in observation frequency through multi-platform integration.

(2) Machine learning methods, particularly Random Forest, XGBoost, and deep learning approaches, have demonstrated superior performance over traditional empirical algorithms, with Random Forest achieving R^2 up to 0.93 and XGBoost achieving R^2 up to 0.98 in optimal conditions.

(3) Sentinel-2 MSI has emerged as the leading satellite platform for inland water monitoring due to its optimal spatial-temporal-spectral characteristics, particularly the red-edge band at 705 nm.

(4) UAVs effectively bridge the resolution gap for small water bodies, enabling centimeter-scale mapping, but require standardized protocols for operational deployment.

(5) Regional transferability of algorithms remains a significant limitation, with site-specific validation and adaptation consistently recommended across studies.

(6) Future progress will depend on platform integration, physics-informed machine learning, hyperparameter optimization, and improved understanding of aquatic ecosystem dynamics.

As water quality monitoring becomes increasingly critical for sustainable water resource management, remote sensing will continue to play an essential role in providing timely, accurate, and comprehensive information for decision-making.

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