

Review

The Application of Remote Sensing Technology in Inland Water Quality Monitoring and Water Environment Science: Recent Progress and Perspectives

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Abstract: Due to its long-term and high-frequency observation capabilities, remote sensing is widely recognized as an indispensable and preferred technology for large-scale and cross-regional water quality monitoring. This paper comprehensively reviews the recent progress of remote sensing for water environment monitoring, predominantly focusing on remote sensing data sources, inversion indices, and inversion models. Specifically, we summarize the inversion methods for commonly monitored water quality parameters, including optically active constituents (such as chlorophyll-a, colored dissolved organic matter, total suspended solids, and water clarity) and non-optically active constituents (including total nitrogen, total phosphorus, and chemical oxygen demand). Furthermore, the applications of remote sensing in the field of environmental sciences such as spatiotemporal evolution and driver factor analysis of water quality, carbon budget research, and pollution source identification are also systematically reviewed. Finally, we propose that atmospheric correction algorithm improvement, multi-source data fusion, and high-precision large-scale inversion algorithms should be further developed to reduce the current dependence on empirical observation algorithms in remote sensing and overcome the limitations imposed by temporal and spatial scales and that more inversion models for non-optically active parameters should be explored to realize accurate remote sensing monitoring of these components in the future. This review not only enhances our understanding of the critical role of remote sensing in inland water quality monitoring but also provides a scientific basis for water environment management.

Keywords: remote sensing; water quality monitoring; inversion model; environmental application; inland water



Academic Editor: Dong Liu

Received: 10 December 2024

Revised: 23 January 2025

Accepted: 23 January 2025

Published: 16 February 2025

Citation: Chen, L.; Liu, L.; Liu, S.; Shi, Z.; Shi, C. The Application of Remote Sensing Technology in Inland Water Quality Monitoring and Water Environment Science: Recent Progress and Perspectives. *Remote Sens.* **2025**, *17*, 667. <https://doi.org/10.3390/rs17040667>

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1. Introduction

Inland waters, such as lakes, rivers, reservoirs, and groundwater, are vital elements of the Earth's water resources and play a crucial role in delivering essential ecosystem services to human society [1]. However, in recent years, global climate change and anthropogenic activities, such as domestic, industrial, and agricultural activities, have seriously disturbed the water quality of inland waters and led to frequently dynamic changes, which have imposed great pressure on both human society and the environment [2–5]. Thus, long-term and large-scale dynamic monitoring of inland aquatic systems is essential [6–8].

Remote sensing technology has been widely used for monitoring inland aquatic environments, attributed to its swift monitoring pace, expansive coverage, and capacity to produce imagery data with high spatial and temporal resolutions. It could effectively overcome the drawbacks of traditional monitoring methods, which are time-consuming and labor-intensive and lack spatial and temporal coverage [9–11]. The utilization of remote sensing for water quality monitoring primarily involves constructing appropriate water quality estimation models based on acquired water body reflectance signals, thereby enabling dynamic monitoring of water bodies. This technology can also reveal pollution sources, pollutant migration patterns, and spatial extents that are challenging to discern using conventional methods, thereby facilitating large-scale water quality monitoring [12,13]. Consequently, remote sensing has increasingly emerged as an indispensable tool for inland water monitoring, particularly on large or global scales [14].

Since the launch of the first Landsat satellite in 1972, multispectral scanners have been utilized for water quality monitoring, expanding the application of optical satellite data from marine to inland waters. Inland water remote sensing instruments have undergone significant development over time. The early period was marked by land-based sensors, including ground-based spectral measurements and Landsat. This evolved into the era of medium-spatial-resolution satellite sensors, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) (USA), Medium Resolution Imaging Spectrometer (MERIS) (European Space Agency), and Visible Infrared Imaging Radiometer (VIIRS) (USA). Currently, we are in a high spatial resolution era represented by the Sentinel-2 MultiSpectral Instrument (MSI) (European Space Agency), the Landsat 8/9 Operational Land Imager (OLI) (USA), and unmanned aerial vehicles (UAVs). Over this progression, both spatial and spectral resolutions have advanced from low to high levels, reflecting a transition from non-existence to maturity. Throughout this developmental process, the retrievable water quality parameters have evolved from initial optical active components, such as suspended solids and yellow substances, to non-optical active components, significantly increasing the number of retrievable parameters and covering a broader and more critical range of water quality indicators [15,16]. This expansion has greatly enriched the dimensions of water quality monitoring and enhanced its comprehensiveness. The methods for water quality parameter retrieval have undergone significant transformations, from traditional analytical methods to empirical/semi-empirical methods, and subsequently to machine learning models driven by the big data context, markedly improving the accuracy and reliability of water quality parameter inversion and greatly enhancing their adaptability and flexibility in practical applications [17]. Concurrently, the scope of research has also broadened, extending from individual water bodies to national and even global scales, providing robust technical support for large-scale systematic water quality monitoring efforts. However, current remote sensing research on inland water bodies still faces challenges such as atmospheric influences, limitations of satellite sensor properties, and the complexity of water optical properties. Therefore, an in-depth understanding of inland water quality remote sensing is indispensable [18].

What practical environmental issues can be addressed by the capability of remote sensing technology to retrieve water quality parameters? Many scholars have conducted extensive research on this topic, primarily focusing on the spatiotemporal evolution and driver factor analysis of water quality, carbon budget research, and pollution source identification. Remote sensing enables the inversion of water quality parameters, which allows for the construction of long-term water quality data series. Such data can reveal long-term trends in water quality evolution, distribution patterns, and the identification of key factors affecting water quality. These applications provide theoretical support for the formulation of water management policies by relevant authorities [19,20]. Additionally, carbon

budgeting has become a global concern. By developing algorithms for remote sensing estimation of carbon-related components, it is possible to assess changes in inland water carbon stocks. This contributes to understanding the role of inland water bodies in the global carbon cycle and provides scientific evidence for addressing climate change and related issues [21,22]. Furthermore, pollution sources in inland waters are often complex and diverse, including industrial wastewater discharge, domestic sewage, agricultural runoff, algal blooms, terrestrial nutrient input, and oil spills. These factors pose significant threats to the ecological health of water bodies. Remote sensing technologies, in combination with relevant indices and models, can be used for tracking and locating pollution sources, offering crucial information for the development of effective pollution control strategies. Integrating research on these three aspects will provide valuable insights for a comprehensive understanding of water quality and is critical for the effective management and protection of water environments [23].

While numerous literature reviews have highlighted the accomplishments of remote sensing in water quality monitoring, primarily focusing on the inversion algorithms of water quality parameters, especially optically active constituents [24,25], there remains a dearth of comprehensive reviews centered on the application of remote sensing in aquatic environments, specifically based on the retrieval of water quality indicators. Consequently, this review offers an exhaustive overview of advancements in optical remote sensing for the surveillance of water quality. It covers a spectrum of topics, including datasets, indices of water quality, algorithmic inversion techniques, and targeted methodologies for the estimation of various water quality parameters, as well as their practical applications. Additionally, the review highlights existing challenges and offers perspectives on future research trajectories, with the goal of deepening the comprehension of remote sensing's role in assessing inland water quality.

2. Research Progress on the Use of Remote Sensing for Water Quality Monitoring Based on Bibliometric Analysis

In this study, we employed “remote sensing”, “water quality”, and “water environment” as primary keywords to probe the Web of Science core citation database, covering the period from 2000 to 2024. This investigation yielded a total of 2838 research articles and review papers. To analyze and visualize the progression of research in this area, we used VOSviewer 1.6.20, a leading tool in knowledge mapping. Over the past 24 years, the number of publications on remote sensing of water environments has shown a steady increase, reaching a peak of 377 papers in 2023 (Figure 1a).

A cumulative total of 200 institutions globally have participated in research endeavors within this field. The top 10 institutions, based on the number of published papers, are presented in Table 1. Notably, China, the United States, and Italy are among the countries with the highest number of publications in this field, with the Chinese Academy of Sciences leading the pack with 353 papers. This statistic highlights the significant contributions made by the Chinese Academy of Sciences in this research domain. Keywords serve as a concise and effective condensation of a paper's core content, efficiently communicating the primary theme of the research. Figure 1b presents a co-occurrence map of keywords in this field. Larger nodes correspond to higher frequencies of keyword occurrence. The more connections between nodes, the higher the frequency of the associated keyword, illustrating the distribution and intensity of research hotspots over the past 24 years. The profusion and dispersion of peripheral keywords indicate the burgeoning diversity of research topics in recent years. Research hotspots in this field center on water quality monitoring, the inversion of optically active constituents, and the exploration of algorithms.

The predominant literature in this field is published in journals such as Remote Sensing, Science of the Total Environment, and Remote Sensing of Environment.

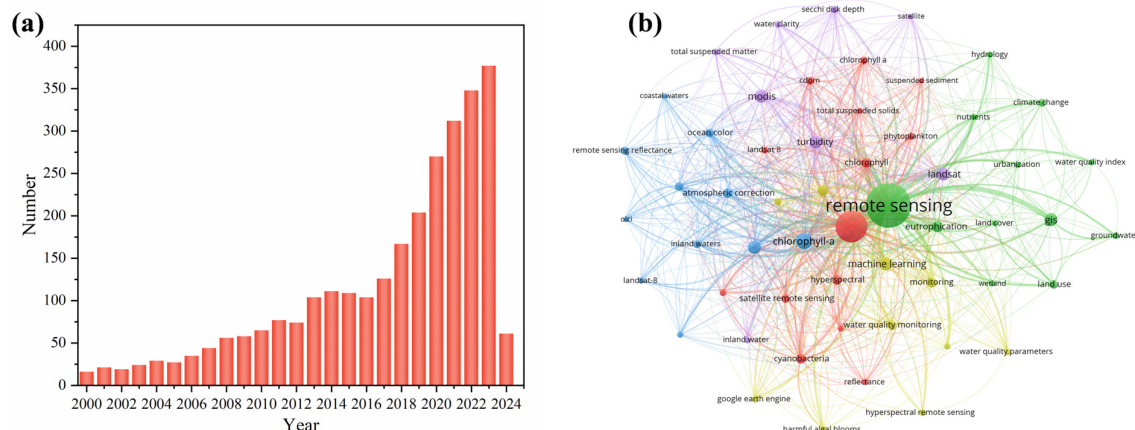


Figure 1. Publication numbers associated with water quality remote sensing monitoring from 2000 to 2024 (a). Visualization of top 50 keywords in water quality remote sensing papers published between 2000 and 2024, the nodes represent keywords, larger nodes correspond to higher frequencies of keyword occurrence. Each cluster represents a set of related keywords, which are denoted by the same color. The lines connecting keywords within the same cluster indicate the co-occurrence relationship or the strength of association between these keywords (b).

Table 1. The top 10 research institutions and their publication numbers in the area of water quality remote sensing.

Rank	Institution	Number (Paper)	Percentage (%)
1	Chinese Academy of Sciences	353	12.44
2	University of Chinese Academy of Science CAS	139	4.90
3	State University System of Florida	101	3.56
4	Nanjing Institute of Geography and Limnology CAS	100	3.52
5	National Aeronautics and Space Administration (NASA)	84	2.96
6	Wuhan University	73	2.57
7	National Oceanic and Atmospheric Administration	65	2.29
8	Consiglio Nazionale delle Ricerche (CNR)	63	2.22
9	U.S. Environmental Protection Agency	55	1.94
10	University of South Florida	54	1.90

3. Principles, Data, and Models of Remote Sensing Monitoring

3.1. Principles of Remote Sensing Monitoring

The optical properties of water are broadly categorized into two types: inherent optical properties (IOPs) and apparent optical properties (AOPs). IOPs are intrinsic to the medium and depend solely on its composition, remaining unaffected by the surrounding light field. Examples include the absorption coefficient, scattering coefficient, beam attenuation coefficient, and scattering phase function. In contrast, AOPs are influenced by both the IOPs of the medium and the spatial distribution of the ambient light field. Key examples of AOPs include remote sensing reflectance and off-water irradiance. The spectral and radiometric characteristics of water-leaving radiance are modulated by the IOPs of dissolved and suspended constituents present in the aquatic environment. The critical aspect of water quality remote sensing lies in establishing the fundamental relationship between remotely sensed reflectance and the inherent optical properties of water.

The core principle of water quality remote sensing is grounded in the interaction between solar radiation and the water–air interface (Figure 2). Water comprises molecules that encompass a variety of suspended and dissolved substances, including organic and inorganic materials, both living and non-living. Before solar radiation or other light sources reach the surface of water bodies, they undergo significant absorption and scattering within the atmosphere. A portion of incident radiation is directly reflected at the water surface, while the remainder penetrates into the water column, interacting with suspended particles and dissolved substances. However, the light scattered and reflected back from within the water column is further influenced by atmospheric molecules and aerosols before being captured by sensors. As a result, the water signals received by sensors are often attenuated or obscured by the combined effects of the atmosphere and the water surface. To accurately retrieve the radiance signals associated with the constituents within water, it is essential to implement effective correction measures to mitigate the impacts of the atmospheric and surface effects [26]. A commonly used method for addressing these interferences is the dark pixel assumption, which posits that the water-leaving radiance in the near-infrared (NIR) band is negligible or approximately zero. While this assumption has been successfully applied in clean oceanic waters, it is not valid for inland water bodies due to its complex optical characteristics, high turbidity, and intricate aerosol compositions, including substantial amounts of absorptive aerosols. That is to say, the algorithms that do not account for inland absorbing aerosols could not precisely represent the remote sensing reflectance of inland waters. To address these challenges, researchers have proposed alternative algorithms, such as extending the dark pixel assumption to the shortwave infrared (SWIR) band, to improve retrieval accuracy [27]. Nevertheless, these approaches are also limited when applied to turbid water bodies. In addition, some atmospheric radiative transfer models, such as the Second Simulation of the Satellite Signal in the Solar Spectrum (6S) model, the Moderate Resolution Transmission (MODTRAN) model, and the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) model, are widely utilized at regional and global scales due to their robust physical foundations and interpretability. However, these models are not specifically designed to address the unique optical and atmospheric conditions associated with water bodies. Therefore, a key focus of future research lies in the development of atmospheric correction methods that comprehensively account for radiative transfer processes and accurately retrieve radiative signals for water bodies with varying constituent compositions [28–30].

The spectral reflectance of pure water within the visible spectrum is nearly linear. In the presence of other substances, the spectral reflectance profile of water displays both troughs and peaks. Apart from the intrinsic properties of pure water, the factors that affect the spectral signature of aquatic environments can be classified into three categories: pigmentation from planktonic algae, yellow substances, and suspended particulate matter, collectively termed as optically active constituents (OACs) [31]. When substances such as chlorophyll-*a* and suspended sediments exist in the water body or the concentration of these components changes, it will cause changes in the absorption and scattering of the water, resulting in changes in the reflectance of the water body and significant differences in reflectance within a certain wavelength range. For instance, when sediment is present in the water, the reflectance in the visible light spectrum increases due to the scattering effect of the sediment. When the water contains chlorophyll, a significant reflection peak will appear in the near-infrared band. These spectral characteristics can be captured by remote sensors and reflected in remote sensing images, which is the basis for quantitative estimation of water quality parameters by remote sensing. By acquiring the spectral reflectance of water bodies, dissecting the absorption and scattering properties of their constituents, and correlating spectral characteristics with water quality concentrations,

a remote sensing-based inversion model for water quality evaluation can be developed. Figure 2 illustrates a schematic depicting the typical light–water interactions prevalent in inland aquatic environments.

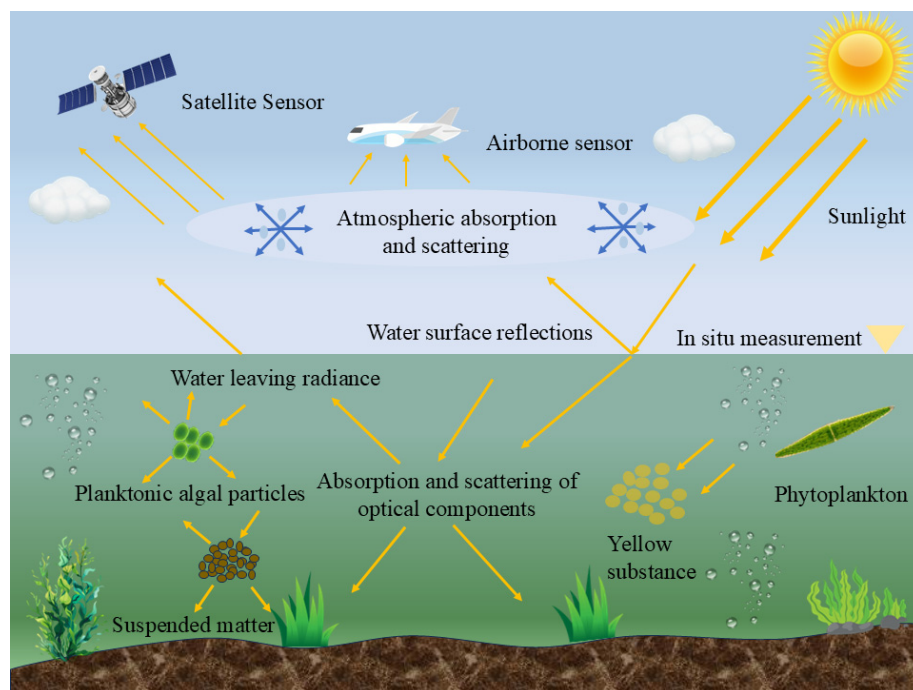


Figure 2. Diagram of light–water interactions. Yellow substance: Absorption; Suspended matter: Absorption and scattering; and Planktonic algal particles: Absorption and scattering.

3.2. Remote Sensing Monitoring Data

3.2.1. Multispectral Data

Multispectral remote sensing, a technology that emerged in the 1980s, primarily exploits spectral differences between targets and their backgrounds to extract objects of interest on the ground. It has found extensive application in water quality monitoring, such as tracking chlorophyll-*a* proliferation and suspended solids concentration.

Multispectral remote sensing data include Multispectral Scanner System (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) data from the U.S. Landsat satellites, Medium Resolution Imaging Spectrometer (MERIS) [32], Sentinel-2 from the European Space Agency (ESA) [33], High-Resolution Visible Sensor (HRV) data from France’s SPOT satellites, Advanced Very High-Resolution Radiometer (AVHRR) data from the NOAA, Indian Remote Sensing IRS system’s LISS data, multispectral image data received by the OPS (Optical Sensor) of Japan’s JERS satellite, and CCD camera data of the China–Brazil Earth Resources 1 satellite (CBERS-1). Among these, Landsat data from the U.S. Landsat satellites are now frequently employed for long-term daily monitoring of inland water bodies [34]. Following the launch of Landsat-1, MSS data have been instrumental in assessing the quality of inland aquatic environments, focusing on parameters like chlorophyll-*a* levels and suspended particulate matter concentrations. Furthermore, TM, ETM+, and OLI data have also shown great potential in studies of water bodies in specific regions [35,36]. The early development of multispectral satellites, coupled with the high spatial resolution of certain multispectral remote sensing systems, facilitates the long-term remote sensing monitoring of large-scale water bodies. For instance, Tao et al. [37] successfully used Landsat data to invert the changes in TSM concentrations in large lakes ($\geq 50 \text{ km}^2$) in China from 1990 to 2020, reflecting the feasibility of multispectral satellites in monitoring water quality changes over long time series.

While multispectral data can glean information from multiple wavebands, most multispectral satellite bands are relatively wide, with a relatively small number of bands, and their spectral resolution is lower than that of hyperspectral data, reflecting the limitations of multispectral data in analyzing fine spectral features.

3.2.2. Hyperspectral Data

In contrast to multispectral sensors, hyperspectral sensors generate data bands with superior spectral resolution [38]. This enables precise optimization of band selection, and hyperspectral data can capture continuous spectral information of terrestrial objects. By combining two-dimensional imaging and spectral measurements of ground objects, hyperspectral data are particularly well-suited for water monitoring. They overcome the limitations of spectral resolution inherent in previous remote sensing data and provide a high-dimensional dataset that can more accurately identify substances, thereby enabling timely assessments of water body pollution [39]. Hyperspectral imagers are classified as star-borne and airborne, and most of the current research focuses on star-borne remote sensing [40], but with low spatial resolution, including the EO-1 (Hyperion) (USA), HJ-1 (China), Advanced Hyperspectral Imager (AHIS) (China), MODIS (USA), and China's Tiangong-1 hyperspectral imager. Airborne remote sensing is now more mature, achieving monitoring with real-time and high spatial and spectral resolution but with high costs [41], including the Airborne Visible InfraRed Imaging Spectrometer (AVIRIS) (USA), AISA (Finland), and Compact Airborne Spectrographic Imager/Shortwave Airborne Spectrographic Imager (CASI/SASI) in Canada, etc.

Nonetheless, hyperspectral data include a large number of bands, with hundreds or even thousands existing, leading to a substantial volume of data and increased information redundancy. This also escalates the complexity of data and image processing. Meanwhile, compared to multispectral satellites, hyperspectral satellites have a smaller coverage range and fewer limitations in monitoring lakes with a large spatial range. Table 2 shows the parameter information of common satellite data sources.

Table 2. Parametric information on common satellite data sources.

	Satellite Sensor	Number of Bands	Temporal Resolution (Day)	Spatial Resolution (m)
Multispectral Data	Sentinel-2 MSI	13	5	10–20–60
	MERIS	15	1	300–1200
	Landsat 5 TM	7	16	30
	Landsat 7 ETM+	8	16	15–30–60
	Landsat 8 OLI	11	16	30
	GOCI	8	-	500
Hyperspectral Data	EO-1Hyperion	220	16	30
	HJ-1A(HIS)	115	4	100
	MODIS	36	1~2	250–500–1000
	GF-5 ASHI	330	2	30
	OHS	32	2	10

Note: The time resolution of the GOCI satellite is 1 h.

In summary, inland water quality monitoring models utilizing remote sensing data excel at various spatiotemporal scales. However, current research is hindered by low signal-to-noise ratios and sensor resolutions. Multi-source data fusion from various satellites is crucial for enhancing inland water quality monitoring accuracy.

3.3. Water Quality Inversion Index

In the process of remote sensing inversion of water quality parameters, selecting appropriate bands or band combinations as input indices is crucial for enhancing model accuracy. By analyzing the spectral characteristics of different substances in water bodies, it is possible to identify which indices are most sensitive to the inversion of specific water quality parameters.

First, single-band indices play a significant role in water quality inversion. For instance, the absorption peaks of algae in water bodies typically occur in the blue and red bands, and in water bodies with high concentrations of chlorophyll-a (Chl-a), there is also a noticeable increase in the near-infrared band. Consequently, in some studies, blue, red, and near-infrared bands are commonly used as inputs to estimate Chl-a levels. Additionally, research has shown that blue and green bands can be used to estimate total suspended solids (TSS) in clear waters, the red band is suitable for extracting TSS in moderately turbid waters, and the near-infrared band is used for estimating TSS in highly turbid waters. Therefore, depending on the specific conditions of the water body, appropriate bands can be selected as input indices to establish suitable models. Furthermore, studies have indicated that the MODIS satellite's visible bands 1 (red), 3 (blue), and 4 (green) are the primary determinants in total phosphorus (TP) concentration inversion algorithms, with band 4, representing the green region, being particularly significant [42]. This also provides a reference for the inversion of non-optical active components.

The second category includes band ratios and combinations. Research has found that using indices such as the blue–green ratio (BGI), red–green ratio (RGI), near-infrared-to-red ratio (NIR-RI), Floating Algae Index (FAI), and Normalized Difference Chlorophyll Index (NDCI) as inputs in inversion models can effectively estimate Chl-a levels [43]. Hu et al. proposed that the B4–B5 and B1–B2 bands of the Landsat satellite can serve as characteristic bands for chemical oxygen demand (COD), achieving good estimation results [44]. Additionally, absorption coefficients are a common approach to estimating the water quality parameters. For example, due to the complexity of colored dissolved organic matter (CDOM), most studies use absorption coefficients to represent its concentration. Since CDOM absorbs strongly in the ultraviolet and blue bands, absorption coefficients at wavelengths of 355 nm ($a_{CDOM}(355)$), 400 nm ($a_{CDOM}(400)$), 420 nm ($a_{CDOM}(420)$), and 440 nm ($a_{CDOM}(440)$) are typically chosen to represent CDOM concentrations, enabling the inversion of CDOM levels.

In conclusion, the flexible selection and combination of various input indices, tailored to specific water body types and target parameters, can significantly enhance the accuracy and dynamic capabilities of water quality monitoring, thereby providing robust support for the management and protection of aquatic environments.

3.4. Inversion Model

At present, the commonly used remote sensing inversion models mainly include analytical models, empirical models, and semi-empirical models.

The fundamental principle of the analytical method is grounded in radiation transmission theory. This process involves the projection of solar rays onto the water surface and their transmission to the signal sensor via reflection and scattering paths of various substances within the water. By utilizing the remotely sensed reflectance, the characteristic absorption coefficients and backscattering coefficients of different water components are calculated. Subsequently, the concentration of each component in the water can be estimated using the reflectance spectra. This method theoretically enables the estimation of various water component concentrations using specific radiative energy, thus overcoming some spatial and temporal limitations. Based on Hyperion data, Giardino et al. [45]

used an analytical model to invert the concentration of chlorophyll-a in Lake Garda and assessed the degree of nutrient uptake of the lake, and the results were roughly the same as the actual situation. Nevertheless, simulating the composition of aquatic bodies and the propagation of radiation is inherently intricate, necessitating the quantification of various parameters, including the intrinsic optical properties of water and associated water quality indicators [46]. Additionally, the discrepancy between the spectral resolution of satellite sensors and in situ spectral measurements poses a challenge for modeling studies. As a result, the implementation of quantitative remote sensing inversions using analytical models is fraught with difficulties and has limitations in practical scenarios [33].

The empirical model involves conducting statistical evaluations to establish the linkage between spectral measurements and related water quality variables. This analysis helps identify the optimal bands or combinations, leading to the development of a regression model [33]. Owing to its simplicity and practicality, the empirical model has been extensively utilized by scholars across disciplines for remote sensing monitoring of diverse water bodies; for example, Joshi and D'Sa [47] employed monthly field observations gathered over a 15-month timeframe in 2010–2011 within Barataria Bay to formulate an empirical band ratio technique for the Landsat-5 (USA). This method demonstrated a strong correlation with the absorption coefficient of CDOM at a wavelength of 355 nm. A major advantage of the empirical model is its simplicity and ease of operation. However, it should be noted that the model lacks physical interpretability as well as regional specificity and seasonal dependence [48].

The semi-empirical model represents a hybrid approach to water quality monitoring, which synthesizes the analytical and empirical models. Grounded in the optical properties of water, the semi-empirical model scrutinizes the spectral curves of targeted water quality parameters, identifies corresponding spectral characteristics, and integrates these characteristics with statistical analysis. This process enables the estimation of the optimal band or band combination for water quality parameters and facilitates the establishment of a water quality remote sensing inversion model to predict the concentration of specific water quality indicators within the study region. Currently, the semi-empirical model is predominantly employed for inland water quality inversion. Some researchers have utilized the semi-empirical approach to monitor some components such as chlorophyll-a, CDOM, and so on, with results demonstrating high accuracy [49,50]. However, owing to the intricacy and nonlinearity of aquatic spectral signatures, the semi-empirical model exhibits specific temporal and spatial constraints. To bolster the robustness of the semi-empirical model, it is imperative to select spectral characteristics that exhibit a notable correlation with the intended water quality indicator and that are relatively insensitive to variations in other water quality parameters [40].

Over the past few years, as computer science has advanced, machine learning has gradually become a hot topic and has been applied across various fields, including remote sensing inversion models. It demonstrates more significant advantages than traditional methods, particularly in handling large-sample data and nonlinear regression problems. The inversion models constructed using machine learning exhibit strong robustness, minimal error, and other desirable characteristics. However, machine learning is highly sensitive to data quality and is susceptible to overfitting.

Although the accuracy of the inland water quality remote sensing inversion model has been continuously improved, the current remote sensing inversion accuracy is still insufficient, mainly due to the following reasons: (1) low spatial–temporal resolution and limited bands in remote sensing data and (2) complex heterogeneous optical properties of inland waters varying regionally and seasonally. Current regional time-sensitive models combining field and remote sensing data struggle with generalization. Future work

should integrate multi-source remote sensing data to enhance complementarity and model portability, aiming for more accurate and universal inversion models.

4. Remote Sensing Monitoring of Water Quality Parameters

4.1. *Optically Active Constituents (OACs)*

4.1.1. Chlorophyll-a

Chlorophyll-a (Chl-a) is a photosynthetic pigment present in plants, algae, cyanobacteria, and other aquatic organisms. It is a key indicator of primary productivity and eutrophication in water bodies and plays a major role in influencing their spectral properties. The spectral features of chlorophyll-a's absorption coefficient typically exhibit two absorption peaks, usually around 440 nm and 675 nm. Since the influence of other water elements at 675 nm is relatively minor, spectral features near 675 nm are often used to invert the concentration of chlorophyll-a. Currently, commonly used data sources, including hyperspectral and multispectral data, have been effectively applied to estimate Chl-a concentration [51].

From the perspective of inversion models, most scholars use empirical models to invert chlorophyll-a, such as the band ratio model. Research has shown that the empirical model based on the ratio of the 665 nm and 709 nm bands is effective in inverting chlorophyll-a concentrations in eutrophic waters [52]. Based on Landsat TM data, Duan et al. [53] estimated chlorophyll-a concentration in Chagan Lake by using a band ratio of TM4 (NIR)/TM3 (red). The findings indicated that the highest coefficient of determination (R^2) for the TM data was 0.67. Jaelani et al. [54] also successfully established the band ratio model of chlorophyll-a in Poteran waters based on the red and blue bands of Landsat8 (USA), providing a new method for water quality monitoring. The three-band model is also one of the models often used for chlorophyll-a inversion. It can weaken the impact of yellow matter and non-pigment particles, and the model's accuracy is relatively high. Compared to the empirical models, it has a certain universality in water bodies with low turbidity. Moses et al. [55] built a three-band NIR-red model and used reflectance data collected by hyperspectral sensors to make highly accurate estimates of chlorophyll-a concentrations in turbidity-producing waters. Additionally, Dall'Olmo et al. [56] also effectively estimated chlorophyll-a in turbid productive water using the three-band model. However, the versatility and robustness of these methods are poor; so, machine learning has become a widely used method for estimating chlorophyll-a and has seen increasing application in recent years [57,58]. Li et al. [59] collected 273 samples from 45 representative lakes in China between 2017 and 2019 and used the SVM model for chlorophyll-a retrieval. Their results outperformed those of other models, indicating that SVM is a powerful tool for large-scale chlorophyll-a monitoring, particularly in water bodies with medium to low concentrations. Meanwhile, Cao et al. [60] successfully verified the feasibility of obtaining Chl-a data of various lakes from satellite images by using a deep neural network (DNN) model and of achieving the ongoing surveillance of 217 major Chinese lakes. Additionally, a large number of previous studies have shown that Chl-a and TSS have high reflectance in the near-infrared band. Thus, the presence of TSS in water could interfere with the inversion of chlorophyll-a. Therefore, some scholars established the machine learning inversion model of chlorophyll-a to study water with different TSS concentrations, such as low-, medium-, and high-turbidity water bodies, and the effect is indeed better than that of the model used before classification [57]. However, most of the current algorithms are generally limited by regions and seasons, and the machine learning model is excessively reliant on the data and quality of samples. Therefore, the algorithm needs to be optimized in the future to establish a more applicable model.

4.1.2. CDOM

Colored dissolved organic matter (CDOM), a component of dissolved organic matter (DOM), exhibits light sensitivity in aquatic settings and is pivotal in the biogeochemical cycling and energy dynamics of aquatic ecosystems [61,62]. Clarifying the spatial distribution and temporal variations of CDOM is crucial for the surveillance and stewardship of inland aquatic systems [63]. CDOM can absorb part of ultraviolet and blue–green bands [64], enabling it to serve as an indicator for assessing water quality through remote sensing techniques. Compared to other optically active substances, CDOM's light signal is relatively low, and its absorption spectral shape is similar to that of non-phytoplankton particles. Therefore, obtaining accurate estimates of CDOM from satellite data is challenging. Due to their simplicity and high inversion accuracy under specific conditions, most current remote sensing inversion algorithms for CDOM are empirical or semi-empirical [65]. Chen et al. [66] formulated an empirical spectral ratio technique for extracting aCDOM(440) values, which is readily adaptable for use with Landsat-8 data (USA). Menken et al. [67] found that the 670 nm and 571 nm band ratio from MODIS effectively estimates CDOM level. Tehrani et al. [68] used three remote sensing datasets to estimate the CDOM level in the Northern Gulf of Mexico. They developed an empirical method based on band ratios and identified that the ratio of bands at 510 nm and 560 nm within MERIS data yielded the highest precision in the results. Although these inversion algorithms are easy to construct, they have more limited applicability in different environmental settings, which somewhat restricts their widespread use.

Machine learning algorithms, due to their efficiency and sensitivity to spectral feature information, have shown great potential in estimating CDOM levels. Kim et al. [69] utilized hyperspectral data and identified the 355 nm absorption coefficient as the most effective indicator of CDOM concentration. They also found that the random forest model provided the most accurate CDOM level. Since the optical properties of CDOM can change due to the influence of other dissolved substances, chlorophyll-a, and suspended particles in the water body, the critical issue of further understanding CDOM in inland waters should consider how to mitigate the influence of these constituents and enhance inversion precision.

4.1.3. Total Suspended Solids

Total Suspended Solids (TSS) concentration is a crucial water quality parameter and a significant indicator for water quality and environmental assessment, including organic and inorganic components. The organic component mainly contains phytoplankton and aquatic plants after the death of the organic debris, and the inorganic component mainly contains insoluble sediment, clay, and other minerals. On the one hand, TSS affects water quality by obstructing light penetration and decreasing dissolved oxygen levels [70]. On the other hand, the content, volume, and composition of TSS can affect the water's color, leading to changes in spectral reflectance [71]. Additionally, TSS can adsorb various nutrients and pollutants, making it a primary factor causing eutrophication in water bodies. Compared to other optically active components, the estimation of TSS is relatively straightforward, making it one of the earliest parameters to be inverted, primarily through empirical/semi-empirical models and analytical/semi-analytical models. The analytical/semi-analytical model is an estimation model based on the relationship between TSS in water and the inherent optical quantity. Due to its complex physical mechanism, it is not widely used. Compared to analytical/semi-analytical models, empirical and semi-empirical models have been widely promoted due to their advantages of simplicity and ease of operation; for example, Du et al. [72] used the empirical algorithm to derive the annual average TSS value of the Songnen Plain water area from 1984 to 2019 by using the red–blue band ratio of Landsat. Using in situ spectral and measured data from Poyang Lake and Sentinel-2 MSI

images, Liu et al. [73] found that the B4-B8b model had high fitting accuracy and could explain 81–93% of the variations in TSS concentrations.

The inversion models for TSS concentration have become increasingly mature. However, water optical complexity constrains TSS algorithm applicability, hindering generalization. Future research aims to devise more versatile algorithms for diverse natural waters.

4.1.4. Water Clarity/SDD

Water clarity indicates the transparency level of a water body and is one of the indices for assessing the trophic status of water, which can intuitively reflect the absorption and scattering degree of light in the water body. It is closely related to nutrients such as chlorophyll-a, TSS, and CDOM [10]. Typically, the Secchi Disk Depth serves as a relative indicator of water clarity. This involves gradually lowering the Secchi disk into the water until it becomes invisible, at which point the depth is recorded as the SDD. Since there are no significant spectral or optical features for clarity in the water body, the inversion of SDD carries a considerable degree of uncertainty. Qing et al. [74] utilized Sentinel-2 MSI (European Space Agency) and suggested that SWIR wavelengths are suitable for clear water bodies, while longer wavelengths might be the best choice for turbid water bodies. Torbick et al. [75] used Landsat images (USA) to assess the SDD of the Lower Peninsula of Michigan, applying band ratio radiance models to map it with good accuracy. Olmanson et al. [76] used the reflectance of TM1/TM2 to study water transparency in 10,000 lakes in Minnesota, USA, showing a good accuracy ($R^2 = 0.77\text{--}0.80$). The empirical algorithms for the above are generally obtained by regression based on a finite number of measurements, which are easy to operate, but the coefficients in the model are varied by the influence of the water column and the measurement time. Alternatively, the semi-analytical algorithm, grounded in underwater visibility theory, provides a stronger theoretical foundation for transparency estimation and significant potential for SDD estimation. In recent years, Lee et al. [77] proposed a new theoretical and semi-analytical remote sensing method for water clarity, and Feng et al. [78] successfully applied this new method to the remote sensing inversion of clarity in the middle and lower reaches of the Yangtze River, demonstrating its applicability to complex inland water systems. However, the semi-analytical method faces great difficulties for water bodies with complex compositions and varying nutrient concentrations; so, the algorithm needs to be further researched and improved to establish a more universal semi-analytical inversion model.

4.2. Non-Optically Active Constituents (Non-OACs)

Non-optically active constituents in natural water bodies exhibit weak absorption and scattering properties, making them difficult to estimate directly. Remote sensing estimation of aquatic nutrients relies on the relationship between these nutrients and OACs, or it requires the application of semi-empirical methods or machine learning for direct analysis. Recently, as remote sensing technology for water quality monitoring has advanced, increasing research has focused on non-OACs.

4.2.1. Total Nitrogen and Total Phosphorus

Total nitrogen (TN) and total phosphorus (TP) are two key indicators for inland water quality evaluation and are also the primary contributors to the eutrophication of water bodies [79]. Hence, monitoring changes in TN and TP levels is essential for managing eutrophication in lakes, reservoirs, and other surface water bodies. However, due to the lack of clarity in spectral response mechanisms, using remote sensing to retrieve TN and TP remains challenging [80]. Globally, scholars have conducted extensive research on this topic, utilizing both traditional methodologies and machine learning approaches. The former are divided into direct inversion and indirect inversion. Due to the simplicity of modeling,

the direct inversion model is widely used. Li et al. [81] employed the reflectance of the four bands of Landsat 8 OLI data from 2013 to 2016 to develop empirical inversion models of TN and TP. Gao et al. [82] discussed the possibility of using band combination and regional multivariate statistical modeling techniques to establish a spatial modeling scheme for estimating TP concentrations in large lakes from multispectral satellite images and validated the effectiveness of this approach. However, since TN and TP are not optically active components, this indicates that changes in TN and TP cannot be directly reflected in the variation of remote sensing reflectance. Indirect inversion, on the other hand, can provide a clearer explanation of the algorithm mechanism. This involves establishing an inversion model for OACs and subsequently determining TN and TP concentrations using the correlation between TN/TP and OACs. For example, Lu et al. [83] used the semi-analytical model to retrieve the concentrations of optically active components based on high-resolution GF-1 data and then used the correlation between TP and OACs to invert the TP level in the urban waters of Guangzhou, China. However, achieving high accuracy is often challenging due to the two-stage nature of the algorithmic computation.

In contrast to conventional algorithms, machine learning demonstrates enhanced proficiency in handling extensive high-dimensional datasets and tackling complex issues with greater adaptability. Therefore, machine learning also offers the potential for estimating TN and TP. Du et al. [84] established TP concentration inversion models for different types of water bodies based on Sentinel-3 (Europe) satellite remote sensing imagery in Lake Taihu. They compared the effectiveness of different machine learning methods and found that the DRF demonstrates the best accuracy. However, the current applicability of TN/TP remote sensing inversion models is limited, either confined to a single watershed or applicable to multiple watersheds with similar optical characteristics. With thousands of lakes and reservoirs globally, each exhibiting diverse types and distinct optical properties, it becomes essential to categorize algorithms based on factors such as optical properties and lake sizes. Furthermore, selecting multiple spectral bands to establish appropriate estimation models is crucial for enhancing the versatility and accuracy of these models.

4.2.2. COD

Chemical oxygen demand (COD) serves as one of the indicators reflecting the content of organic substances in water bodies, demonstrating the extent of pollution by reductive substances. In contrast to OACs such as CDOM and chlorophyll-a, there are relatively few remote sensing models for COD. This scarcity can be primarily attributed to the fact that COD, as a chemical index, may not induce noticeable changes in water color, thereby posing significant challenges to its remote sensing estimation. Furthermore, the intricate nature and transformation processes of organic matter sources contribute to significant spatiotemporal variability in the dynamics of COD in water bodies. The spectral response mechanisms of these dynamics are not yet fully understood, further complicating the remote sensing estimation of COD [85]. Commonly used COD inversion methods are mainly divided into two categories; the first is the traditional empirical model, which can be divided into direct inversion and indirect inversion. Direct inversion refers to the establishment of a statistical correlation between remote sensing reflectance and COD levels and has the characteristics of simple and practical modeling. Wang et al. [8] applied an empirical method to invert the concentration of COD in Shenzhen Reservoir using TM data and confirmed the feasibility of remote sensing for estimating COD concentration through correlation analysis with the measured data of laboratory water samples. Also, based on Landsat data, Yang et al. [86] successfully estimated COD in East Dongting Lake by using a band ratio model. However, since COD lacks optical activity, this implies that the empirical model lacks some theoretical properties. In contrast, the indirect inversion

model established by the connection between COD and OACs has wider applicability. For example, Huang et al. [87] developed a regression model utilizing remote sensing data, grounded in the association between the optical properties of CDOM and COD. However, the relationship between COD and OACs becomes complicated and difficult to relate when involving water bodies with complex optical properties, which could bring challenges for the inversion of COD.

Another popular inversion method is based on machine learning algorithms. Compared to the traditional empirical model, machine learning can handle complex nonlinear regression challenges and offer significant advantages in estimating non-OACs [88,89]. Zhu et al. [90] successfully inverted the COD in the coastal waters of the northern part of the South China Sea using the XGBoost model based on MODIS data. Sun et al. [91] combined machine learning and proximal remote sensing to estimate COD in Lake Taihu waters with an accuracy of more than 90%. This showed that machine learning models could be successfully applied in COD inversion. However, the provenance and constitution of organic materials vary across distinct aquatic systems, and the COD inversion models based on machine learning may be different. Therefore, for different types of water bodies, COD inversion algorithms with massive data should be explored in the future. The establishment of inversion algorithms for COD in different types of water bodies is an important research direction in the future. Table 3 shows some inversion models for the above parameters.

Table 3. Data source and inverse models for some OAC and non-OAC parameters.

Parameter	Data Source	Type	Model	Accuracy	References
Chl-a	Landsat	Empirical method	$28.1 \times e^{0.72 \times R(562)/R(483)}$	$R^2 = 0.77$	[92]
	HJ-1A	Semi-analytical method	$31.97 \times [R_{rs}^{-1}(661.6) - R_{rs}^{-1}(706.7)][R_{rs}^{-1}(714.8) - R_{rs}^{-1}(682.2)] + 28.66$	RMSE = $1.47 \mu\text{g L}^{-1}$	[93]
	Hyperion	Analytical method	Bio-optical algorithms	$R^2 = 0.59$	[45]
	Landsat	Machine learning	XGBoost	MAPE = 35%	[94]
CDOM	MODIS	Machine learning	SVR	$R^2 = 0.7058\text{--}0.9068$	[95]
	Landsat	Empirical method	$\ln(a_{440}) = a_1 + a_2 \ln(\text{OLI3}/\text{OLI4})$	$R^2 = 0.84$	[96]
	VIIRS	Empirical method	$a_g 412(\text{m}^{-1}) = 3.184 \times (R_{rs} 551/R_{rs} 671)^{-1.046}$	$R^2 = 0.87$	[97]
	MODIS	Machine learning	SVM	$R^2 = 0.9$	[98]
TSS	Sentinel-3	Machine learning	MDN	$R^2 = 0.83$	[99]
	Landsat	Analytical method	Bio-optical algorithms	$R^2 = 0.99$	[100]
	MODIS	Empirical method	$\exp(15.4 \times [R_{rc}(645) - R_{rc}(1240)] + 1.994$	$R^2 = 0.55$	[101]
	MODIS	Empirical method	$9.65 \times \exp[58.81 \times R_{rs}(645)$	$R^2 = 0.70$	[102]
SDD	MODIS	Empirical method	$132.83 \times X^2 - 52.618 \times X$ $X: R_{645}/R_{555}$	$R^2 = 0.88$	[103]
	MODIS	Machine learning	SVR	MAPE = 25.6%	[104]
	Landsat	Empirical method	R_{red}/R_{blue}	$R^2 = 0.75$	[105]
	Landsat	Empirical method	$1.7351 \times \exp[-2.141 \times R_{rs}(B4)/R_{rs}(B3)]$ $0.11608 + 2.0716 \times (R_{rs}(B4)/(R_{rs}(B2) + R_{rs}(B5)))^{1.26477}$	MAPE = 21.68%	[106]
TN	Landsat	Empirical method		$R^2 = 0.58$	[81]
TP	Sentinel-2	Machine learning	XGBoost	$R^2 = 0.45$	[107]
	MODIS	Empirical method	$0.2553 \times (B2 - B5)/(B2 + B5) - 0.0084$	$R^2 = 0.68$	[108]
	MODIS	Machine learning	DNN	$R^2 = 0.83$	[109]
	MODIS	Machine learning	XGBoost	$R^2 = 0.74\text{--}0.84$	[110]
COD	Landsat	Machine learning	BPNN	$R^2 = 0.937$	[111]

5. Application of Remote Sensing Monitoring in Water Environments

Leveraging the ability of remote sensing technology to estimate various water quality parameters, we examined its specific applications in water environment management, focusing on three main areas: spatiotemporal analysis of water quality and its driving factors, carbon budget studies, and pollution source identification. These efforts aim to offer a solid foundation for effective water environment management (Figure 3).

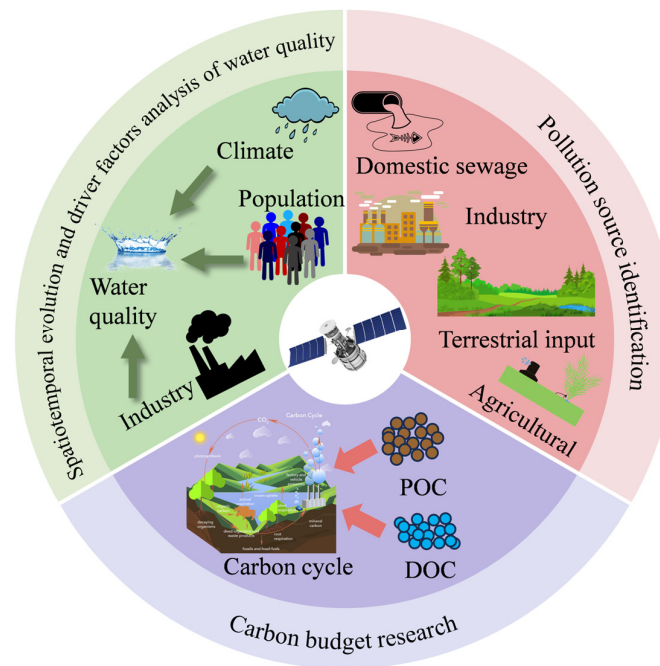


Figure 3. Summary of applications of remote sensing monitoring in water environments.

5.1. Spatiotemporal Evolution and Driver Factor Analysis of Water Quality

Due to the inherent cyclical and repetitive characteristics of remote sensing technology, it is feasible to achieve repeated observations of the same region at various temporal intervals and to conduct broad, continuous, and synchronous monitoring. This capability enables the creation of long-term spatiotemporal sequences and real-time tracking of dynamic changes in water quality parameters [112,113]. For instance, by measuring the spectral reflectance properties of a water body, it is possible to invert key water quality indicators' levels [114]. These indices offer valuable information about the nutrient levels, pollution extent, and overall condition of the water body [115–117]. Thus, spatiotemporal dynamics of water quality at the regional or county level based on remote sensing monitoring and inversion are widely applied in water environment sciences nowadays.

Additionally, the dynamics of water quality are typically influenced by a multitude of factors, encompassing both natural factors (such as geographical features, climate change, and hydrology) and anthropogenic influences (including industrial, agricultural, and domestic activities). For instance, excessively high temperatures can stimulate algal growth in water, subsequently deteriorating water quality, while increased precipitation may lead to the influx of more sediments and nutrients into water bodies. Concurrently, pollution from agricultural and industrial activities, along with an increasing population, exerts significant pressure on inland water quality, primarily through the acceleration of eutrophication [118]. Additionally, in order to alleviate these problems, the government has invested heavily in the implementation of a series of environmental protection projects. Thus, it is important to assess how these natural and human factors affect water quality and evaluate the performance of government efforts. Remote sensing technology could also provide an effective strategy for factors driving analysis.

Through in-depth statistical analysis such as Pearson statistical analysis and random forest, it is feasible to analyze the correlation between water quality and driving factors and uncover the underlying driving mechanisms responsible for water quality evolution, thereby offering insights into the management of inland aquatic ecosystems. For example, Gbagir et al. [119] used satellite observation data from 1997 to 2019 to study the trend of the nutrient status of Lake Ladoga and found that chlorophyll-a showed a gradual

decline and that the high-concentration area was mainly found on the southern coast. Also, they revealed that climate warming and precipitation increased and that industrial and agricultural sewage discharge contributes substantially to the dynamic nutrients. Zhao et al. [120] traced the long-term spatiotemporal sequences of CDOM in 2462 Chinese lakes from 1986 to 2021 through a high-resolution CDOM model based on Landsat satellite images and identified the major factors of CDOM dynamics using a GLM model. Zhang et al. [121] established an inversion model of TSS concentration in Jiaozhou Bay utilizing Landsat and MODIS data, obtained the change in TSS concentration in Jiaozhou Bay from 1984 to 2021, and identified wind speed as a significant determinant of TSS content fluctuation. Wang et al. [122] also explored the spatiotemporal variations in the mean Z_{SD} and their driving factors for 153 large lakes in China in 2000–2017 through MODIS data, which provided an important reference for the protection and management of lake water quality in China. In addition to remote sensing monitoring of water quality by a single water quality parameter index, some scholars have evaluated the long-term nutrient status of water bodies through a comprehensive evaluation index. For example, Hu et al. [123] conducted 40 years of eutrophication observations of lakes in China, identifying the spatiotemporal pattern of changes in the TSI of lakes in China and quantifying the contribution of human activities and natural factors to eutrophication. This highlights the effectiveness of satellite remote sensing in water quality monitoring and their driving factor analysis at both regional and country scales over a long period of time.

Nonetheless, numerous contemporary investigations merely scratch the surface in their analysis and exploration of basic linkages between climatic variables and human activities influencing localized variations in water quality. Moreover, the determinant factors vary significantly across studies, posing obstacles to a profound comprehension of water quality dynamics. In addition, forthcoming research endeavors must aim to dissect the intricate interplay and adaptations of inland water quality to both climatic shifts and human-induced modifications on a broader geographical and global scale.

5.2. Carbon Budget Research

Inland water bodies serve as vital regulators of global carbon cycles and climate change by transporting, mineralizing, and sequestering substantial amounts of organic and inorganic carbon [124]. As responders to climate change, freshwater ecosystems such as lakes, reservoirs, and rivers have become the forefront and focal point of global carbon cycle research. The flexibility, extensive range, and periodicity of satellite remote sensing, combined with the acquisition of surface reflectance spectral information from water bodies and appropriate inversion algorithms, allow for the estimation of the distribution and magnitude of carbon stocks in water bodies.

The levels of dissolved organic carbon (DOC) and particulate organic carbon (POC) in waters are closely related to the carbon budgets since their degradation and precipitation are linked to the global carbon fluxes and carbon balance [125,126]. Thus, the assessment of DOC and POC based on remote sensing is generally applied to explore carbon budgets in watersheds. In diverse inland aquatic systems, the light absorption of CDOM exhibits a strong correlation with the total DOC concentration. Consequently, the absorbance of CDOM serves as a reliable surrogate measure for quantifying DOC levels, offering a practical and accessible proxy in ecological and environmental monitoring studies. Li et al. [127] estimated the DOC of optically shallow waters by examining the correlation between DOC and CDOM and better understood the carbon cycle at the land–water interface through remote sensing. The POC is often associated with TSS and chlorophyll-a; for example, Duan et al. [128] established an empirical inversion model of POC based on the reflectance in red and near-infrared bands of TSS and chlorophyll-a inversion algorithms to realize long-term

monitoring of POC in lakes of the Yangtze River and explored the spatial and temporal variability of POC concentrations across numerous lakes, thereby furnishing novel insights into the dynamics of this crucial component within the aquatic carbon cycle. In addition, some scholars directly established machine learning models for DOC and POC, studied the changes in carbon storage in 24,366 lakes in China from 1984 to 2023, and revealed that China's organic carbon storage increased significantly in the past 41 years, providing theoretical support for China to achieve the goal of carbon peak and carbon neutrality [129]. By estimating the concentration and distribution of these parameters using remote sensing technology and enabling long-term dynamic monitoring of these parameters, it is possible to achieve a more profound comprehension of the carbon cycle processes and mechanisms within water bodies, thereby furnishing theoretical underpinnings for carbon budgeting.

Additionally, significant quantities of greenhouse gases, such as carbon dioxide (CO_2) and methane (CH_4) released from microbial activity, photochemical degradation, respiration, and mineralization, play a pivotal role in the carbon budget within the ecosystem. Presently, empirical remote sensing algorithms based on water temperature, chlorophyll concentration, and light conditions are widely used to estimate water body CO_2 concentrations or partial pressure (pCO_2) [130]. It provides a valuable strategy for the assessment of carbon budgets. Currently, global-scale CO_2 studies are emerging. Li et al. [131] constructed a comprehensive global dataset of CO_2 emissions with high spatiotemporal detail by employing the extreme randomized trees model, facilitating a deeper understanding of carbon budget balances and thereby providing a scientific basis for the formulation of effective carbon emission reduction policies. At the same time, satellite remote sensing has demonstrated its advantages and significant capabilities in estimating methane concentrations. Duan et al. [132] successfully assessed the emissions of dispersed CH_4 through random forest models based on Aqua/MODIS imagery and field-measured data, providing novel and timely perspectives for precisely grasping the scale of aquatic greenhouse gas emissions.

Remote sensing aids in monitoring aquatic carbon dynamics, pivotal for understanding global carbon budgets and climate change. As technology advances, its significance in carbon budgets will grow. However, remote sensing monitoring of DOC, POC, and greenhouse gases confronts challenges in algorithm accuracy and universality, necessitating further research to enhance carbon budget estimation insights.

5.3. Pollution Source Identification

Contaminant source identification is critical in water environment management. Remote sensing technology, in conjunction with laboratory fitting and model analysis, could provide effective information for the origins of pollutants. In particular, the combination of fluorescence spectra and remote sensing inversion was a breakthrough point since both of them could be established through a correlation with the chemical composition of CDOM. It is known that different pollution sources such as domestic sewage, industrial wastewater, agricultural contaminants, algae, and terrestrial inputs have distinct fluorescence spectroscopic characteristics due to their distinct composition. Thus, fluorescence indicators could be filtered out to distinguish the sources. Through the relationship between remote sensing-derived water quality and heterogeneity fluorescence indicators for distinguishing the sources, the contaminant source could be identified. Recently, Cai et al. [133] applied this strategy and successfully identified four urban water pollution source types using hyperspectral data. Also, Zhao et al. [134] observed that terrigenous organic matter emissions increased due to human activities in the lakes of China using a combination of remote sensing models and fluorescence indicators. In addition to using the fluorescence index combined with remote sensing technology to identify pollution sources, there are other

indices that can track pollution sources. For example, the VIS–NIR Reflectance Index (VNRI) has been successfully applied to detect and monitor oil spills and hydrocarbon contamination in aquatic environments. Laneve et al. [135] employed Sentinel-2A satellite data (European Space Agency) and the VNRI index to identify oil pollution in Lake Pertusillo, Italy. By combining VNRI with ground measurements, they were able to distinguish areas affected by hydrocarbons and observe their spatial distribution. This highlights that remote sensing could serve as a powerful tool for dynamically tracking oil and hydrocarbon pollution sources in water bodies.

In addition to using index methods, some scholars have combined remote sensing technology with hydrological models to precisely locate the positions of pollution sources and quantify their emissions. Luo et al. [136] transformed the spatial distribution of water quality parameters obtained through remote sensing into estimations of pollutant discharges, introducing an innovative approach for identifying point pollution sources that integrates remote sensing inversion techniques with the analysis of water body flow patterns. It is evident that remote sensing technology can dynamically and accurately track the source components of pollutants to some degree, which can help to predict and control the pollution status of water bodies and help to implement effective measures to protect water resources and maintain the ecological balance. However, it is worth noting that there are still limitations in the current assessment of pollution sources. For example, identifying the origin of more components in addition to CDOM based on remote sensing and quickly quantifying the contributions from different pollution sources in polluted surface waters are challenging problems that should be focused on to urgently solve environmental issues in the future.

6. Conclusions and Prospects

Satellite remote sensing is pivotal for assessing water quality and advancing research in water environmental sciences. This study examined recent advancements in remote sensing technologies for water environment monitoring and their practical applications. In this process, we systematically reviewed the remote sensing data sources and inversion models, especially for commonly monitored water quality parameters. It was concluded that satellite remote sensing offers a more efficient and streamlined approach for inland water quality monitoring. This information enables relevant departments to take timely measures to address water quality issues both for optically and non-optically active constituents and it could be extended to many areas, such as spatiotemporal analysis, carbon budget research, and pollution source identification in water environments. However, despite its many advantages, it also has certain limitations. Based on the insights gathered from this review, we offer the following perspectives:

- (1) **Atmospheric correction improvement:** In the process of water quality inversion, the atmospheric path radiation received by sensors often significantly exceeds the water-leaving radiation. Therefore, eliminating the radiance errors caused by atmospheric effects is crucial for more accurate monitoring. Traditional atmospheric correction methods rely on the assumption of zero reflectance in the near-infrared (NIR) band, an approach that proves limited or even ineffective in inland waters, particularly in areas with high concentrations of chlorophyll-a and TSS. Moreover, for optically complex inland water, the performance of atmospheric correction algorithms varies widely in terms of accuracy. Consequently, the development of additional algorithms, identification of methods suitable for specific water bodies, and enhancement of algorithm transferability remain key challenges in quantitative remote sensing of water quality.

- (2) Multi-satellite data fusion: Remote sensing-based water quality monitoring primarily relies on multispectral data with a confined number of broad spectral bands, whereas hyperspectral, microwave, and Light Detection and Ranging (LiDAR) data remain underutilized. Furthermore, substantial variations exist in the physiographical characteristics of diverse regions, accompanied by corresponding discrepancies in the extent of interference from factors such as cloud cover and atmospheric conditions. Consequently, there is an urgent need for the cohesive utilization of diverse datasets to mitigate issues related to cloud obstruction, enhance spatial resolution, and optimize their efficacy in monitoring and assessing aquatic environments. Additionally, the integration of multi-source data, including remote sensing, ecological, environmental, meteorological, and socio-economic information, represents a crucial pathway for future progress.
- (3) Inversion accuracy and versatility improvement of water quality parameters: Remote sensing models are typically developed based on the correlation between observed spectral reflectance and various water quality parameters within specific regions. However, this spatial dependency limits the applicability of these inversion models, making them suitable only for the sampled water bodies and restricting their transferability to other areas. Over time, the optical properties of a given aquatic system may also fluctuate due to seasonal meteorological variations. Therefore, future algorithms for estimating water quality parameters should be classified and optimized based on the distinct characteristics of different aquatic environments. Moreover, the establishment and verification of models hinge on field-measured data, albeit with inherent inaccuracies in the process of acquiring such on-site information. Therefore, reducing the reliance of retrieval models on ground-based measured data and developing high-accuracy and large-scale algorithms that are not restricted by time and space are future research directions.
- (4) Exploration estimation of non-optically active parameters: Currently, most research is largely confined to select parameters, such as chlorophyll-a, TSS, and CDOM. A notable dearth of research exists regarding the spectral signatures and remote sensing-based monitoring of other vital water quality indicators, including DOC, COD, and CH₄. Future research should endeavor to broaden the scope of monitored water quality parameters, delve deeper into non-optically active components, enhance the feasibility analysis and quantitative remote sensing monitoring of these components, and ultimately improve the accuracy of inversion models.

In summary, the future use of remote sensing for water quality development should focus on integrating multi-source data to advance universal and accurate inversion models, transcending time–space constraints. As technology and application methods evolve, remote sensing is poised to offer more comprehensive and efficient support for inland water monitoring and environmental science.

Author Contributions: Conceptualization, S.L.; methodology, writing—original draft, L.C.; writing—review and editing, L.C., L.L., S.L. and Z.S.; supervision, C.S.; and funding acquisition, S.L. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the Key Program of the National Natural Science Foundation of China (Grant No. 42230713), National Key Research and Development Program of China (No. 2022YFC3201902; 2023YFC3210200), Fundamental Research Funds for the Central Universities (FRF-TP-20-059A1), and the Open Foundation of State Key Laboratory of Environmental Criteria and Risk Assessment, Chinese Research Academy of Environmental Sciences (No. SKLECRA2023OFP02).

Data Availability Statement: Data will be made available upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

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