

Review

Not peer-reviewed version

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Posted Date: 7 September 2023

doi: 10.20944/preprints202309.0489.v1

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Review

A Review of Remote Sensing Applications for Determining Lake Water Quality

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Abstract: Remote sensing methods have the potential to improve lake water quality monitoring and decision-making in water management. This review introduces novel findings in the field of optically active water quality parameters using remote sensing. It summarizes existing retrieval methods (analytical, semi-analytical, empirical, semi-empirical, and artificial intelligence/machine learning (AI/ML)), examines measurement methods used to determine concentration of specific water quality parameters, summarizes satellite systems that enable temporal data for understanding the state of the lake with focus on water quality parameters, and proposes enhancements for future research of lake water quality using remote sensing. As part of this review, eight optically active biological and physical water quality parameters were analyzed, including chlorophyll- α (chl- α), transparency (Secchi disk depth (SDD)), colored dissolved organic matters (CDOM), turbidity (TUR), electrical conductivity (EC), surface salinity (SS), total suspended matter (TSM), and water temperature (WT). The research proposes a shift from point-based data representation to a more reliable raster representation and encourages optimizing grid selection for in situ measurements by combining hydrodynamic model with remote sensing methods. This review presents a comprehensive summary of the bands, band combinations, and band equations per sensor for eight optically active water quality parameters as listed in Tables A1-A8. The review's findings indicate that use of remotely sensed data is an effective method for estimating water quality parameters in lakes, with a significant increase in global utilization. The review highlights potential solutions and limitations to the challenges of remote sensing water quality determination in lakes.

Keywords: water management; remote sensing; lake; water quality; optically active; water quality parameters

1. Introduction

Lakes and other inland waters are very important for their environment. Lakes are essential ecosystems covering less than one percent of the surface area [1], and are an essential component of water resources (Goal #6) in the Sustainable Development Goals (SDGs) of the United Nations [2]. They provide living space for a large number of species and are vital components of hydrological, nutrient and carbon cycles [3]. Lake water is used as drinkable water, industry, irrigation, energy production, transportation, biodiversity, aesthetics, fishing, and recreation [3–5]. The necessity for sustainable water supplies include an ongoing assessment of the quality of existing available water resources.

Globally, eutrophication is a severe problem for inland waters [6]. Anthropogenic exploitation, eutrophication, inorganic and organic pollutants, morphological changes, population growth, and the effects of climate change like acidification or rising water temperatures increased nutrient input and primary output, worsened water quality, decreased biodiversity, and endangered the ecological functioning of inland waters worldwide [1,7–9]. Climate changes are increasingly affecting the quality of lake water, the health of the lake ecosystem [10] and ecology [11–13]. According to the Global Risks Report 2023 [14], the natural resource crisis, including water shortages due to human overuse and mismanagement, is ranked sixth among the top 10 long-term global risks. These risks are assessed based on their importance over a 10-year period.

Shallow lakes are the most common lake type in the world [15], and they are especially vulnerable to eutrophication, which threatens the ecological, social, cultural, spiritual, and economic aspects that these ecosystems provide [16,17]. In reality, shallow lakes are more sensitive to anthropogenic eutrophication, have a higher risk of water quality issues, and are more receptive to acquiring huge amounts of nutrients due to strong water-sediment interactions, sedimentation, export, and sedimentary exchange [18]. Improving lake management techniques requires greater knowledge of the dynamic interactions between lake depth and social and environmental variables [19]. Locations of in situ measurements should consider hydrodynamic models, especially in shallow lakes due to their unique hydrodynamic behavior. In situ measurements calibrate and validate models for retrieving water quality, while remote sensing is used for comprehensive lake-wide analysis. The choice of bands, band combinations, and equations for retrieving optically active parameters using remote sensing should not solely depend on water depth but on in situ measurements. Because the results of remote sensing methods for evaluating lake water quality often coincide regardless of lake depth, the major emphasis of this review is to give an insight into remote sensing methods for retrieving water quality and water quality metrics for lakes in general. Although, in optically shallow water, a portion of the light emitted includes reflection at the bottom and it should be taken into account in the analysis.

The term “water quality” encompasses the physical, chemical, and biological attributes of water that must be upheld to satisfy diverse water applications such as drinking, irrigation, and recreation [20]. Traditionally, physical, chemical, and biological indicators of water quality include comprehensive field monitoring networks that include in situ measurements, sampling, and laboratory analysis. In situ measurements can acquire numerous water quality parameters with fine accuracy by utilizing specific sampling points. However, they are long-lasting, tiring, and expensive, with large-scale monitoring restrictions [21,22]. The typical in situ sampling method is unable to readily determine spatial or temporal variability in water quality because sampling points are not properly distributed, which can lead to incorrect classifications of water quality [23,24]. Since the 1970s, breakthroughs in space science, the expanded use of advanced computers and their capabilities have made remote sensing methods viable instruments for effective and efficient monitoring and identification of large-scale regions and inland waterbodies with quality issues while offering data continuity for the following decades [25–44]. Increasingly, remote sensing (airborne and/or spaceborne) it is used as a means in the analysis of stagnant water, frequently combined with conventional approaches, to overcome some of the shortcomings of in situ methods [45–48]. Dekker et al. [49] were among the first to compare water quality assessment methods (in situ monitoring of water quality, mathematical modeling, and remote sensing) to determine the importance of remote sensing as a source of unique spatial information. Remote sensing is cost-effective and time-efficient for researchers operating at the local, regional, and global levels [47,50], allowing for the survey of sensitive or hazardous sites while the operator remains at one safe point [51,52]. Furthermore, modern remote sensing methods and databases are a priceless source for obtaining data from the previous years on lake ecological indicators, especially in unstudied lakes where information and in situ monitoring are limited and there are significant data gaps. Data from remote sensing can deliver immediate information on quick changes in a lake, such as algae blooms, strong rainfall, or droughts. With adequate in situ validation, remotely sensed airborne and/or satellite imagery is essential for the full assessment and management of waterbodies [25] and may be further enhanced via interdisciplinary cooperation to enable high-accuracy interpolation, requiring less time, work, and financial inputs [53–56].

The traditional method for monitoring water quality encompasses three categories of water indicators: (1) physical parameters such as water temperature (WT), transparency (Secchi disk depth (SDD)), surface salinity (SS), turbidity (TUR), total suspended matter (TSM), Colored Dissolved Organic Matters (CDOM), odor, and electrical conductivity (EC); (2) chemical parameters such as pH, dissolved oxygen (DO), chemical oxygen demand (COD), biochemical oxygen demand (BOD), total organic carbon (TOC), dissolved organic carbon (DOC), total nitrogen (TN), ammonia nitrogen (NH₃-N), nitrate nitrogen (NO₃-N), total phosphorus (TP), orthophosphate (PO₄), heavy metal ions,

and nonmetallic toxins; and (3) biological parameters such as chlorophyll- α (chl- α), total bacteria and total coliforms. The analyzed water quality parameters are divided into two categories using remote sensing techniques. The initial classification comprises of indicators that possess active optical characteristics such as chl- α , TSM, and CDOM. These indicators impact the radioactive transfer process of waves through varying absorption of the spectrum. The second classification comprises of indicators that lack explicit optical properties, such as TN, TP, and DO. Indicators of this nature are frequently evaluated through statistical correlations with other indicators [56]. In this review, the focus of research is on eight optically active water parameters (Table 2), as follows: chl- α [30,32,33,35,57–111], transparency (SDD) [33,35,57–59,67,77,87,88,90,93,95,97,101–103,110,112–126], CDOM [60,75,77,82,83,90,92,102,115,127–147], EC [148–154], TUR [32,33,35,58,60,67,75,98,102,104,109,110,150,152,153,155,156], SS [150,157–181], TSM [30,58,59,67,75,82,90,92,97,99–101,113,119,182–192], and WT [87,103,150,193–213].

1.1. Objectives

In order to facilitate further comprehension and implementation of remote sensing methods, including sensors mounted on spaceborne and airborne Earth observation (EO) platforms, in water quality monitoring and evaluation for lakes, a systematic literature analysis was conducted to summarize the current research status and general trend.

This review presents a summary of numerous research studies assessing water quality using remotely sensed data. It emphasizes the potential usefulness of these findings for environmental researchers and encourages further research and innovation in the field. The review aims to gain a centralized resource for researchers to gain insights into current practices and draw conclusions on potential areas for improvement or additional contributions. It examines optically active parameters retrievable through satellite imagery and focuses on lakes, gathering in situ and satellite data from experts in ecology, biology, chemistry, and hydrology. Satellite images serve as the sole source of information in the absence of available data, and Landsat 5 and other older satellite systems provide temporal, historical data.

The manuscript contributes new knowledge in the field by aiming to improve data representation reliability by moving from point to raster representation. The review takes into account a considerable number of articles published since 2015 and highlights the practicality of methods for selecting and computing relevant parameters for monitoring lakes.

The objectives of this paper are to (1) provide bibliometric analysis, (2) to provide insight into the current state of using remote sensing methods to monitor water quality for lakes, (3) summarize retrieval methods used in literature, and (4) highlight specific optically active water quality parameters in depth depending on the methods used to measure their concentrations.

Finally, potential solutions and limitations to the current challenges of remote sensing water quality determination in lakes are presented in this paper.

2. Bibliometric Analysis

Long ago, remote sensing was acknowledged as a method for global tracking of inland water quality. Airborne and satellite spectral data collection have been used since the early 1970s to analyze a broad collection of water quality parameters [213,214] (Figure 1). Previous reviews [55,56,215–219] have offered excellent summaries of hundreds of publications presenting models for evaluating the biological, chemical, and physical properties of complex waterbodies published by scientists during the past 50 years. General trends in this sense were revealed after extensive bibliometric research of the Elsevier Scopus database (conducted in April 2023). Database titles, keywords, and abstracts from 1971 until 2022 for the terms ‘remote sensing’, ‘water quality’, and ‘lake’ in the English language were searched. The search found 27,950 unique publications published for terms ‘water quality’ and ‘lake’ and 1,593 unique publications published for terms ‘remote sensing’, ‘water quality’, and ‘lake’. Globally, the number of publications employing remote sensing for lake water quality falls significantly behind those that do not, as shown in Figure 1.

Since the 1970s, papers describing the monitoring and assessment of water quality for lakes utilizing remote sensing methods have arisen (Figure 1). Publication numbers for the specific dataset follow a power law distribution, with a similar increase after 2008. The greatest increase in remote sensing studies from one year to the next happens after 2008, coinciding with the availability of free Landsat imagery. This conclusion is consistent with prior research indicating that the publication of the Landsat archive led to an increase in the frequency and scope of EO studies in different domains [220] and has resulted in a more comprehensive understanding of inland waterbodies to concentrate on demanding scientific problems and expanding research scales. In the publications based on remote sensing analyzed for this research on lakes, in the past decade, twice as many studies have been published (2013–2022), as in the previous 42 years combined (1971–2012). The majority of the publications was published from United States of America and China. More than half of the publications from the bibliometric analysis are from those two countries. The origin of rest of the publications is from countries across Europe and India, Canada, Japan, and Australia, as seen in Figure 2.

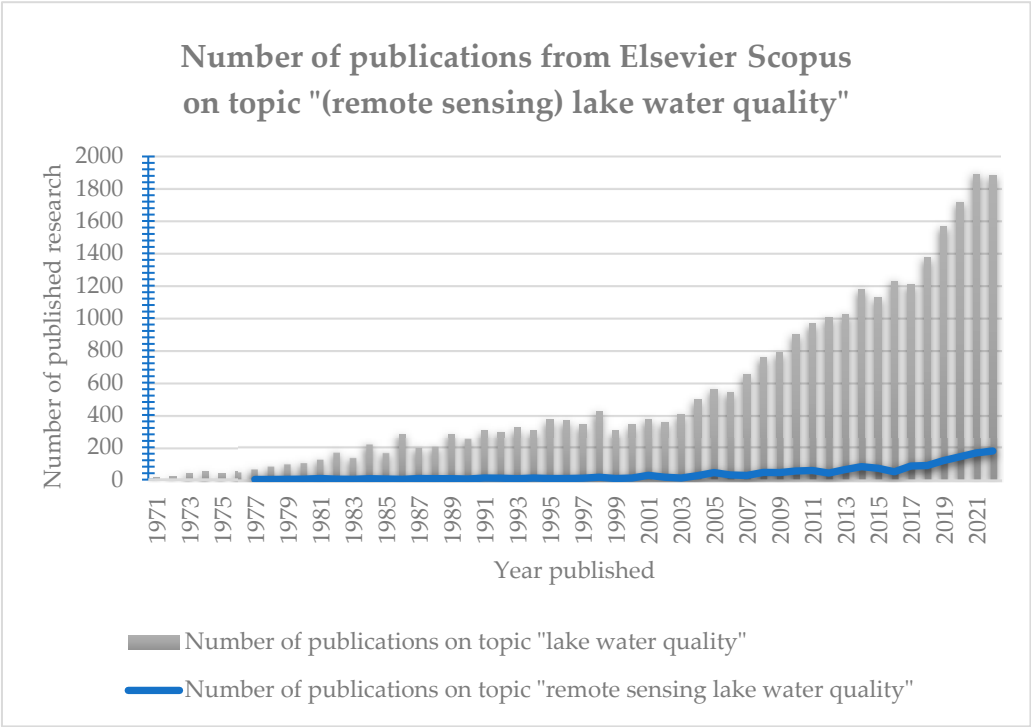


Figure 1. Visualization of number of publications selected from Elsevier Scopus on the search topic “(remote sensing) lake water quality”.

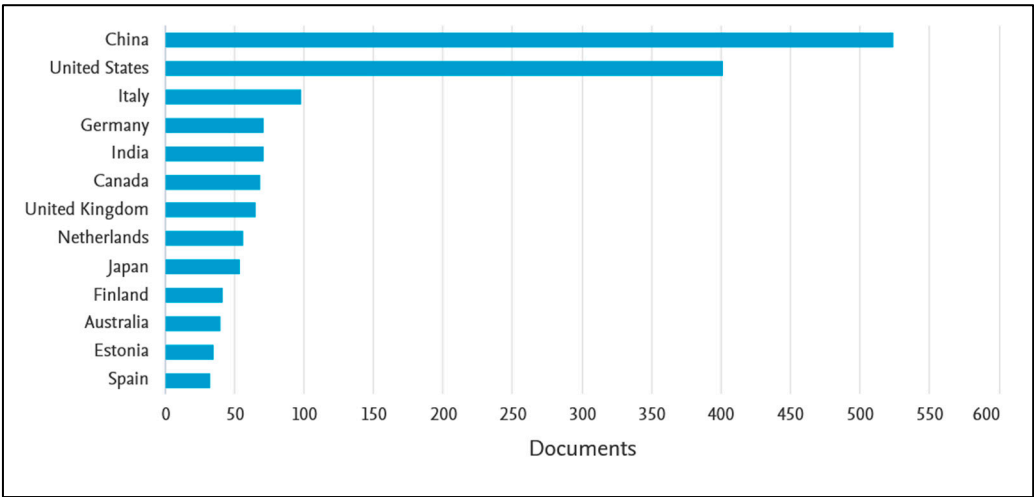


Figure 2. Visualization of documents per country of origin (showing only records for more than 30 documents per country).

The literature review suggests that the recent advancement in evaluating inland water quality through remote sensing initiatives can be attributed to the challenges associated with remote sensing of complex waterbodies and the limited availability of suitable sensors for this purpose (namely hyperspectral airborne or space-borne remote sensing which capture extensive spatial and spectral information, especially in small lakes) [221]. The complex bio-optical property of a static waterbody (vegetation, pollutants) creates problems in establishing an internal correlation between spectral responses and optically inactive water quality parameters. In tandem with the increase in remote sensing data accessibility during the past decade, in situ data accessible for model calibration and validation has increased. Modern databases offered by government agencies, nongovernmental organizations, and scholars provide a variety of freely accessible in situ data. In Europe, these include Eye on Water (www.eyeonwater.org) and Seen-monitoring (www.seen-transparent.de) [218]. These established databases can be enhanced with innovative datasets collected through citizen science activities. In this way, data continuity is offered, cost and time savings for researchers, as well as a multitude of samples for calibration and validation of derived models.

Figure 3 shows the results of the bibliometric analysis, which identifies the waterbodies that have been most frequently studied in relation to the estimation of lake water quality using remote sensing techniques. Reservoirs are often studied alongside lakes due to their comparable water quality complexity. Inland waterbodies typically include lakes and rivers. Despite their distinct characteristics (lakes being stationary and rivers being moving waterbodies), researchers often study and review both types of waterbodies simultaneously. Coastal areas often contain lakes that are influenced by the nearby marine environment, such as estuaries, seas, lagoons, or oceans. The marine influence on lakes is crucial for saline and brackish lakes, as inland waters experience notable variations in salinity. These variations are primarily caused by seasonal changes in river runoff and interactions with the ocean through tides and flushing times.

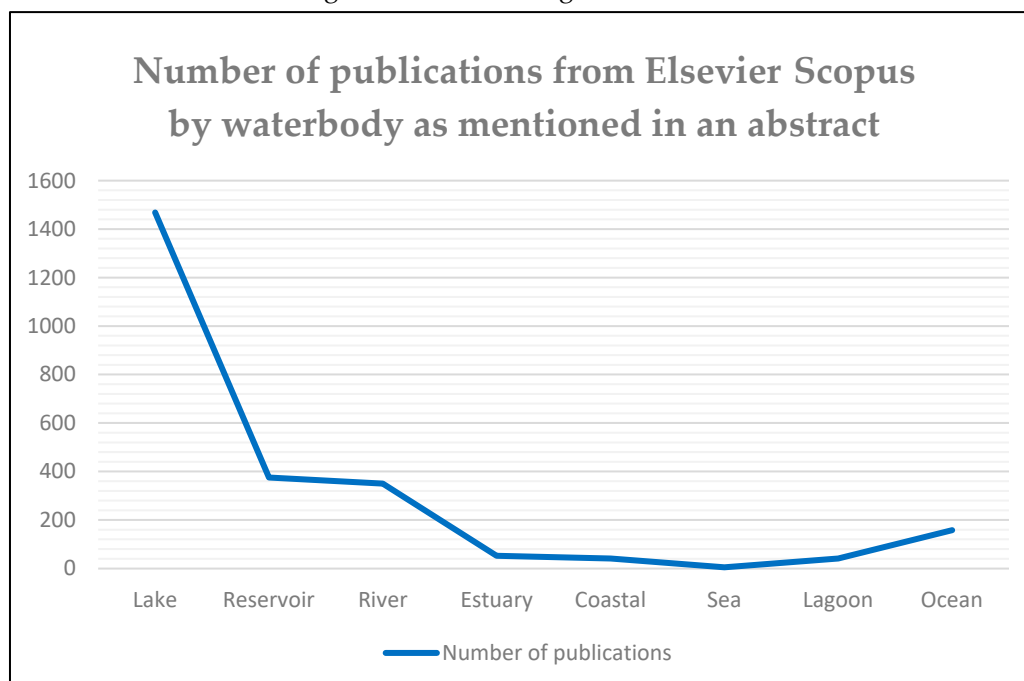


Figure 3. Visualization of number of publications selected from Elsevier Scopus by waterbody as mentioned in the publication's abstract.

1.3. An overview of methods for retrieving water quality and water quality parameters based on remote sensing

3.1. Methods for retrieving water quality

The basic principle of inversion of water quality using remote sensing methods consists in the following. First, using in situ water quality monitoring data and equivalent remote sensing imagery, a model is established. After that, the distribution of water quality over a longer period over a larger area is monitored based on the model (i.e., inverse modeling) [56]. Bio-optical methods use the correlation between a waterbody's optical properties and its optically active parameters to assess water quality [222]. Optically active parameters, such as TSM, CDOM, and chl- α , interact with light and modify radiation in the water column by absorption and scattering processes unique to each parameter [26] and can be obtained through direct retrieval [106,192,223]. Additional parameters include acidity, chemicals, pathogens, TN, TP, COD, and DO which lack optical activity, don't alter the spectral features of reflected light and have no clearly distinguishable signals, but can be interpreted and inferred from those measurable water quality parameters with which there have substantial relationships [26,224]. Bio-optical models can also describe and predict the water's "bio-optical state", or its optical properties as a function of biological activity [225].

Five methods—empirical [49,55,56,108,214,215,226–233], semi-empirical [49,67,76,127,218,227,234–250], semi-analytical [39,56,191,215,218,219,225,251–266], analytical [39,56,232,234,262–268], and artificial intelligence/machine learning (AI/ML) [73,218,227,269–295]—can be used to monitor and assess water quality using remote sensing imagery. The analytical method is also called physical. AI/ML methods are characterized by computational complexity and nonlinear relationship management, even though they are empirical. Analytical and semi-analytical methods require theoretical analyses of spectral data, while empirical and semi-empirical methods use statistical analyses and are widely used due to their complexity. The empirical and analytical methods differ in how they develop models based on water quality concentration and reflectance. Linear and non-linear regression methods may fail to model complex nonlinear relationships. Unlike statistical or physical models, AI/ML method can capture linear and nonlinear relationships. Methodically examining the inherent optical characteristics of water quality parameters can reduce or eliminate the effect of irrelevant parameters and anthropogenic actions on the quantified parameter.

Usually, water quality models, based on remote sensing imagery, are created for specific waterbodies by examining the correlation between spectral responses and in situ measured water quality parameters, serving as indicators of water pollution, sky background, and weather conditions. The performance of water quality retrieval models is dependent on spatial factors, which may render them effective in certain regions but unsuitable for others. This is particularly true for bio-optical models, where the inherent optical properties of a region are crucial in determining their applicability [215]. Satellite-based water quality models have temporal limitations due to their reliance on short-term in situ data for their design. The water quality parameters in a given water area exhibit seasonal variation owing to meteorological factors [296].

3.1.1. Analytical methods

Analytical methods use inherent and apparent optical properties to model reflectance and vice versa. Underwater light fields, remotely detected radiance, and water quality parameters are physically related [49]. Analytical models link water quality parameters with water-leaving radiance using radiation transmission theory [267]. The analytical method's physical mechanism can simultaneously identify all water parameters using well-established parameter properties and large in situ data [55] and portability is good, but it requires a highly accurate measuring instrument, high application costs, and challenges to widespread adoption [234]. Most satellite sensors' spectral resolutions differ from those measured close to the ground, making model development harder. Analytical model-based quantitative remote sensing inversion is difficult and rarely used for all water quality parameters [232,268].

3.1.2. Semi-analytical methods

Analytical and semi-analytical models use the physics-based optical properties of water and the atmosphere [251,252]. Semi-analytical methods simplify analytical models. Semi-analytical model parameters require statistical analysis [253,254]. Most semi-analytical models are three-band models [255]. The three-band model identifies the optimal three-band combinations related to the absorption coefficient and quantifies the correlation between the coefficient and water quality parameters. Theoretical absorption and backscattering values are calculated by modeling the inherent optical properties of a waterbody with apparent optical properties including illumination conditions, sensor orientation, and field of view [225,251,256,257]. Some scientists created semi-analytical models based on water column radiative transfer (e.g., [258–260]). The radiative transfer equation separates optically active parameters from water-leaving radiation. Inversion and look-up tables are the main radiative transfer equation solutions. The radiance spectra that have left a waterbody are cataloged in the look-up tables, which are a huge library of such spectra with known parameter concentrations, inherent optical properties, bathymetry, and bottom characteristics. The closest match for each variable is calculated using the spectral signatures of the images and the database entries. Inversion methods use radiative transfer and constant and variable model parameters to replicate lake spectral signatures. Variable parameters are repeatedly adjusted for each pixel until the simulated and real-world spectral signatures match [219]. An inverse equation can predict optically active parameters from these values. Semi-analytical models that use in situ observations to parameterize the inverse equation are the most common physics-based algorithms for remote sensing inland water quality [215]. This inverse modeling method provides simultaneous estimates for several water quality parameters. However, model development is difficult and requires knowledge of atmospheric composition, bottom reflectance, and substantial in situ sampling, depending on atmospheric corrections [218]. Semi-analytical models have been successfully applied on broad spatiotemporal scales. Semi-analytical modeling is better explained in Dekker, Vos, and Peters [191,261], Giardino et al. [256], Morel [225], and IOCCG [251]. Semi-analytical and analytical methods are used to retrieve mainly optically active parameters, such as chl- α , TSM, CDOM, and SDD [39,56,262–266].

3.1.3. Empirical methods

The empirical method computes statistical correlations between in situ water quality parameter values and spectral response values to derive distinctive channels or channel combinations [55,56,226]. Regression models establish a relationship between water quality parameters and characteristic channels or combinations of channels, which is used to derive the inversion algorithm [108]. Empirical methods include linear regression, single-channel, channel-combination, principal component analysis, and others. The empirical method uses regression analysis to quickly create a water quality inversion model without complex physical parameters. Regression methods show the relationship between remotely observed radiance and water quality parameters, but they lack physical mechanisms and multitemporal validity, resulting in uncertainty and limited applicability across spatial and temporal domains. Most empirical models use multivariate regression because inland waterways are optically complex [227]. Since the downwelling irradiance field and water surface conditions may change between remote sensing missions, empirical model estimates will always require in situ data [49]. During empirical modeling, at the local level, the optical properties of water specific to that location are taken into account, however, optically inhomogeneous waterbodies and variable atmospheric conditions make parameterization difficult [228,229]. Model transparency, simplicity, and low computational needs often outweigh these drawbacks. These methods are more accurate than spectral and bio-optical models because they take into account the waterbody's specific properties [215]. The empirical method is easier to implement because it is not necessary beforehand knowledge of the frequently complex interactions between water and light [227]. The empirical method is most commonly used to assess TUR, chl- α , and trophic status [214,230,231]. These methods may not work for complex compositions of water quality parameters, such as phytoplankton pigments, TSM, and CDOM, because they do not have unique absorption features and greatly increase the uncertainty in inversion [232,233].

3.1.4. Semi-empirical methods

Semi-empirical methods combine empirical and analytical methods [234]. Semi-empirical models identify wavebands to correlate water quality parameters with remote sensing data, it combines statistical analysis with water spectral theory [235]. They require statistical and measured spectral analysis [236]. Selecting characteristic bands and models requires spectral analysis of water quality parameters. The statistical analysis integrates this knowledge by focusing on carefully selected spectral regions and using relevant wavebands as correlates. Semi-empirical methods use physical and spectral data, such as absorption features, to create algorithms that correlate with measured parameters. Statistical coefficients usually have a calibration time and place. The semi-empirical method integrates waterbody reflectivity with measured parameter concentration, giving it physical significance and ease of implementation [234]. Validity is only assumed within the algorithms' often-limited range of optical water quality data [49]. Semi-empirical models do not model the inherent optical properties of a waterbody like semi-analytical models. Instead, they improve the parameter's spectral properties and reduce optical parameter noise. Physically based semi-empirical models are more generalizable than completely empirical ones. Since they measure absorption characteristics and scattering peaks at certain wavelengths, they can only be used with sensors with properly positioned band centers and enough spectral resolution [218]. Spectral band ratios and shape algorithms are popular because they are generalizable and easy to use in many locations. Since they assume consistent water and atmospheric conditions, inland applications are easy to implement but lack precision. This may cause large estimation errors across a time series. Spectral band ratios and spectral shape methods are better for assessing regional water quality parameter distributions than precise estimates [227]. The semi-empirical method's large amount of in situ measured data limits its temporal and spatial applicability. Chl- α , TSM, CDOM, SDD, and TUR are often assessed semi-empirically [67,76,127,237–250].

3.1.5. Artificial intelligence/machine learning (AI/ML) methods

Along with artificial intelligence (AI), remote sensing has increasingly used machine learning (ML) techniques. AI/ML are empirically based and outperform band ratios, spectral shape, and bio-optical inversion methods. Empirical data underlies machine learning, thus, AI/ML models are limited by the data used to train them, like empirical models. AI/ML models use iterative learning to minimize error and optimize model fit, unlike empirical models [269]. This approach needs distinct training and testing datasets with representative samples of relevant parameters to avoid overfitting. Algorithms can generate models that capture complex and nonlinear relationships between water quality parameters and remotely sensed reflectance when given appropriate inputs [218]. AI/ML models use statistical methods to learn from data and create a model for detection, estimation, or classification. AI/ML method involves giving a computer system data to train on predetermined features or objects to automatically detect, classify, and recognize patterns [227]. ML and statistical modeling use iterative optimization procedures to find the most favorable results by averaging a selected number of iterations. In order to ensure that representative samples of a data set are selected, a random split of 70% training data and 30% testing data should be used, according to Sagan et al. [227]. AI/ML methods may be divided into two groups: traditional machine learning (e.g., partial least squares regression (PLSR) and support vector regression (SVR)) and deep learning-based methods (e.g., deep neural network (DNN) and convolutional neural network (CNN)). Because traditional machine learning algorithms excel at solving complex nonlinear problems, PLSR and SVR have been used to estimate water quality parameter concentrations [73,270–273]. Deep learning uses hierarchical neural networks (NNs) for powerful machine learning. DNN models can simulate complex nonlinear relationships using a large number of hidden layers between input and output layers to categorize and predict spectral data [274]. CNN models classify hyperspectral images best because they capture extensive spatial and spectral information [275,276]. AI/ML methods' downsides are they only work if they have a lot of training data as in situ measurements (difficult to achieve in reality), the use of remote sensing data often involves multiple modes (requires the creation of new AI/ML models that can combine features from different spectral, spatial, and

temporal information – it poses a challenge to the transferability), having enough amount of knowledge in the field of deep learning to get a full idea of the complicated structure of input variables, and if AI/ML models are used to model physical phenomena, the presence of solutions that can't be explained can lead to wrong outputs or problems that aren't well-posed [277–281]. Due to algorithm development, sensor systems, computing power, and data accessibility, remotely sensed water quality estimation through artificial intelligence and machine learning has become more popular [282]. Deep learning outperforms many other remote sensing methods at estimating all water quality parameters, as found in recent studies [278,283–289]. AI/ML methods are often used for calculating chl- α , TSM, TUR, NO₃-N, and PO₄-P [227,286,290–294] [295].

3.2. Parameters

The properties of water molecules: scattering, reflecting and absorbing the electromagnetic spectrum, create problems for it on its way from the Sun through the object to the sensor [297] (Figure 4). Water absorbs light at wavelengths longer than 680 nm. This limits optical remote sensing in aquatic environments to the visible area of the electromagnetic spectrum [297], although the near infrared (NIR) region can provide some information [46], especially if the water column is very shallow (less than 1 m). Using remote sensing, optically active parameters, such as TSM, CDOM, and chl- α , interact with light and modify radiation in the water column by absorption and scattering processes unique to each parameter [26]. Optically active parameters indicate a body of water's inherent optical properties [216]. Optical water quality parameters can be measured correctly by nonintrusive sampling and without the errors associated with in situ measurements using optical remote sensing. In optically shallow water, a portion of the light emitted by the water includes radiation reflected at the bottom [219]. In addition to water contents, the water leaving radiance contains information on the bottom substrate and bathymetry [298].

The apparent optical properties (i.e. attenuation or remote sensing reflectance) depend on the water quality as well as the radiation geometry [299]. The retrieval model can be built for various optically active parameters based on the interaction between inherent optical properties and remote sensing reflection. The inherent optical property is a property of water that excludes external conditions and concerns only the composition of the waterbody.

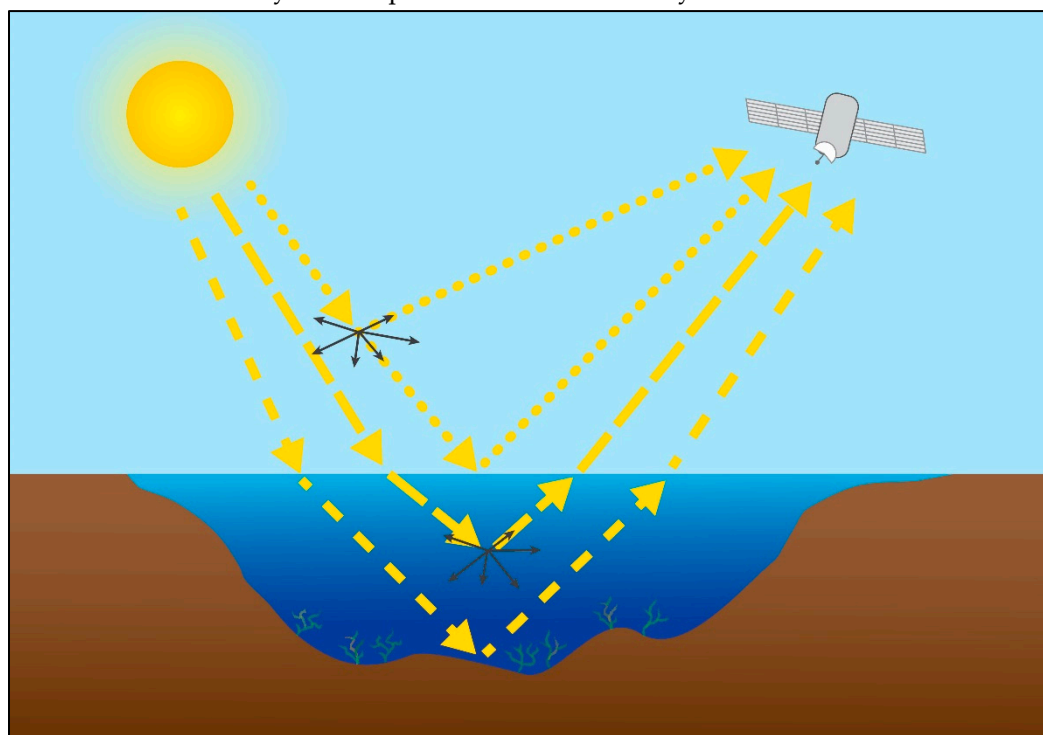


Figure 4. Schematic overview of the path of electromagnetic spectrum between the Sun, a waterbody, and a sensor.

Remote sensing has been used successfully to measure the majority of the optically active water quality parameters, including Chl- α , SSD, TSM, TUR, SS, and WT due to their accessibility and high spatial, temporal, and spectral resolution [7,81,106,120,127,192,223,227,251,252,257,261,286,295,300–317]. The remote sensing community faces a considerable challenge in estimating parameters that exhibit weak optical properties and are therefore considered optically inactive, namely pH, DO, TN, NH₃-N, NO₃-N, TP, and heavy metals such as cadmium (Cd), nickel (Ni), and zinc (Zn) [98,101,108,131,227,231,295,312,318–324]. The water quality parameters that lack optical activity are associated with water eutrophication and hold significant importance in environmental evaluation, particularly in relation to human health, such as TP and TN [295,325]. However, it is possible to estimate these parameters by initially establishing the internal correlation with the optically active parameters and subsequently conducting correlation analysis [302,312]. A list of water parameters researched in this review is given in Table 1.

Table 1. A list of water parameters researched in this review – an emphasis is given on optically active biological and physical indicators (chemical indicators stated in *italics* are mentioned throughout the review but are not explained in detail).

Water Quality Parameter	Abbreviation	Units	Optical Activity	Type
Chlorophyll- α	chl- α	mg/L	Active	Biological
Transparency (Secchi Disk Depth)	SDD	m	Active	Physical
Colored Dissolved Organic Matters	CDOM	mg/L	Active	Physical
Electrical Conductivity	EC	μ S/cm	Active	Physical
Turbidity	TUR	NTU	Active	Physical
Surface Salinity	SS	PSU	Active	Physical
Total Suspended Matters	TSM	mg/L	Active	Physical
Water temperature	WT	$^{\circ}$ C	Active	Physical
<i>pH</i>	<i>pH</i>	-	<i>Active</i>	<i>Chemical</i>
<i>Total Organic Carbon</i>	<i>TOC</i>	<i>mg/L</i>	<i>Active</i>	<i>Chemical</i>
<i>Dissolved Oxygen</i>	<i>DO</i>	<i>mg/L</i>	<i>Inactive</i>	<i>Chemical</i>
<i>Chemical Oxygen Demand</i>	<i>COD</i>	<i>mg/L</i>	<i>Inactive</i>	<i>Chemical</i>
<i>Biochemical Oxygen Demand</i>	<i>BOD</i>	<i>mg/L</i>	<i>Inactive</i>	<i>Chemical</i>
<i>Total Nitrogen</i>	<i>TN</i>	<i>mg/L</i>	<i>Inactive</i>	<i>Chemical</i>
<i>Ammonia Nitrogen</i>	<i>NH₃-N</i>	<i>mg/L</i>	<i>Inactive</i>	<i>Chemical</i>
<i>Total Phosphorus</i>	<i>TP</i>	<i>mg/L</i>	<i>Inactive</i>	<i>Chemical</i>
<i>Orthophosphate</i>	<i>PO₄</i>	<i>mg/L</i>	<i>Inactive</i>	<i>Chemical</i>

3.2.1. Chlorophyll- α (chl- α)

Photosynthesis absorbs light energy through chlorophyll. Plants and other photosynthetic organisms depend on them to convert light into energy. Remote sensing research focuses on chl- α [215], the most common chlorophyll pigment in photosynthetic organisms like plants, algae, and cyanobacteria. Chl- α is the most important indicator of waterbody primary productivity and eutrophication and the main indicator of trophic status because it links nutrient levels—particularly phosphorus—to algal production. Phytoplankton's nutrient availability directly affects freshwater ecosystems' trophic states [326]. Chl- α absorbs blue and red light while reflecting green, making chlorophyll green. Algal blooms with phycocyanin-producing cyanobacteria can harm humans, livestock, and wildlife [327]. Anthropogenic nutrient loading and climate change have increased harmful algal blooms worldwide [328]. Cyanobacterial blooms may be toxic [76,81,329,330], so local authorities must act quickly and forecast them.

The remote sensing spectral signature of chl- α depends on its concentration relative to other water quality parameters and the phytoplankton phenotypes that generate the signal [331,332]. Due to sunlight-induced fluorescence, the chl- α spectrum peaks at 680 nm in oligotrophic to mesotrophic aquatic environments [333–335] (Figure 5). Narrow bands of imagery are needed for remote sensing chl- α concentration and its geographical and temporal fluctuations [336]. Numerous studies have shown that increasing chl- α concentration reduces spectral response at short wavelengths,

particularly in the blue band [22,95,96,316,337,338]. Chl- α assessment often uses optical spectral band ratios because can reduce irradiance, atmosphere, and air-water surface effects in remotely detected signals [95,339]. Empirical and semi-analytical methods are limited to precise atmospheric correction and geographical inapplicability [234]. Remote sensing (satellite and aerial) may be feasible and affordable for regional-scale chl- α monitoring. Neural network models were more geographically transferable than three-band models [270,340]. Table A1 (the abbreviation A stands for Appendix in Supplementary Materials) lists selected remotely measurements of chl- α using various sensors and spectral bands, band ratios, and band combinations. As seen from Table A1, a conducted literature review showed Landsat-5 TM and MERIS as most suitable and popular for chl- α evaluation – easy accessibility, temporal coverage, and spatial resolution may make these sensors a good choice.

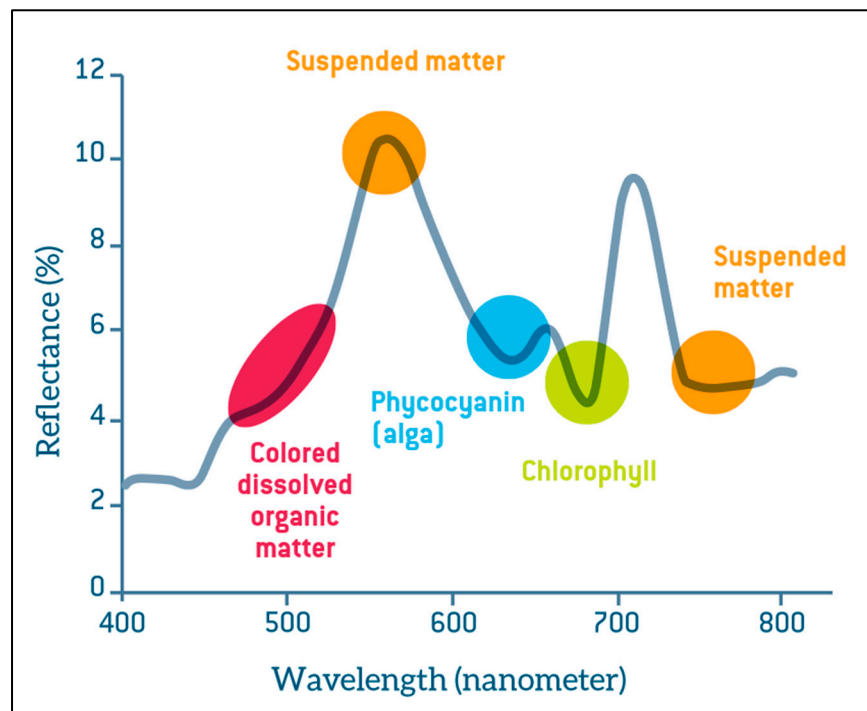


Figure 5. Reflectance (relationship between reflected energy and total incident energy) according to the typical wavelength of continental water and the spectroscopic signatures of the water quality parameters [341].

3.2.2. Total Suspended Matter (TSM) and turbidity (TUR)

TSM, total suspended solids, pollution-sediment, suspended sediment concentration, and particulate matter are often used interchangeably. TSM includes inorganic and organic particles suspended in water. TUR is a precise measurement of the amount of suspended and dissolved particles that cause light to scatter inside a water column. TUR and TSM, nonalgal particles, reduce water column transparency and often carries contaminants and nutrients [219]. TSM dominates scattering, chl- α and colored dissolved or particulate materials control absorption [342], while TUR scatters and absorbs light. The high concentration of TSM in inland lakes will disturb the true light layer's depth, affecting waterbodies' primary production, aquatic plant growth, and water quality [343–345]. High TSM increases TUR and decreases light penetration, affecting local macrophyte species composition and primary production [346,347]. A water sample's TUR depends on its suspended particles. Because suspended particles block light, water TUR increases. TUR and TSM are important factors in many studies because they affect sunlight, which affects algae and plankton photosynthesis. These parameters also affect SDD.

Remote sensing is used to map TUR and TSM concentrations and their geographical and temporal variations. Researchers have successfully calculated TSM concentrations using remote sensing data in practical applications [185,189,190]. TSM concentration spectral fingerprints vary

depending on particle size and organic-to-inorganic component content [348,349]. Organic-dominated systems with abundant algae have the same absorption and backscatter peaks as chl- α [350]. When inorganic TSM concentrations rise inside a waterbody, the spectral maximum shifts from ~550 nm to the red or NIR wavelengths (700–900 nm) [351] (Figure 5), depending on chl- α and CDOM concentrations. A single band can create a robust and TSM-sensitive algorithm if chosen properly [352]. Because complex water parameters change waterbody reflectance and color, TSM retrievals can use different spectral bands [351–353]. Signal bands or band ratios can improve waterbody concentration measurements and quantify TUR and TSM. Table A2 lists selected remotely measurements of TSM and Table A3 lists selected remotely measurements of TUR using various sensors and spectral bands, band ratios, and band combinations. Using Landsat-5 TM, most studies examined TSM's spatiotemporal dynamics and causes.

TSM concentrations estimated from remote sensing have been correlated with several optically inactive water quality indices to estimate small-scale phosphorous [55], mercury [354], and other metals [355]. TSM fluxes strongly affect the biogeochemical cycling of nutrient transport [356], heavy metal loading [357], light conditions [358], and global carbon budgets [359].

3.2.3. Colored Dissolved Organic Matter (CDOM) and Total Organic Carbon (TOC)

The measurable parameter that is most frequently utilized in remote sensing as an indication of both DOC and TOC is CDOM. CDOM, also known as gelbstoff, gilvin and yellow matter, are organic compounds that are naturally occurring, water-soluble, biogenic, heterogeneous, and range in color from yellow to brown [360]. These compounds may be found in both fresh and saltwater. TOC is a general indicator of water quality that includes both particulate and dissolved organic carbon. The colored component of all total DOC is referred to as colored (or "chromophoric") dissolved organic matter. The origin of DOC can be allochthonous, which indicates that it originates from sources outside of the system, such as soils, terrestrial plants, and decaying wooden plants in the catchment, or autochthonous, which refers to aquatic plants or algae (i.e., phytoplankton) that have decomposed in surface water [134,361,362]. DOC concentration cannot be detected in situ, but it can be assessed by the optical characteristics of CDOM, which is the proportion of DOC that can absorb light in both the ultraviolet and visible ranges [363]. A better knowledge of carbon imports and processing in freshwater systems may be obtained via ongoing monitoring of CDOM, both directly and as a proxy for total DOC. Elevated levels of CDOM provide stratified, dark waterbodies with little light penetration because they absorb a lot of light in the visible spectrum [364]. These brown compounds have the ability to turn water yellowish brown when present in large quantities.

As in the case of TSM, the reflectance spectra of waterbodies with different concentrations of CDOM rely greatly on the composition of other optically active parameters, and in some locations, the presence of colloidal iron, which has related optical characteristics, might complicate matters [365]. The water color, underwater light field, and chemical processes are all significantly influenced by CDOM, which has a highly complex composition. CDOM absorption is often described as color and PCU (Platinum-Cobalt Units) color in the majority of water quality monitoring programs [366]. Since spectral signals from CDOM typically conflict with chl- α and TSM, remote sensing of CDOM in inland waters is difficult and vulnerable to significant errors when compared to oceanic waters [367,368]. The appropriate bands for CDOM measurement, due to spectral signal interference, they are not always at the same wavelengths as for chl- α , TSM, as well as the geographical and temporal variability of inland waters. Along with high spatial resolution underwater CDOM observation, it is also important to calibrate and confirm the remotely detected CDOM concentrations with in situ measurements. Furthermore, CDOM is frequently utilized as a crucial marker for DOC dynamics in freshwater and coastal marine environments [369] and several studies have shown a correlation between CDOM and DOC [368,370–374]. The use of remote sensing to evaluate DOC/TOC concentration by measuring CDOM fluorescence will be address. According to the literature, which is compiled in Table A4, CDOM might be measured utilizing visual spectral bands and their ratios.

Chl- α , TSM and CDOM typically dominate the water's color. When measured at 443 nm, the CDOM absorbance spectrum can account for more than 50% of the overall absorption [366]. The

reflectance values in the blue and green region of the spectrum are mostly impacted by a rise in CDOM content (particularly below ~ 500 nm), and its absorbance grows exponentially with decreasing wavelength (Figure 5). CDOM substantially absorbs radiation in the ultraviolet and blue wavelengths, with an exponential decline in absorption with rising wavelengths [375].

3.2.4. Water transparency (Secchi disk depth (SDD))

Water transparency is a significant indication of lake water quality and the ecosystem of waterbodies, and it directly reflects the light transmittance of waterbodies, which is widely employed in water quality monitoring and management [376,377]. The presence of chl- α , TSM, and CDOM collectively affects water clarity.. In situ data collection for observing water transparency and relative measurements of clarity have been frequently employed from the invention of the Secchi disc [378–380]. The Secchi disk, invented in 1865 by Pietro Angelo Secchi SJ and used for measuring clarity in lakes and seas, is the most well-known operational assessment of water transparency. A white and black disk is suspended on a line () and gently lowered into the water until the pattern on the disk is not visible and measures the greatest apparent depth of the disk [381]. This method, however, is labor-intensive, expensive and has a low sampling efficiency. In addition, it is difficult to represent the spatial variation of the entire lake due to the limitations imposed by the discrete samples. Since the aquatic environment of lakes increasingly deteriorates, it is imperative to use effective and savvy monitoring techniques for water quality such as remote sensing. In remote sensing, Secchi disk depth in water approximates inverse variation of diffuse attenuation coefficient (K_d). The diffuse attenuation coefficient of downwelling irradiance, which is frequently measured at 490 nm, shows the exponential drop in irradiance with increasing water depth [382]. Diffuse attenuation coefficient is influenced by TSM scattering, CDOM, phytoplankton, and pure water absorption [219]. Remote sensing can thus be a great technique for tracking water transparency and calculating the SDD.

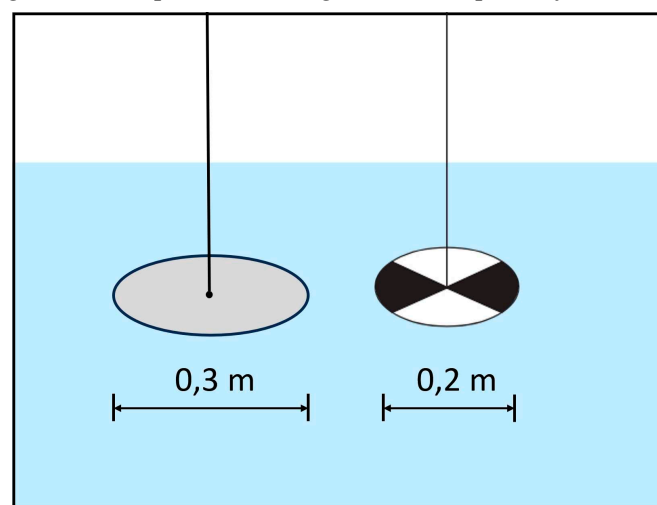


Figure 6. Different kinds of Secchi disks – a marine style on the left and the freshwater version on the right.

Remote sensing water transparency estimation uses semi-analytical and empirical models. The semi-analytical bio-optical model assumes that water reflectance is a nonlinear function of the backscattering coefficient and absorption coefficient. Water transparency measurement is then correlated with the coefficients [383–385]. The empirical method uses a regression model to determine the complex relationship between water transparency and band reflectance. Water's optical properties and transparency vary across regions and seasons [386]. Remote sensing and water transparency retrieval empirical models have spatial and temporal limitations. Random forests, artificial neural networks, and support vector machines are solutions [387–389]. These models solve the nonlinear regression between water remote sensing reflectance and transparency. Deep learning, which uses a neural network with multiple hidden layers to learn features [390], may improve water

quality retrieval models [391]. The network learns complex environmental parameter relationships to achieve this. Thus, this model solves the nonlinear regression problem of establishing a relationship between multi-dimensional spectral vectors and water quality parameters [283].

Remote sensing studies commonly employ water clarity as a proxy for overall lake trophic state (oligotrophic, mesotrophic, or eutrophic) [120,392,393] since it has long been recognized as a proxy for nutrient availability and chl- α concentrations within lakes [222,394,395]. TSM levels in the waterbodies have an inverse correlation with the SDD. The SDD is a measurement that is also correlated with water TUR. Various band ratios and visual spectral bands are effective at measuring SDD. Wavelengths and band ratios that incorporate the red spectrum in some form are used in remote sensing retrievals of water clarity [116,396–402]. Table A5 summarizes these findings. Although a number of satellite remote sensing systems have been employed to evaluate the SDD, the Landsat+5 TM and MERIS are notably most effective for the evaluation of this water quality parameter because to their comparatively low cost, temporal coverage, spatial resolution, and data availability. This method has been effectively applied to estimate water clarity for inland lakes where there is a lack of in situ data.

3.2.5. Water temperature

Because it influences physical, chemical, and biological interactions in water, affects the photosynthesis of aquatic plants, and regulates DO levels in water, WT is regarded as another crucial indicator of ecosystem health and water quality condition [55]. For operational weather and climate research as well as atmospheric investigations, accurate surface WT remote sensing measurements are particularly essential. Remote sensing can provide accurate surface WT measurements but these measurements can be affected by emissivity and atmospheric absorptions (such as water vapor, aerosols, and subvisible clouds) [403]. IR radiometers provide surface WT with a precision of around 0.5 °C, but before detection of the WT using TIR radiation, normal remote sensing methods should be done to identify and mask clouds and fog out of the used imagery. The relatively substantial change in microwave emissivity with surface conditions, such as wind speed, allows for the application of passive microwave approaches in cloudy locations with an accuracy limit of roughly 1.5–2 °C [404]. Passive microwave radiometers show the emission of thermal radiation in the microwave region of the spectrum, whereas IR radiometers measure the thermal radiation emitted by the water surface in the TIR region of the spectrum [405]. Passive microwave radiometers have lower accuracy and resolution when compared to TIR surface WT measurement, and they are sensitive to surface roughness and precipitation but not to air and cloud influences [405].

When it is justified to suggest that the water is stratified, which happens soon after precipitation or solar warming and in areas affected by freshwater runoff, WT estimates derived by remote sensing must be evaluated very carefully because TIR is emitted from the surface [406]. In such circumstances, it is impossible to predict a relationship between WT and those found below the water surface. Remotely sensed emission of TIR radiation of surface WT in the terrestrial environment has mostly been employed for lakes [407,408]. TIR satellite imagery is a desirable source of broad-scale data because of their affordability, capability for regional coverage, revisit times, and pixel size, assuming they are available for the research period. Estimating primary production and phytoplankton growth rates may be done using WT determined by remote sensing and in situ measurements, which also serves as a useful indicator of the vertical mixing condition and water mass type [55]. The use of remote sensing in conjunction with conventional in situ WT measurements may deliver accurate data on temperature zones at a reasonably low cost. Following a conducted review of the literature, Table A6 summarizes how combination of bands may be used to measure WT. The most commonly utilized instruments mounted on satellites used for remote sensing retrieval of WT are NOAA AVHRR and MODIS Terra.

The overall relationship between heat, energy fluxes and WT is what controls thermal stratification [202]. However, depending on the wind speed, skin surface temperature is often lower than the top 50 cm of the water column [409]. As oxygen solubility decreases with rising WT, this

parameter has an impact on DO concentrations in water. There is a strong correlation between the WT and the distribution, movement, and interaction of some contaminants, such as nutrients.

3.2.6. Surface salinity

Surface salinity is a significant water quality parameter for brackish lakes, as inland saline water makes up approximately 45% of total inland water [410]. However, this parameter is not relevant for freshwater lakes. WT and salinity are crucial variables in determining the density of brackish and saltwater, and density is a key element influencing the water currents. The exchange of gases between the air and the water depends heavily on salinity. A small layer of fresh surface water can fool shallow satellite measurements because precipitation makes water fresher and less thick, which sits on top of the salty water below. It can significantly slow down the pace of gas transport across the pycnocline and enhance the stability of the top layer of the water column. Inland waters exhibit significant spatial and temporal variations in salinity, primarily due to the influence of climatic factors such as precipitation and evaporation, seasonal variations in river runoff, and interactions with oceans through tides and flushing times [55]. Data with greater temporal and spatial resolution are provided by satellite remote sensors.

For instance, salinity has been measured with excellent accuracy using the SMOS satellite with microwave MIRAS sensor [157,411,412]. Another salinity-related sensor, NASA's Aquarius, offers the global perspective of salinity variations needed for climate research [413]. For instance, monthly salinity maps might be used to determine variations in freshwater input and outflow to the waterbody due to precipitation, evaporation, ice melting, and river runoff. SMOS and Aquarius are the most often utilized sensors for salinity remote sensing. To maintain the accuracy of the geophysical data, salinity-measuring satellites need rigorous internal and external calibration and validation methods. The validation procedure includes both the processing of terrestrial data and the spaceborne instrument [158,414]. Salinity and its fluctuation have also been effectively mapped using airborne microwave radiometers like STARRS and SLFMR. Depending on the sensor employed, some of the studies are mentioned in Table A7. SS is remotely sensed almost exclusively based on L-band, regardless of the chosen satellite microwave sensor. Although, a combination of bands to successfully retrieve SS based on MODIS Aqua and ASTER Terra have been noted in Table A7.

To determine salinity variability, researchers have utilized indirect methods such as brightness temperature, CDOM, and temperature profiles derived from satellite data.. Due to the lack of a direct color signal from salinity, the color signal can instead be estimated using relationships between SS, WT, and brightness temperature [166,171,179,415–421] and between SS and CDOM [136,368,422,423].

3.2.7. Electrical Conductivity (EC)

The EC of water is a measure of its capacity to conduct electricity and is directly proportional to the concentration of ions or salt in the water [424]. MicroSiemens per centimeter ($\mu\text{S}/\text{cm}$) is the standard unit of measurement for EC. Oxygen absorption decreases as salinity rises. Solubility of oxygen in sea water is around 20% higher than in freshwater at the same WT [425]. Changes in EC that occur too quickly may be an indicator of contamination in the water. Anions like chloride, phosphate, and nitrate added to sewage discharge or agricultural runoff will increase EC [424]. Warm water has a greater conductivity. The combination of chemical and biological processes has prompted EC changes, and diurnal EC variations have been documented during low-flow cycles [426]. A conductivity probe is used to test conductivity in the laboratory or out in the field. Some devices may also measure SS or TSM by converting the conductivity reading. The complicated and highly variable interactions between EC and optically active water quality elements make it more difficult to draw correlations to spectral measurements [227]. Table A8 lists selected remotely measurements of EC using various sensors and spectral bands, band ratios, and band combinations. Based on the conducted literature overview, the most commonly used sensor for retrieving EC is Landsat-8 OLI as a single band or band combinations, as seen in Table A8.

3.3. Sensors

Remote sensing data, such as multispectral and hyperspectral data, are commonly employed for the purpose of monitoring water quality. Both satellite and airborne remote sensing techniques are valuable tools for evaluating the quality of inland waterbodies [55]. Regarding the monitoring of water quality over an extended period, it is imperative to calibrate, validate, and rectify multisensory satellite data with abundant in situ measurements [427]. This involves obtaining depth- and time-resolved water quality profiles along with meteorological and sampling data on a frequent basis [428]. In unstudied lakes without monitoring networks or data, modern remote sensing technologies and data archives are helpful for collecting historical lake ecological indicator data.

UAVs, aircrafts, and satellites are moveable aquatic remote sensing systems. Spaceborne or airborne sensors analyze waterbody radiation at different wavelengths. Water quality monitoring relies on water and contaminant spectra. Sensors can be passive, active, acoustic, or optical, depending on the energy source. Sensors record varying numbers of energy wavelength bands. Multispectral and high-resolution remote sensing devices use reflected or emitted electromagnetic radiation in different parts of the spectral sections they cover a considerable section of the electromagnetic spectrum for inland water quality monitoring [102,133,429,430] (Figure 4). Hyperspectral sensors measure contiguously across the electromagnetic spectrum in up to 200 numerous narrow spectral bands [431]. Due to their high spatial and spectral resolutions and simultaneous acquisition of narrower and contiguous bands, hyperspectral airborne sensors can measure and monitor many water quality parameters and locate contamination sources, particularly in lakes [35,67,321,432,433]. Spaceborne sensors with visible, IR, and microwave wavelengths can monitor water quality due to their high frequency data gathering and extensive coverage. Numerous researchers use the visible and NIR bands of the solar spectrum (mostly from the blue to NIR region) to find reliable correlations between water column reflection (or emission) and physical and biogeochemical parameters [26,30,31,57,58,63,120,122–124,247,293,389,434,435]. Thermal bands can measure surface WT [436]. Radiometers and synthetic aperture radars may estimate surface WT and SS in microwaves [437]. Satellite sensors are preferable for bigger waterbodies, while airborne sensors can accurately recover more water quality indicators due to its higher spatial and spectral resolution for smaller waterbodies. Non-satellite remote sensing data is also less affected by atmospheric conditions. Due to their versatility and mobility, compact and lightweight UAV systems (< 25 kg) integrated with a variety of sensor configurations, such as a multispectral camera, high spectrometer, IR sensor, and LiDAR, are practical and efficient water management solutions [46,52,226,293,438–442]. UAVs vary in size and flight capabilities [439,443]. The project budget, spatial and spectral resolution, and geographic coverage area determine the remote sensing platform.

A virtual satellite constellation with data integration of remote sensing imagery from different satellites have higher spatial, temporal, and spectral resolution [444], which improves the ability to retrieve water quality parameters from remote sensing images and provides unprecedented opportunities for long-term, high-frequency water quality monitoring, especially in small inland waterbodies [445,446]. For high spatiotemporal resolution, Landsat-8 and Sentinel-2A/B data fusion [447,448] and Landsat and MODIS data fusion [449,450] have been used. Data fusion from several satellite sensors needs atmospheric correction. Both robust atmospheric correction and addressing adjacency effects, which must be performed across sensors to provide comparable datasets, must be taken into account during post-processing. Water component characteristics, water bottom absorption, and atmospheric scattering affect a sensor's top-of-atmosphere water-leaving radiance when retrieving water quality [451–456]. Atmospheric correction reduces atmospheric radiation error and improves results for evaluation of water quality parameters [20,22]. The atmospheric contribution to a signal is related to the thickness and composition of the atmosphere between the sensor and target [457–459]. UAV systems with high-resolution sensors can measure water quality without atmospheric impacts [460]. White caps, sun glare, wave motion, reflection, and refraction at the air-water interface hamper remote sensing imagery processing [297,461–464]. Refraction and reflection have little effect on radiation's trajectory when the sensor is at nadir to the water's surface. As the angle of incidence deviates from the nadir, reflected light increases, and refraction alters the light path [297]. Water waves alter the angle of incidence of light, leading to uneven reflection and

refraction across pixels and time in the image. Scholars limit reflection and refraction by not collecting data during strong winds and using a nadir sensor setup [465]. Additionally, vegetation density and bottom reflectance strongly affect shallow water reflectance signals. Internal reflection can affect shallow water nadir measurements [466]. The water column contribution to the measured profile rises with depth. Bathymetric data (referring to the depth of waterbodies) enhances water column correction.

4. Discussion

Since the 1970s, there has been a growing number of case studies on water quality monitoring and evaluation for lakes using remote sensing methods. The number of publications on this topic has particularly increased since 2008, which aligns with the introduction of freely available Landsat imagery. Since then, Landsat satellite sensors have been widely used for remote sensing lake water quality estimation due to their global availability and acceptable spectral, spatial, and temporal acquisition ratios. By utilizing remote sensing techniques, researchers can better understand the complex water systems and their impact on water quality. With the increase in remote sensing data availability, in situ data accessible for model calibration and validation has increased. Remote sensing has been used successfully to measure the majority of optically active water quality parameters, including chl- α , SSD, TSM, TUR, SS, and WT.

Recent advancements in remote sensing techniques have made significant progress in addressing these issues. Recent advancements in the technology have improved capabilities, but the issue of limited precision in broad spectral bands still persists. Remote sensing methods have become increasingly used in aquatic studies to overcome the shortcomings of in situ methods. The analysis of parameters obtained through remote sensing methods has enhanced the understanding of processes occurring in lakes. Remote sensing is cost-effective and time-efficient method used by researchers at local, regional, and global levels. It enables the surveying of fragile or hazardous sites while maintaining a single point of safety. Satellite remote sensing can analyze trends and deviations of indicators from long-term averages, identifying patterns of outbreaks, and predicting future water quality problems.

Remote sensing is a useful technique for studying water quality variations, but it faces several constraints. The main limitations regarding the retrieval of lake water quality using remote sensing are that calibration and validation of models require in situ measurements, and their applicability is limited to cloud-free conditions. Remote sensing methods, by themselves, have limited ability to measure absolute values, but rather indicate relative values where higher values of one parameter correspond to lower quantities of the other parameter. Additionally, the accuracy of extracted parameters may be questionable due to atmospheric correction or processing errors. Atmospheric corrections are crucial for accurate estimation of water quality parameters, but the lack of transferability between sensors and the influence of adjacent land areas hinders comparison. Atmospheric interference restricts optical signals from waterbodies, and some water quality parameters are not well investigated due to their weak optical characteristics and low signal-to-noise ratio, such as pH, TN, and TP. Current optical sensors' limited spatial, temporal, and spectral resolution restricts their use for water quality assessment. Furthermore, the cost of hyperspectral or airborne data and equipment for in situ measurement pose significant limitations. Chl- α , TSM, and CDOM have been the most researched parameters in lake water quality estimation by remote sensing so far, as seen from Table A1, Table A2, and Table A4. The optical complexities of inland waters also limit remote sensing applications – the differentiation between spectral signatures for these three parameters is challenging due to their influence on each other.

Based on conducted research and taken into account challenges and opportunities of water quality retrieval from remotely sensed data, AI/ML methods have shown superior accuracy in predicting water quality issues when compared to analytical, semi-analytical, empirical, and semi-empirical methods. Therefore, remote sensing monitoring system, combined with in situ measurements for validation and mathematical modeling using AI/ML methods, can be used to

retrieve a wide range of water quality parameters. This system enables users to monitor both direct and indirect factors that affect water quantity and quality.

The intention and motivation of the research for this review is the design and establishment of a lake water quality monitoring system, based (mainly) on data and results of remote sensing methods. Determining in situ measurements grid in a lake requires considering both qualitative and quantitative factors. Selection should be based on water changes, tributaries, drains, sewers, and related infrastructure, considering hydrological characteristics. This research emphasizes combining hydrodynamic model with remote sensing techniques to predict water quality in lakes. The integration of hydrodynamic modeling and remote sensing provides valuable data on spatial and temporal variations of water movement and circulation patterns. Hydrodynamic models provide input parameters like water velocity, currents, and circulation patterns, which contribute to understanding ecological processes in remote sensing data interpretation. The primary objective is to evaluate the benefits of combining hydrodynamic modeling and remote sensing data to improve comprehension and evaluation of water quality parameters, which can be applied to other research fields for better water resource management and environmental monitoring.

5. Conclusions

Modern remote sensing methods and databases are invaluable sources for obtaining historical data on lake ecological indicators, lakes that have not been extensively studied and lack in situ monitoring, resulting in significant data gaps. Experts in the fields of remote sensing and water management collaborate to improve knowledge about lake ecology by leveraging existing knowledge. Moreover, large scale, multi-temporal monitoring supports the analysis of spatiotemporal patterns of ecological indicators. Remote sensing techniques cannot guarantee the accuracy of in situ measurements in determining water quality parameters and are by no means intended to replace in situ measurements with any other means of collecting the same information. The integration of in situ measurements and EO data contributes to raster data collection in shorter time periods. This process, known as data densification, is crucial for better management of water resources.

This review provides a comprehensive overview of the bands, band combinations, and band equations used for different sensors at local and regional levels to measure eight water quality parameters. The information is based on an analysis of 131 references, which are listed in Tables A1-A8. It examines the various sensors and modeling techniques employed in previous studies to accurately estimate eight optically active biological and physical parameters through remote sensing, with validation conducted through in situ methods. Furthermore, remote sensing techniques enable the monitoring of temporal changes, both historical and prospective. Data from the past are analyzed to develop models that predict changes in parameter values for future periods. Models derived from remote sensing data require adequate calibration and validation using in situ measurements, and may only be utilized when there are no clouds present (for the visible and near and mid-infrared region of the electromagnetic spectrum). In other words, an integrated use of remote sensing, in situ measurements, and computer water quality modelling may result in a greater understanding of the water quality in order to gain a deeper understanding. Multitemporal data can be most effective when seasonality is included to capture spectrum variance and yield accurate findings. Remote sensing results can be used for quantitative analysis and comparison over space and time, as well as tracking slow, progressive changes in ecosystems by acquiring precise quantitative data. Four benefits of utilizing remote sensing in conjunction with other water quality monitoring systems are outlined by Kallio [224]: provides a comprehensive view of the entire waterbody for enhanced monitoring of spatial and temporal fluctuation; allows for a synchronized view of the water quality in a group of lakes across a large region; gives a detailed historical record of the water quality in a region and illustrates the resulting patterns; prioritizes sampling locations and surveying periods in the field.

In conjunction with conventional in situ sampling, remote sensing is the most efficient, cost-effective, and dependable method for monitoring water quality parameters in various waterbodies.

Depending on the type of model, mathematical water quality models can be used not only to simulate in situ data but also to estimate (predict) future water quality. This review suggests the integration of hydrodynamic modeling and remote sensing data, which can aid in decision-making for water quality management, identifying at-risk areas, planning monitoring strategies, and developing effective management interventions to mitigate water quality issues.

The main conclusion is that conventional measurements and remote sensing data collection methods are complementary, which helps address current limitations in monitoring waterbodies and their quality. Advancements in sensors, open data and software, and deep learning techniques will enhance the potential of remote sensing for monitoring standing waterbodies. It is recommended that lake ecologists, water managers, and authorities make use of remote sensing and its ability to provide a comprehensive view of lake properties. Therefore, the potential solution is that the future research should concentrate on (1) better detection of anomalies in water quality parameters, (2) better in situ measurements grid selection considering qualitative and quantitative factors based on hydrodynamic models, water changes, tributaries, drains, sewers, and infrastructure, (3) indirect estimation of non-optically active parameters using very high-resolution spectral data, and (4) AI/ML driven estimation of water quality parameters.

Supplementary Materials: Data sharing not applicable.

Author Contributions: Conceptualization, A.B. and A.K.; methodology, A.B. and A.K.; validation, A.B. and A.K.; investigation, A.B.; resources, A.B. and A.K.; writing—original draft preparation, A.B.; writing—review and editing, A.K.; visualization, A.B.; supervision, A.K.; project administration, A.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding

Data Availability Statement: Not applicable.

Acknowledgments: We express our sincere thanks to the reviewers and editors at the journal who provided comments on our paper, which helped us enhance its quality.

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

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