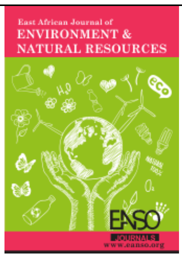

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Original Article

Remote Sensing-Based Water Quality Parameters Retrieval Methods: A Review

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ABSTRACT

Water quality is one of the sensitive global environmental issues, and it is broadly defined as the biological, chemical, and physical characteristics of water to be maintained to meet the needs of various water usages including drinking, irrigation and as an indicators of ecosystems health. It is often measured by a number of parameters, i.e., concentrations of chlorophyll-a, turbidity, total suspended matter, dissolved oxygen, nutrients, and harmful algae, etc. Laboratory analysis is used to measure and analyse water quality parameter, however, this approach is expensive, labour-intensive, time-consuming, and not suitable for large-scale analysis, while remote sensing methods is a cost effective and accurate methods of water quality monitoring with a high spatial and temporal resolution for large area of waterbodies. To this end, this review focused on novel findings of water quality evaluation using remote sensing method, and the result revealed that water quality parameters which are optically active (Chl-a, SDD, Water temperature, Water Turbidity, Total Suspended Matter, Electrical conductivity, Sea Surface Salinity and CDOM), and optically non active (DO, COD, BOD, TN, Ammonia Nitrogen and TP) can be retrieved by remote sensing technique. The resolution of the most used multi spectral and hyper spectral sensors of both satellite and non-satellite-born data sources are summarized in an effort to select for further research. Moreover, this review points out the most important retrieval algorisms (analytical, empirical, and artificial intelligence) have used in retrieving the water quality parameters. As a whole, remote sensing technique is a permissible method for water quality valuation across the world in its spatio-temporal coverage, accuracy, and its cost effectiveness.

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INTRODUCTION

Monitoring water quality (WQ) in aquatic environments is critical for the proper management of water resources to guarantee a sustainable use (Pizani1 and Maillard, 2022). It is also a means to get an insight on the dynamics of the surrounding human activities (Odermatt et al., 2008). The quality of these environments can be determined through their physical, chemical, and biological characteristics which will be addressed as WQ "parameters" (Gholizadeh et al.,2016). water quality parameters can be analysing in laboratory, and it also offers high accuracy, but it is expensive, labour-intensive, time-consuming, and not suitable for large-scale analysis (Pizani1 and Maillard, 2022). Moreover, the conventional methods are not easily able to identify the spatio-temporal variations in water quality which is vital for comprehensive assessment of water quality (Liu et al., 2003).

With advancement of remote sensing techniques, water quality evaluation is possible in more effective way for large scale water bodies regions that suffer from qualitative data problems due to conventional methods. In hence, remote sensed data have empowered the abilities of researchers and water managers to monitor water quality in more effective way. These techniques involve the use of satellite imagery, aerial photography, and other technology to collect data about water bodies from a distance. The method has been used since the 1970s and is still often used to obtain water quality indicators in water quality assessments in the modern world (Giardino et al., 2014).Various parameters such as chlorophyll-a concentration, water turbidity, and total suspended solids can be retrieved using satellite imagery. This is done by analysing the reflectance properties of the water surface, as different substances exhibit unique spectral signatures. Given the importance of remote sensing techniques for water quality estimation, reviewing remote sensing-based water quality estimation techniques is very critical for sustainable management of water resources. Hence, this review summarizes different information related to remote sensing sensors used for water quality retrieval, water quality parameters, and the mainly used retrieval algorithms for specific water quality variables.

METHODOLOGY

Published papers on remote sensing-based water quality evaluation were searched in English language on different sources like Web of Science and Scopus using the terms "water quality evaluation" and "remote sensing" as topic, and then papers on evaluation of water quality using remote sensing methods have been collected, and then a detailed check was done by scanning the collected papers. Then after, water quality parameters are identified using selected papers, and the type of sensors, retrieval algorisms and selected water quality parameters were also tabulated using the obtained information.

FINDINGS AND DISCUSSION

Importance of Remote Sensing for Water Quality Evaluation

Water is made up of molecules that contain a wide variety of organic and inorganic, living and non-living, suspended solids and dissolved components. While a larger portion of incident solar radiation or other light penetrates the water column itself and begins to interact with both suspended and dissolved matter within the water, the remaining portion is reflected off the surface of the water body as a remotely sensed signal (Figure 1) (Kirk, 1994). According to Schott (2007), surface reflectance is the ratio of light leaving the water's surface upward to sunlight entering the surface. According to Chen et al. (2015) water quality can be estimated by calculating the concentrations of constituted matter based on the spectrum of light reflected and scattered from the water column determined by remote sensing. To evaluate the optical properties of the water, the "atmosphere correction"

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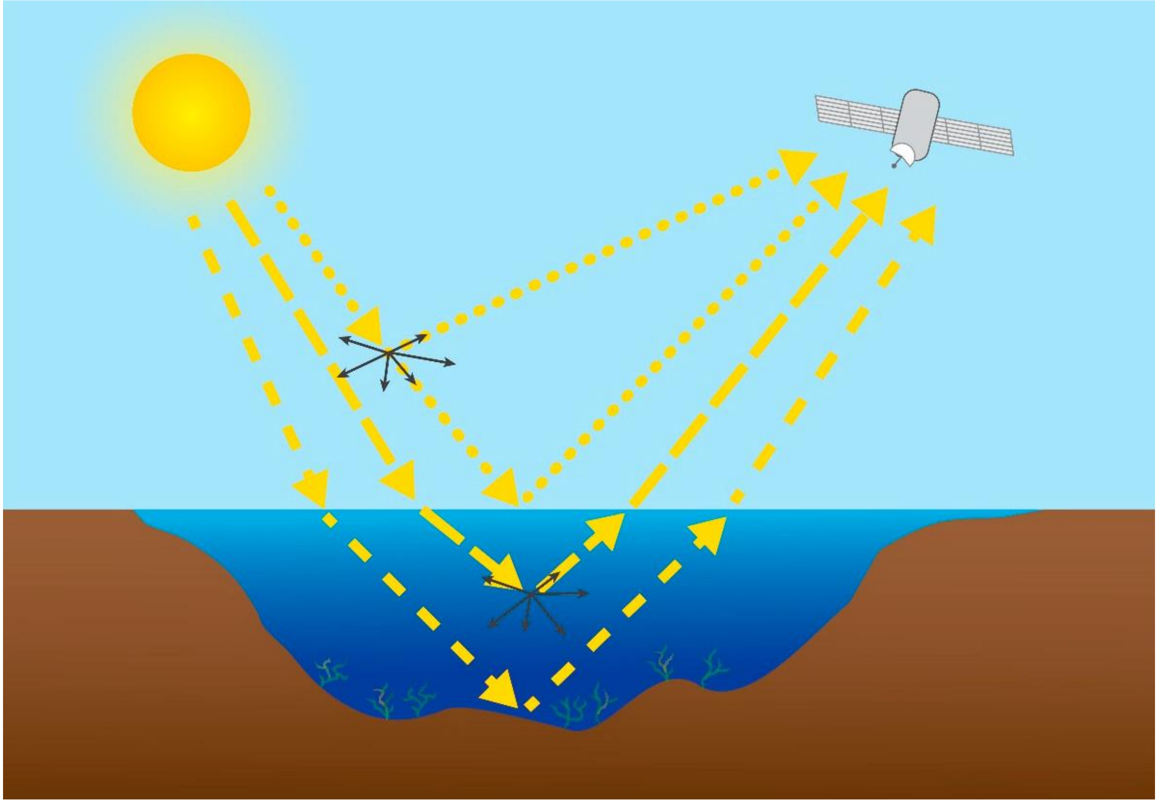
approach must be applied in order to take the atmosphere and sun glare into consideration.

Figure 1: Diagram showing the electromagnetic spectrum's passage between a sensor, a body of water, and the Sun



Source: Adopted from Batina and Andrija (2023)

The Potential of Remote Sensing for Water Quality Monitoring

Remote sensing-based water quality monitoring techniques began in the early 1970s, and offer a clear possibility to solve the shortcomings of traditional water quality monitoring (Bazel et al., 2021). The development of new remote sensing techniques has been aided by the increased interest in creating long-term environmental monitoring programs. This is primarily due to the technology's capacity to offer a perspective that cannot be obtained by any other means (Haibo et al., 2022). The advancement of remote sensing techniques, particularly the introduction of hyper-resolution satellites, has made possible for long-term and large-scale water quality monitoring with quick way (Haibo et al., 2022). The use of remotely sensed data in aquatic ecosystem monitoring has taken numerous forms, including the measurement of river system flow velocity, hydrologic recharge, volumetric storage fluctuation rates, and hydrologic connectivity (Pavelsky and Smith, 2009). For the purpose of researching water quality trends and the possible effects of changing land use and land cover on water quality, a number of remote sensing projects offer historical data. Moreover, future water quality monitoring will make greater use of remote sensing techniques due to ongoing advancements in satellite and sensor technologies (Dekker and Hestir, 2012).

Water Quality Parameters

There are three types of water indicators included in a conventional water quality monitoring system: chemical indices (such as pH, DO, COD, BOD, TOC and, heavy metal ion etc.), physical indices (such as temperature, turbidity and electrical conductivity), and microbiological indices (such as total bacteria and total coli

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forms). Water quality indicators can be divided into optically active and non-active factors based on remote sensing techniques (Table 1).

Optically Active Constituents

Optically active constituents (OACs) are substances that can affect the polarization or rotation of light passing through water, and they include chlorophyll a (and other phytoplankton pigments), suspended particulate matter, turbidity and CDOM which affect the radioactive transfer process of the spectrum of light.

Chlorophyll-A

Chlorophyll-a is a type of chlorophyll pigment found in plants, algae, and cyanobacteria. In water, chlorophyll-a can be found in aquatic plants and algae, where it helps them to capture and use light energy for photosynthesis (Kutser, 2009). High concentrations of Chlorophyll-a in water can indicate eutrophication, a process in which excess nutrients such as nitrogen and phosphorus cause excessive growth of phytoplankton. This can lead to algae blooms, oxygen depletion, and ecosystem disruptions (Zhou et al., 2018). Hence, monitoring Chlorophyll-a levels in water bodies can help researchers and environmental authorities to assess water quality, identify sources of pollution, and implement management strategies to protect aquatic ecosystems. In water bodies with low phytoplankton biomass levels, the chlorophyll-a spectrum is characterized by a sun-induced fluorescence peak around 680 nm. This peak is typically associated with the presence of phytoplankton containing chlorophyll-a, which is a pigment involved in photosynthesis and gives plants and algae their green colour (Gower, 2004). In eutrophic water bodies with high biomass levels, the fluorescence signal of Chlorophyll-a can be difficult to detect due to the presence of absorption features and backscatter peaks at specific wavelengths. Specifically, these absorption features and backscatter peaks are centered at 665 nm and 710 nm, respectively, which can interfere with the accurate measurement of Chlorophyll-a levels using traditional spectrophotometry methods (Matthews et al., 2012). To address this challenge, researchers have developed alternative methods that utilize the ratio between these two wavelengths (665 nm and 710 nm) to accurately determine the amount of Chlorophyll-a present in the water. The Band ratio model, first order differential model (Rundquist et al., 1996), three-band model (Gitelson et al., 2008), and machine learning model (an empirical neural network) can all be used to determine the concentration of Chl–a.

Total Suspended Matter

Total suspended matter (TSM) is the concentration of solid particles that are suspended in water bodies, such as rivers, lakes, or oceans. These particles can include silt, clay, organic matter, and other debris that remains suspended in the water column rather than settling to the bottom (Hou et al., 2017). TSM levels are often used as an indicator of water quality, as high concentrations can affect the clarity of the water, interfere with light penetration, and affect aquatic organisms. According to the available literatures, Total suspended matter (TSM) concentrations estimated from remote sensing data have been correlated with various optically inactive water quality indices in order to estimate concentrations of phosphorus, mercury, and other metals in water bodies. Therefore, remote sensing technique involves using satellite or aerial imagery to remotely sense the levels of TSM present in the water, which can serve as a proxy for other water quality parameters and pollutants (Chen et al., 2015).

Turbidity

Turbidity is an optically active water quality parameter that indicates the presence of particles in the water column that can provoke the scattering or absorption of light (Avdan et al., 2019). The source of particles can be matter of phytoplanktonic origin (Sabat-Tomala et al., 2018) and materials of mineral origin from soil erosion (Menken et al., 2006). High levels of turbidity have an impact on clarity of the water,

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interfere with light penetration, and affect aquatic organisms (Quang et al. 2017). Indeed, turbidity detection assumes great significant importance for aquatic ecosystems management. Because, it can scatter and absorb light, affecting the penetration of sunlight into the water column (Dekker and Hestir, 2012). Reflectance at 700 nm is commonly used to derive turbidity from remotely sensed signals. This is because the reflectance at this specific wavelength is sensitive to the presence of suspended particles and can be a good indicator of turbidity levels in water bodies (Hicks et al., 2013). These turbidity measurements can provide important information about water quality, sediment transport, and ecological dynamics. Literature indicates that a good accuracy in turbidity prediction is possible using visible bands (Liu et al., 2019) and the combination of visible and infrared bands (Alparslan et al. 2010). Good results are described with both empirical and analytical models but the choice of spectral regions for the development of turbidity estimation algorithms may also be dependent on the season, especially in eutrophic environments (Dekker and Hestir, 2012).

Secchi Disk Depth (SDD)

The water transparency assessment represents an important factor in the monitoring and management of water resources. Remote sensing technology allows for the collection of information about water transparency over large spatial areas in a cost-effective and non-invasive manner. By analyzing data obtained from satellites, drones, or other remote sensing platforms, researchers can assess changes in water transparency levels in lakes, rivers, coastal areas, and other water bodies over time (Lee et al., 2015).Various remote sensing techniques can be used to estimate water transparency, including measuring the reflectance of specific wavelengths of light, such as near-infrared or red spectrum bands, or using algorithms to derive water transparency values from satellite imagery. This information is crucial for understanding the health of water bodies, managing water resources, and implementing conservation efforts to protect and restore aquatic ecosystems (Liu et al., 2019). Studies that measure SDD from optical sensors like MSI and OLCI sensors have also a relatively high level of success in part because SDD is a direct consequence of all optical characteristics of water and the elements it contains (Underberg et al. 2020). The literature that is currently available demonstrated that SDD can be estimated using visual spectral bands and various band ratios (Alparslan et al. 2010).

Water Temperature

Since temperature controls chemical, biological, and physical processes in water, water temperature (WT) is a crucial parameter for both air-water interactions and the physical and biological activities that take place in the water. Because of this, WT is one of the one of the key indicators of the health of aquatic ecosystem (Gholizadeh et al., 2016). The solubility and consequent availability of different chemical constituents in water are influenced by water temperature. The most significant impact of this parameter is on the concentrations of dissolved oxygen in water, since rising water temperatures cause a decrease in oxygen solubility. Remote sensing can provide accurate surface WT measurements, and water temperature parameter retrieval using remote sensing techniques has been an active area of research in recent years. Satellite-based remote sensing platforms equipped with thermal sensors can provide valuable information on water surface temperature over large areas and at regular intervals. These sensors measure the emitted thermal radiation from the water surface, which is correlated with water temperature. To retrieve water temperature from remote sensing data, various algorithms are employed that utilize the relationship between surface temperature and the captured radiance values. These algorithms incorporate atmospheric correction, which accounts for the interference of atmospheric conditions on the thermal signals (Batina and Krtalic, 2023). These data are crucial for understanding the thermal dynamics of aquatic ecosystems, assessing the impacts of climate

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change, and managing water resources effectively.

Coloured Dissolved Organic Matter (CDOM)

Coloured Dissolved Organic Matter (CDOM) refers to the fraction of dissolved organic material in water that absorbs light in the visible spectral range, giving it a yellow to brown colour, and it is a key component of the dissolved organic carbon (DOC) pool in aquatic ecosystems and plays a significant role in water quality, biogeochemical processes, and the optical properties of water. (Chen et al., 2017). DOC can originate from either an autochthonous source, which is derived from algae or aquatic plants that break down in surface water, or an allochthonous source, which is derived from sources outside the system, such as soils or terrestrial plants (Kritzber et al. 2004). According to Coelho et al. (2017), CDOM is a significant WQ indicator that affects the water's potability (Chen et al., 2017). Its ability to absorb solar radiation also serves as an indirect defence against pathogenic organisms by causing photochemical reactions that happen when light and water interact (Kutser et al., 2005). The presence of CDOM in an aquatic environment can provoke its brownification, a phenomenon causing the water to acquire a yellow/brown tint as a response to the high concentration of organic matter. Remote sensing techniques can be used to estimate CDOM concentrations in water bodies by measuring the light absorption properties of the water. CDOM absorbs light predominantly in the blue wavelength spectrum, so analysing remote sensing data in this range can provide information on the distribution and concentrations of CDOM in aquatic environments (Carvalho et al., 2013). Monitoring CDOM concentrations through remote sensing can help scientists better understand the dynamics of organic matter cycling in aquatic ecosystems, assess water quality parameters, and study the impacts of climate change and human activities on water bodies. In turn, this information can support resource management decisions, biodiversity conservation efforts, and the development of strategies to protect and restore water quality in lakes, rivers, and coastal areas. The phenomenon can negatively affect the quality of the water by changing the amount of nutrients, the pH, the thermal stratification, and the whole food chain. Unlike TSM or chl-a, there are no recognized specific spectral band associated with CDOM. However, the visible absorption bands (blue and green) associated with other bands (red edge, NIR) is important to increase chances of producing good estimates (Hestir et al., 2015).

Optically Inactive Constituents

In addition to optically active water quality parameters, there are optically inactive water constituents that can affect the optical properties of water bodies. Optically inactive water quality parameters do not directly affect the reflectance or absorption of light in water (Gholizadeh et al., 2016). According to the same author, these constituents do not absorb or scatter light in the visible and ultraviolet spectrum, but they can still impact the overall optical characteristics of water. Some examples of optically inactive water constituents include inorganic nutrients like nitrates, phosphates, and silicates can impact the growth of algae and other aquatic plants, altering water clarity and the availability of light for photosynthesis. In addition to inorganic nutrients, minerals and dissolved salts such as calcium carbonate or gypsum, and microorganisms like bacteria, viruses, and other microorganisms in water are typically optically inactive but can influence water quality and ecosystem health. Remote sensing techniques can help scientists study the relationships between optically inactive and optically active water constituents by measuring the spectral reflectance properties of the water column and developing models to estimate the concentrations of different constituents (Isenstein and Park, 2014). By monitoring these relationships over time and space, researchers can gain insights into the sources and dynamics of organic and inorganic matter in aquatic environments and assess the impacts of environmental changes on water quality and ecosystem health.

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Estimating the concentration of optically inactive constituents in water using retrieval algorithms based on relationships with optically active water constituents is a common approach in remote sensing studies. According to Song et al. (2011) and Yang et al. (2012), there is a strong relation between the concentrations of TN and TP and the optically active water quality measures, such as TSS, SDD and chl-a.

Table 1: The most often used remote sensing technique to measure the qualitative characteristics of water

Water quality parameter	Abbreviation	Units	Optical activity
Chlorophyll-a	Chl-a	Mg/l	active
Secchi Disk depth	SDD	M	»
Water temperature	WT	^{0}c	»
Turbidity	TUR	NTU	»
Total amount of Suspended Matter	TSM	Mg/l	»
Electrical conductivity	EC		»
Sea Surface Salinity	SSS	PSU	»
Coloured Dissolved Organic Matter	CDOM	Mg/l	»
Total amount of Organic Carbon	TOC	»	»
Dissolved amount of Oxygen	DO	»	inactive
Chemical Oxygen Demand	COD	»	»
Biochemical Oxygen Demand	BOD	»	»
Total of Nitrogen	TN	»	»
Ammonia	NH3-N	»	»
Total of Phosphorus	TP	»	»
Soluble reactive phosphorus	PO4	»	»

Available Data Sources for Remote Sensing Water Quality Retrieval

Observing sensors can be broadly classified into two groups according to the platforms they are located on. Airborne sensors are mounted on a platform inside the Earth's atmosphere (such as a boat, balloon, helicopter, or aircraft), whereas spaceborne sensors are delivered to areas outside of the atmosphere by a spacecraft or satellite. These sensors use different technologies to gather data on various indicators of water quality, such as chlorophyll-a concentrations, turbidity, and suspended sediment levels. Understanding of various sensors' characteristics is important for selecting the right sensor for the specific studies. Indeed, a variety of airborne and satellite-based remote sensing systems that are frequently employed in water quality s are listed, along with their spectral characteristics (*Table 2*).

Satellite-Borne Remote Sensing Data

Multispectral Data

Multispectral data typically consists of a few discreet spectral bands (usually ranging from 3 to 30 bands) across the visible and near-infrared spectrum. These bands can be used to estimate water quality parameters such as chlorophyll-a concentration, turbidity, and suspended solids. By analysing the reflectance values at specific bands, mathematical models can be developed to correlate these values with the desired water quality parameters. Multispectral data such as MSS, TM, ETM+, OLI, ESA's Sentinel-2, ENVISAT MERIS, France's SPOT satellite data, NOAA's AVHRR, and China's GF series are accessible for remote sensing water quality retrieval (Batur and Maktav, 2018). For example, Landsat series and sentinel data are most used multispectral Data for water quality evaluation due to its fine resolution (Vakili and Amanollahi, 2019; Wang et al., 2019).

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Hyperspectral Data

Hyperspectral data provides a much higher spectral resolution than multispectral data, typically consisting of hundreds of narrow contiguous bands across the electromagnetic spectrum. This detailed spectral information allows for more accurate and precise retrieval of water quality parameters. Hyperspectral data can be used to estimate specific water quality parameters such as chlorophyll-a, dissolved organic matter, and mineral content (Yang et al., 2022). The ability of hyper spectral data to define surface features with a higher spectral resolution led to recent scholars can retrieve water quality parameters with the application of hyper spectral imagery (Hestir et al., 2015).

Table 2: Satellites that can be used to remotely sense and retrieve water quality data

	Satellite Sensor	Launch Date	Spatial resolution (m)	Spectral Resolution Band	Temporal Resolution (Day)
Multi-spectral	NIMBUS-7 CZCS	1978.10	825	6	6
	Landsat-5/7/8/9	1984-2020	30	5	16
	SeaWiFS	1997.8	1130	8	16
	NOAA-16AVHRR	2000.10	1100-4000	6	9
	EO-1 AL1	2000.11	10	9	16
	WorldView-2/3	2009/2014	1.85/1.24	8	1.1
	MERIS	2002.3	300-1200	15	1
	MODIS	1900.12	250-500-1000	9	0.5
	Landsat-8 OLI	2013.2	30	7	16
	Sentinel-2 A	2015	10	13	5
	Sentinel-3A/ OLCI	2016	300-1600	21	27
	Sentinel-2 B	2017	10	13	10
	Sentinel-3B	2018	300-1200	21	4
Hyper-spectral	HY-1A COCTS	2002.5	1100	10	3
	PROBA CHRIS	2001.10	18-36	19	7
	Hyperion	2000.11	30	42	16
	HJ-1A HSI	2008.9	100	128	4
	MICO	2009.9	100	128	10
	VIRS	2011.10	375-750	22	0.5
	OHS	2018.4	10	32	2
	GFS-AHSI	2018.5	30	330	3
	ZYI-02D	2018.9	30	166	3
	ZK-VNR-FPG4S0	/	0.09	270	/
	Gala Sky-mini	/	0.04	176	/

Non-Satellite Remote Sensing Data

Non-satellite remote sensing techniques can be used for water quality parameter retrieval in addition to satellite remote sensing data. By using sensors mounted on aircraft or drones, airborne remote sensing can provide detailed spatial information and better temporal resolution compared to satellites. With the advancement of UAV technology, light and compact UAV systems with multispectral cameras, high spectrometers, infrared sensors, and Lidars are useful and efficient for managing water management (Ouma et al., 2018). Airborne photography can be used to collect water quality parameters using methods and algorithms that are similar to those used in satellite remote sensing, such as spectral analysis and mathematical models. For instance, the 48-channel Compact Airborne Spectrographic Imager (CASI) from Canada utilized for monitoring aquatic environment. When combined, shortwave infrared (SWIR) and near infrared (NIR) can enhance applications, even though they are primarily utilized for turbid and clear waters separately (Liu et al., 2019). In addition, ground-based remote sensing techniques involve collecting data from the water surface or near-

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shore areas using handheld sensors and spectroradiometers can be used for monitoring water quality parameters in specific locations. They are particularly useful for studying near-shore environments, littoral zones, and small water bodies. Ground-based remote sensing data can be processed using similar techniques as satellite or airborne data for water quality parameter retrieval.

Water quality retrieval algorithms and modelling approaches

Retrieval algorithms can be created using a variety of methods, such as radiative transfer theory-based spectrum additive models or straightforward empirical relationships between radiant reflectance at particular wavelengths and in situ samples (Politi et al., 2015). The basic principle of the inversion of water quality by remote sensing approaches is the combination of in situ data from water quality monitoring with similar remote sensing imagery for model establishment. Retrieval techniques are used to determine the concentration of a water quality parameter from the spectrum of water-leaving radiance that was captured by the sensor. The parameters of water quality can be extracted from remote sensing data using a variety of modelling techniques and algorithms. Here are some commonly employed methods (Table 4).

Empirical Models

Empirical algorithms are developed by the construction of statistical correlations between water quality parameters and remotely sensed data. Empirical methods require in situ data on each water quality indicator in order to build a statistical relationship between the reflectance of spectral bands and the concentration of constituents at the moment of picture acquisition (Olmanson et al., 2015). The training dataset used by these algorithms typically consists of remote sensing data that correlates with field observations of water quality indicators. The program then makes use of this training dataset to establish a mathematical connection between the goal water quality metric and the observed spectral signatures. Then, the inversion method is developed utilizing statistical analyses between the water quality indicators and specific characteristic bands or band combinations (Cheng et al., 2015, Zhou). Apart from exclusively empirical methods, there exists an additional category of empirical models known as Semi-empirical methods, which integrate both analytical and empirical techniques (Keller, 2001). Measured and statistical spectrum analysis is necessary for semi-empirical models (Li, 2009). The semi-empirical approach combines observed parameter concentration with waterbody reflectivity, improving the parameter's spectrum characteristics and reducing optical parameter noise while also offering physical significance and ease of use (Keller, 2001). Even if a significant quantity of in situ measurable data limits the temporal and spatial application of semi-empirical models, they are nevertheless more generalizable than fully empirical ones. As a result, they are frequently used to evaluate parameters like Chl-α, TSM, CDOM, SDD, and TUR (Hunter et al., 2010; Yang et al., 2022).

Analytical Methods

Analytical algorithms are mathematical models or equations that directly relate the spectral reflectance properties of water to the concentrations of optically active constituents by simulating light propagation in the atmosphere and water bodies using radiation transmission models and bio-optical models (Yang et al., 2022). These algorithms are typically based on empirical relationships derived from field measurements and calibration. According to Batina and Krtalic (2023), the analytical technique, also known as the physical method, requires theoretical analyses of spectrum data rather than statistical studies like the empirical and semi-empirical methods. With the use of extensive in situ data and well-established parameter properties, the analytical method's physical mechanism can concurrently identify all water parameters (Gholizadeh et al., 2016). Its portability is also good, but there are obstacles to its widespread adoption (Keller, 2001) and it

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needs a very accurate measuring instrument. In models that are strictly analytical, the inverse equation is parameterized. Thus, semi-analytical models—which parameterize the inverse equation using in situ observations—are the primary class of physics-based algorithms developed for inland water quality remote sensing retrievals (Matthews, 2011). This modelling technique is based on the reflectance approximation developed by Morel and Prieur (1977), who studied turbidity and chlorophyll in ocean waters (Batina and Krtalic, 2023). This type of algorithms combines radiative transfer models with empirical relationships to estimate water quality parameters. These algorithms consider about the natural visual characteristics of water. and use physical models to simulate the light interaction with the water column. Semi-analytical algorithms recover the optical characteristics from measured remote sensing data and utilize empirical connections to relate them to the desired water quality parameter. The NASA MODIS algorithm for chlorophyll-a retrieval is an example of a semi-analytical algorithm. Wang et al. (2019) state that optically active parameters such chl-α, TSM, CDOM, and SDD are primarily retrieved using semi-analytical and analytical approaches. Dekker (1991) has also developed applications of semi-analytical models to looking through the same parameters across large spatiotemporal scales.

Machine Learning Models

New techniques for data analysis have been made available by improvements in processing capacity and data availability, enabling the estimation of water quality parameters at a range of spatiotemporal scales. Therefore, in the field of retrieving water quality, machine learning methods such as support vector machines, random forests, and neural networks are becoming more and more common (Chang et al., 2014; Lary et al., 2016; Lin et al., 2018; Hafeez et al., 2019). Machine learning techniques can handle complex relationships and non-linearities in the data, offering potentially improved accuracy and robustness. These methods use large datasets of in situ measurements to train models to predict water quality parameters.

In order to avoid overfitting, machine learning techniques require the availability of separate training and testing datasets with representative samples of the pertinent parameters. Most machine learning algorithms' scalability and power are dependent on the calibre and volume of training and testing data. With the correct inputs, these algorithms can provide generalizable models that capture complex, non-linear relationships between bio-geophysical variables and remotely measured reflectance. Xiang et al. (2021) discovered that machine learning yielded 20% higher classification accuracy for trophic states than multivariate regression.

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Table 3: Details of the more often used aerial sensors for assessing water quality

Types of Sensors		Number of Bands	Spectral Range (μm)	Resolution (m)
Multispectral	MIVIS	102 VIS/NIR (28), MIR (64)	TIR (10) VIS (0.43–0.83), NIR (1.15–1.55), MIR (2.0–2.5) TIR (8.2–12.7)	3 to 8 depending on altitude
	MSS		0.42–14.00	25
Hyperspectral	AVIRIS	224	0.40–2.50	17
	HYDICE	210	0.40–2.50	0.8 to 4
	HyMap	128	0.40–2.50	3 to 10
	APEX	Up to 300 VIS/NIR (114), SWIR (199)	VIS/NIR (0.38–0.97), SWIR1 (0.97–2.50)	2 to 5
	CASI-1500	Up to 228	0.40–1.00	0.5 to 3
	EPS-H	VIS/NIR (76), SWIR1 (32), SWIR2 (32)	TIR (12) VIS/NIR (0.43–1.05), SWIR1 (1.50–1.80), SWIR2 (2.00–2.50), TIR (8–12.50)	Dependent upon flight (min 1 m)
	DAIS 7915	VIS/NIR (32), SWIR1 (8), SWIR2 (32), MIR (1), TIR (12)	VIS/NIR (0.43–1.05), SWIR1 (1.50–1.80), SWIR2 (2.00–2.50), MIR (3.00–5.00), TIR (8.70–12.30)	3 to 20 depending on altitude
	AISA	Up to 288	0.43–0.90	1

Table 4: Satellite sensors and water quality retrieval algorisms

Satellite/remote sensing data	Water quality parameters involved	Algorithm used	Sources
MODIS/Aqua	salinity, temperature, CDOM	Polynomial regression	Wouthuyzen al., 2020
MERIS	Chlorophyll-a	MLP	Martinez et al., 2020
GEE	DO, temperature, salinity, Chl-a, and Ph	Random Forest	Yniguez and Ottong, 2020
Landsat-8	Chl-a, TP, TN	Artificial Neural Network, Random Forest and k-nearest neighbour	Yniguez and Ottong, 2020
Sentinel-2	TP, TN, COD	Artificial Neural Network followed by Random Forest	Guo et al., 2021
Sentinel-3/OLCI	Chlorophyll-a	Hierarchical Bayesian Spatio-temporal modelling	Myer et al., 2020
MODIS/Aqua	Chlorophyll-a	Linear Regression	Abbas et al., 2019
Landsat 8/OLI	Chlorophyll-a	Support Vector Machine	Peterson et al., 2020
SMOS	Water temperature and salinity	Random Forest	Ruescas et al., 2018
Sentinel-2A	Chlorophyll-a, TSS	Random Forest	Qasem et al., 2022
Landsat-8, Sentinel-2	Dissolved Oxygen and turbidity	Support Vector Machine regression, Multiple Linear Regression and Extreme Learning Machine	Peterson et al., 2020
Sentinel-2	Microphytobenthos	Random Forest	Martinez et al., 2020

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Satellite/remote sensing data	Water quality parameters involved	Algorithm used	Sources
VIIRS	Chlorophyll-a	In comparison to in-situ data, RF has a greater accuracy on satellite observations	Park et al., 2020
GEE	DO, temperature, salinity, Chl-a, and p	RF bestowed significant accuracy	Martinez et al., 2020
SeaWiFS	Chlorophyll-a	Support Vector Machine	
Landsat-5-8	TSS, Chlorophyll-a, turbidity	Artificial Neural Network	Hafeez et al., 2020
MODIS	Chlorophyll-a	Random Forest	Chen et al., 2019
MODIS/Terra	Turbidity, temperature	Artificial Neural Network	Chen et al., 2019
SeaWiFS, MERIS,	Chlorophyll-a, temperature	Extremely Randomized Tree overperform Random Forest	Park et al., 2019
Landsat 8/OLI	Chlorophyll-a, TP	Multiple Regression was reported significant	Lim and Choi, 2015
Sentinel-3/OLCI	CDOM, TSS	Support Vector Machin and Random Forest	Ruescas et al., 2018
MODIS/Aqua	Water temperature	Artificial Neural Network	Sunder and Ramakrishnan, 2017
MODIS/Aqua	Chlorophyll-a, Total Nitrogen, SDD	Artificial Neural Network	Chang et al., 2017
MODIS	Chlorophyll-a	Support Vector Machin	Wattelez et al., 2016
GOCI	TSS and CDOM	Support Vector Machin	
MERIS, MODIS	Chlorophyll-a	SVM combine with Linear, polynomial, RBF, sigmoid regression analysis improves the precision of the algorithm	Davila and Zaremba, 2016
VIIRS	temperature, salinity, Chlorophyll-a	Multiple Linear Regression	Park et al., 2019
Landsat-5/TM	suspended solids	Support Vector Machin	Park et al., 2019
MODIS	TP	Artificial Neural Network	Chang et al., 2017
MERIS	Suspended solids, Chlorophyll-a	Support Vector Machin	Tang et al., 2019
SeaWiFS	orthophosphate, silicate, salinity, temperature	Multiple Linear Regression	Green and Gould, 2008
SeaWiFS	CDOM, suspended solids, temperature, salinity	Multiple Linear Regression	Green and Gould, 2008
MODIS	Chl-a	Convolutional Neural Network	Yu B et al., 2020
Landsat-8, GEE, Sentinel-2	Water turbidity, TSS, Total phosphorus	Support Vector Machin	Govedari and Yakovlev, 2019

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CONCLUSION

Increasing stresses on aquatic ecosystems all over the world have generated the need for cost effective and quick water monitoring techniques. Hence, with space science has advanced and computer applications have become more widely used, remote sensing-based water quality monitoring have been practiced across the world, and has proven to give better results in both temporal and spatial scale. This review summarizes the space-born and airborne data sources, retrieval algorithms and water quality parameters. Furthermore, the review showed that a variety of multispectral and hyperspectral data, are frequently utilized in water quality evaluation and offer adaptable and effective solutions that address the need for water quality analysis using higher resolution sensors.

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