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Application of Satellite Data on Water Pollution: An Intensive Review

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ABSTRACT. Evaluation of water pollution is a priority work nowadays. The signature of the waterbody reveals its excellence or mediocrity and reflectance that can measure by a sensor used to analyse the health status of the waterbody. The remote sensing analysis has become the latest state of art technologies for monitoring large-scale waterbodies. High-resolution satellite data are now available to estimate water pollution through various water quality parameters like clarity, chlorophyll, suspended solids, turbidity, temperature, salinity, organic matter, etc. In this review study, a special emphasise has been given to the various satellites like Landsat, sentinel, satellite pour l'Observation de la terre (SPOT), moderate resolution imaging spectroradiometer (MODIS), medium resolution imaging spectrometer (MERIS), Indian remote sensing satellites (IRS) and its application on water pollution. Availability of satellite data, algorithms, and models to assess water quality has also been reviewed in detailed. The review suggests development and innovation in satellites, sensors and techniques to assess the non-optically active constituents of water quality for better understanding and management of water pollution.

Keywords: optically active parameters, remote sensing, sensors, sewage, water quality

1. Introduction

Water is an essential resource among all-natural resources. In spite of 70% of the earth's surface being covered by water, nearly 1.2 billion people live with chronic water shortages (UNESCO, 2017). Due to the drinking of unsafe water, 3.2 million children die every year (Dakkak, 2016). Waterbodies are getting polluted due to the discharge of sewage across the world (Nakate, 2019). Sewage pollution is considered a significant threat to human beings as well as the environment (Denchak, 2018). Sewage is basically wastewater produced due to the use of water by human activities (UNESCO, 2017). Due to the growing rate of demand for water, sewage generation and overall pollution load are also increasing across the world. Due to rapid urbanization (Bhardwaj, 2005) and industrialization, the ocean, estuaries, river, lakes, ponds and other waterbodies are receiving a huge load of sewage, and industrial effluent every day. Uncontrolled use of pesticides and fertilizer for agriculture practices are also accountable for the deterioration of water quality (PERMACULTURE, 2017). Discharge of fertilizer residues in waterbody can increase the nutrient concentration and allows microbes to proliferate; as a result, waterbodies are facing a massive challenge in terms of eutrophication, algal growth, increase of disease-causing microorganisms (Nakate et al., 2018). The poor condition of sanitation facilities has a major contribution to water pollution (WHO, 2022). Developing countries are facing enormous challenges in the management of sewage or industrial effluent (Dakkak, 2016). It is reported that in India, 72,368 million litres (MLD) of sewage is used to generate per day, but only 22,963 MLD is being treated (CPCB, 2021). Untreated sewage is not only harmful to surface waterbody but it affects the groundwater also (CPCB, 2021). It is reported that 75~80% of surface water is getting contamination by domestic sewage (CPCB, 2021).

Remote sensing technology is an advanced technique to assess water quality efficiently. The water has certain physical, chemical, and biological characteristics that can address the quality of the water (Sagan et al., 2020). Water quality like clarity (similar to Secchi depth), chlorophyll concentration, suspended solids (SS)/sediment, coloured dissolved organic matter (CDOM), trophic status, sea surface temperature (SST), and sea surface salinity (SSS), etc. can be effectively assessed and monitored through the optical remote sensing. This technology also provides temporal data that is helpful to assess the periodic changes and spatial extent of contamination in the waterbody. Characteristics of waterbody can be measured based on their reflection in different spectral bands of the satellite. As certain pollutants react differently with the selective range of the electromagnetic spectrum and produced significant signatures on satellite images have huge potential to study water pollution. Critical analysis of those signatures with the help of the state of software, algorithms, models, and field data can be helpful to identify the various parameters and their dynamics (Shirke et

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al., 2016; Nakate et al., 2018). Several satellites with different resolution capacities are available to assess water pollution (Usali and Ismail, 2010; Morozov et al., 2015). Therefore, a review study has been carried out to understand the effectiveness of remote sensing techniques for the assessment of water pollution considering satellites, sensors, methods, equations, and algorithms. The procedure of the water quality assessment through remote sensing technique that has been reviewed, described through a suitable flowchart (Figure 1).

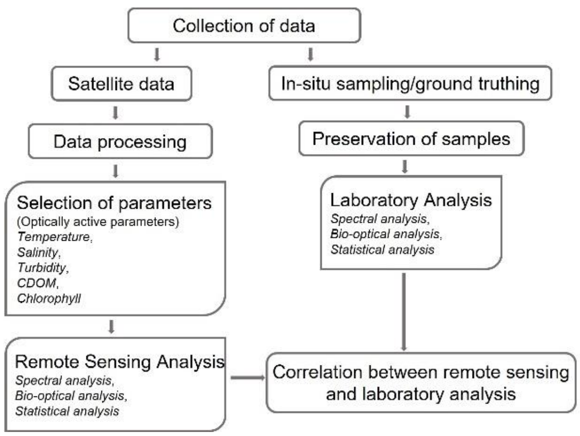

Figure 1. Flow chart for assessment of water quality using remote sensing technique.

2. Water Pollution Assessment and Remote Sensing

To assess water pollution, physicochemical and biological parameters water quality indicators (Gholizadeh et al., 2016) are required to be checked. The traditional method of data collection is only possible for specific locations, while in the case of large-scale studies, spatial and temporal information are difficult to collect and monitoring (Ritchie et al., 2003). There are some inadequacies related to traditional procedures:

- The conventional methods are agitated and overlong as it takes time, and energy and is not cost-effective as well as incompetent to provide desired output considering the low level of accuracy.
- Spatial-temporal analysis and trend assessment for quality checking of huge waterbodies and regional planning of waterbodies are inefficient by regular methods.
- The routine sampling procedure is quite inadequate for inaccessible terrain.

To avoid the above-said inadequacy, remote sensing analysis is an effective tool for the assessment of water pollution (Gitelson et al., 1997). The remote sensing analysis have been flourished before few decades for monitoring and estimation of inland water quality (Gholizadeh et al., 2016; Shirke et al., 2016). Coastal waterbodies can also monitor through multispectral image analysis (Thiemann and Kaufmann 2000; Vijay et al., 2015). Spectral reflectance of wastewater effluent (Gitelson et al., 1997; Ekercin, 2007) can be detected by a specific portion of the electromagnetic spectrum. In the present decade, satellites with high-resolution sensors with advanced techniques are available for assessment of the water quality (Ritchie et al., 2003). Visible and near-infrared (NIR) bands of spectrum are widely used for water quality assessment. Even though remote sensing is a powerful technique for sewage pollution assessment, conventional data is necessary for validation and establishing a relationship between satellite analysis and ground truth. The collaboration of remote sensing and traditional practice is more effective to monitor the pollution assessment study (Kallio et al., 2000). The probable benefits are described below:

- Synoptic coverage of the waterbody can be made available for spatiotemporal investigation, change of detection, and trend analysis of the study area.
- Harmonized view of the bulk of waterbodies and large water masses like bays, sea, and ocean.
- Identification of the prime locations for a ground survey to carry out analysis and time management.

3. Platform and Sensors for Water Quality Assessment

Based on the remote sensing platforms, two major categories of sensors are available, namely airborne and space-borne. Airborne sensors (airplanes, helicopters) are limited to aerial medium and space-borne sensors are carried out by satellites (Chuvieco, 2016). Although air-based sensor provides high-resolution images, it is limited to a specific region, are expensive, can't provide temporal data and availability depends on weather conditions (Chang and Clay, 2016). On the other hand, space-based sensors provide images with synoptic coverage, and historical and temporal datasets (Roy et al., 2017). Satellite images are stable and clear, can minimize field activities, cost-effective. Some open source images are also available that could be effectively used for natural resources monitoring and management purposes. In view of this, space-borne sensors are more beneficial compared to the air medium sensors, for estimation of water quality. The different platform-based sensors for water quality assessment are described in Table 1.

4. Estimation of Water Quality Using Remote Sensing Technique

Assessment of water pollution using remote sensing is a challenging task. Discharges of sewage, runoff of pesticides and fertilizer, and industrial effluent degrade the water quality (Gholizadeh et al., 2016). This process is involved investigating the physical, chemical, and biological parameters and quantification of the concentration of contamination with probable sources (Usali and Ismail, 2010). To evaluate the efficiency of remote sensing data for water quality (inland, estuary, and ocean) analysis, various satellite data and their applicability to water pollution study have been reviewed as follows.

4.1. Landsat Series of Satellites

The Landsat mission is one of the longest satellite programs that provide continuous data for the assessment of the aquatic environment (Waxter, 2014). Landsat images are calibrated and

Table 1. Air and Space-Borne Sensors for Water Quality Assessment

Category		Sensor	Application
Airborne		Electronically scanning thinned-array radiometer	SSS
		Two-dimensional electronically scanning thinned-array radiometer	SSS
		Scanning low frequency microwave radiometer	SSS
		Passive active L- and S-band sensor	SSS and SST
Space-borne	High resolution	Digital globe WorldView 1,2,4	Chlorophyll, turbidity, TSS,
		NOAA WorldView 3	Chlorophyll, turbidity
		GeoEye, IKONOS	Turbidity
		Sentinel	CDOM, chlorophyll
		SPOT	Turbidity, suspended solids, total phosphate
	Moderate resolution	Landsat 5(MSS & TM); 7(ETM+); 8(OLI, TRS)	SST, chlorophyll, turbidity, salinity, suspended solids
		EO-1 (Hyperion, ALI)	Chlorophyll
		Terra ASTER	SST
		OceanSat	CDOM, algalbloom, yellow substance, SST, wind speed, and atmospheric water vapour
	Regional/Country level resolution	Terra MODIS	Floating algae
		MERIS	Chlorophyll, cynobacteria
		SeaWiFS	Ocean colour, chlorophyll

multispectral and it has 30 m of spatial resolution (moderate) and 16 days of revisit capacity that makes them suitable for continued analysis (Abbas et al., 2019). Landsat 4 and 5 have thematic mapper (TM), 7 have enhanced thematic mapper (ETM) and 8 have operational land imager (OLI) and thermal infrared sensor (TIRS) that users can utilize for water quality assessment. The visible and infrared bands of the electromagnetic spectrum are mostly used to assess different water quality components (Barrett and Frazier, 2016). The Landsat series of satellites are worldwide used for water quality analysis since the past (Lim and Choi, 2015; Barrett and Frazier, 2016). Several studies have been carried out to evaluate the efficiency of remote sensing data on water quality assessment (Lim and Choi, 2015). The Landsat data has been recognised as one of the most frequent and efficient satellite images to monitor and analyse the water quality across the globe (Moges et al., 2017). The Landsat data are useful to assess different water quality parameters like turbidity, temperature, suspended solids, chlorophyll, coloured dissolved organic matter (CDOM), phycocyanin, etc. (Lim and Choi, 2015; Sun et al., 2015).

4.1.1. Temperature

Temperature is one of the components of water quality that is highly influenced by land use surroundings (Poole and Berman, 2001) and it has a strong impact on aquatic life (McCullough et al., 2009). In oceanography, estimation of SST is a routine work (Kilpatrick et al., 2001; Parkinson, 2003) that uses thermal remote sensing data. The SST is a crucial and influencing climatic parameter (Minnet et al., 2019) that reflects the equilibrium between the hydrosphere and atmosphere (Bentamy et al., 2017). The pattern of SST is efficient to analyze the subsurface dynamics, thermal expression, surface momentum, etc. (Tandeo et al., 2014). Landsat data are significant for research studies on the modeling of SST in several ways it has two thermal bands, which are useful to create a multiband equation and it has a high spatial resolution that offers an advanced way to monitor coastal and marine areas (Bayat and Hasanlou, 2016).

4.1.2. Sea Surface Salinity

Salinity is one of the key parameters that reflect the density of the seawater and density has a strong influence on ocean currents. Salinity is also important for water balance, evaporation, ocean productivity, etc. Thus, frequent monitoring of SSS is necessary to understand the ocean's circulation. Satellite remote sensing has the potential to monitor the SSS in an efficient manner. High-resolution (spatial and temporal) data are available to assess the SSS across the globe. The Landsat series of satellite data are now been popular among researchers to estimate the salinity in the marine environment.

4.1.3. Turbidity

Turbidity is one of the optically active constituents of water quality. When lights interact with turbid water it is scattered and absorbed rather than transmittance. The presence of suspended materials and colloidal components in the water column makes the water turbid. Therefore, the concentration of turbidity in water depends on the amount of suspended particles present in the water sample. Literature shows that the use of the single band and band combinations has huge potential to monitor and assessment about turbidity. In the near and mid-infrared region

Table 2. Landsat Data and Water Quality Parameters with the Method

Parameter	Dataset	Method	Band/Index	Reference
Temperature	Landsat 5, 7, 8	Split window method	Band 10 and 11	Bayat and Hasanlou, 2016; Minnet et al., 2019; Meng and Cheng., 2019; Vanhellemont, 2020
Salinity	Landsat 5	Multiple linear regression	B1, B2, B3, B4 and B5	Baban, 1993; Bonansea et al., 2015
Turbidity	Landsat 7	Linear regression	−63.717 + 1587.8 × Band4	Hicks et al., 2013
	Landsat 5, 7, 8	Normalized difference turbidity index	(Red band − Green band)/(Red band + Green band)	Lacaux et al., 2007; Sharma et al., 2016; Wang et al., 2013; Akbar et al., 2010
	Landsat 5	Ratio	Ratio between blue and red bands	Cox et al., 1998
	Landsat 5, 7	Single band	Green band Red band NIR bnad	Khorram et al., 1991 Norsaliza and Hasmadi, 2010 Onderka, 2014
Suspended solids	Landsat 5	Multiple linear regression	Band1, 2, 3,4, and 5	Baban, 1993, Alparslan et al., 2007
	Landsat 7	Linear regression	−52.817 + 1449.4 × Band4	Hicks et al., 2013
	Landsat 5,7,8	Non-linear regression	R(Red) ×0.99 + 0.8	Lobo et al., 2015
CDOM	R_t based model (quadratic equation) aCDOM(440) = $2.7x^2 - 6.14x + 4.19$		Description of equation $x = R_t(650)/R_t(480)$ apparently here $x = R_t(650)/R_t(480)$ if $R_{rs} = R_t/\pi$	Alcântara et al., 2016
	R_{rs} based model (exponential) aCDOM(440) = $40.75e - 2.463x$		Description of equation $x = R_{rs}$	Chen et al., 2017
	R_{rs} based model (power) CDOM(440) = $3.346x - 2.193$		Description of Equation $x = R_{rs}(B3)/R_{rs}(B4)$	Chen et al., 2017
	Landsat 5	Multiple linear regression	Blue Band	Brezonik et al., 2005
Chlorophyll	Landsat 5, 7	Multiple linear regression	B 1, 2, 3 and 4	Dekker and peters, 1993; Alparslan et al., 2007
	Landsat 5, 7	Linear mixture modelling	B 1, 2, 3	Tyler et al., 2006
	Landsat 7	Genetic algorithm	B 1, 4, 5 and 7	Chen et al., 2008
	Landsat 5	Radial basis function neural network models	NA	Panda et al., 2004
	Landsat 5, 7	Band ratio	Green and red band	Miksa et al., 2004; Hellweger et al., 2004; Mancino et al., 2009;
	Landsat 5, 7	Band ratio	Green and blue band	Sudheer et al., 2006; Turner, 2010
	Landsat 5, 7	Band ratio	Blue and red band	Han and Jordan, 2005; Mancino et al., 2009
SDD	Landsat 5	Multiple linear regression	B 1, 2, 3 and 4	Baban 1993; Alparslan et al., 2007
	Landsat 5, 7	Linear mixed model	B4, B4/B1	Bonansea et al., 2015
	Landsat 7	Linear regression	−2.0298 + 2.7517 × ln(B:B3) - 0.6022 × ln(B1)	Hicks et al., 2013

absorption of lights is high based on the depth of the waterbody and the appearance of the waterbody on the image looks darker. The increasing organic matters in waterbody are responsible for the shifting of reflectance peak from green to the red band (turbid water). Assessment of water turbidity using remote sensing has been carried out by many researchers across the globe. It is reported that the reflectance of the red band is efficient to study the turbidity concentration in the waterbody. The Landsat series of satellites have been highly recommended by researchers to assess turbidity.

4.1.4. Suspended Solids

The SS is the major component responsible for water turbidity. To monitor and assess the level of suspended solids and their seasonal variations researchers suggest a different remote sensing based methodology that could be beneficial for the assessment of SS from the water sample.

4.1.5. Coloured Dissolved Organic Matter

CDOM also called yellow substance is another optically active constituent of water quality (Chen et al., 2017). These organic matters can absorb photons in ultra-violet (UV) and visible range and plays a key role in the carbon cycle. This is also helpful to quantify the dissolved organic carbon (DOC) in the water sample. CDOM influences the water environment in several ways like water quality, carbon dynamics, and overall aquat-

Table 3. Sentinel Data and Water Quality Parameters with the Method

Dataset	Method	Parameter	Reference
Sentinel-2 MSI and sentinel-3 OLCI	Spectral analysis (water leaving radiance) along with in-situ measurement	Suspended particulate matter (SPM)	Salama et al., 2022
	Linear regression, radiometric matchup	Chlorophyll-a	Salama et al., 2022
	Linear regression	Coloured dissolved organic matter (CDOM)	Salama et al., 2022
Sentinel-3 OLCI	Water leaving radiance	Total phytoplankton biomass	https://sentinel.esa.int/web/sentinel/search
	Water leaving radiance	Transparency	https://sentinel.esa.int/web/sentinel/search

Table 4. SPOT Data and Water Quality Parameters with the Method

Dataset	Parameter	Method	Band/Index/Equation	Reference
SPOT	Chlorophyll	Genetic programming, ratio	$(R_{rs}(B4))/(\ln(R_{rs}(B2) + R_{rs}(B3))) + \ln(61.6)$, green and red band	Chen, 2003, Yang et al., 2011
SPOT 5	COD, NH_3-N, DO	Support vector machine regression	NA	Maier and Keller, 2018
SPOT	SDD	ratio	Green and red band	Yang et al., 2011; Lathrop et al., 1989
SPOT	Turbidity and suspended solids	Single band	NIR	Mohd Hasmadi and Norsaliza, 2010
SPOT	Total phosphorus	Ratio	Blue and green band and integration of red and green band	Yang et al., 2011

ic life. Using remote sensing techniques, researchers have developed multiple algorithms to assess the CDOM in the water column. There is an optical proxy method to estimate the CDOM, which used an absorption coefficient at 440 nanometres of electromagnetic radiation (EMR). The Landsat data has been considered for assessment of CDOM because of its mission continuity and comparatively higher spatial resolution. To retrieve the CDOM of remote sensing remote sensing irradiance reflectance (R_t) is required that calculated as the ratio between upwelling (E_u) and downwelling (E_d) irradiance. Apart from this model researchers have been developed a more efficient model that used remote sensing reflectance (R_{rs}) of band 3 and band 4 of Landsat 8. To calculate the R_{rs} a simple equation has been used that may be expressed as $R_{rs} = R_t/\pi$. Although retrieval of CDOM is now popular through proxy method literature showed useful using the single band or band ratio of Landsat satellite.

4.1.6. Chlorophyll

Chlorophyll is the photosynthesizic element, present in aquatic macrophytes, algal blooms, etc., that are considered as biological parameters of water quality. The presence of toxic algal bloom and macrophytes in waterbody could be responsible for the degradation of the aquatic environment and it can disturb anthropogenic activities (Han and Jordan, 2005). The overgrowth of aquatic plants can clog the reservoir, reduce the navigability of the river, and quality disruption of any other waterbodies (Miksa et al., 2004). The remote sensing offers a comprehensive way to monitor and assess the algae/microphytes. Multispectral datasets are very efficient to map the algal bloom and its temporal variation. There are bands and band ratio models to effectively assess the chlorophyll concentration in the waterbody. Band ratios are important because they minimize the atmospheric, irradiance, and air-water impact on remote sensing data (Alparslan et al., 2007). The significant literature has been showed that chlorophyll can be strongly absorbed between blue and red band regions (0.450 ~ 0.475 µm) and reflectance is highest in the green to NIR region (0.550 ~ 0.700 µm).

4.1.7. Secchi Disk Depth

Secchi disk depth (SDD) refers to the clarity of the water. SDD is inversely related to turbidity and suspended solids. This is also useful to evaluate the relative nutrients and solids loading in the waterbodies (Hicks et al., 2013). SDD can reflect the trophic status of the waterbody. SDD is one of the optically active constituents of the waterbody that can measure through remote sensing techniques (Bonansea et al., 2015). After atmospheric correction of satellite data, it is useful to assess the SDD of the water environment. Researchers have demonstrated that the green band of Landsat thematic mapper (TM) and multispectral scanner (MSS) data are efficient to measure the SDD. The water quality parameters that could be retrieved using Landsat data, along with methods, equations, or algorithms are represented in Table 2.

4.2. Sentinel Satellite

The Copernicus Sentinel-2 satellite is a polar satellite that aims to monitor the earth's ecosystem. The Sentinel-2 was sent to space in 2014, which opened up a new door toward sustainable environmental management in several ways (Salama et al., 2022). The high resolution (spatial and temporal) of Sentinel data makes it adequate and efficient for monitoring of natural resources. Monitoring of inland waterbodies as well as the marine environment is the major application of the Sentinel data (https://sentinel.esa.int/web/sentinel/thematic-areas/marine-monitoring). The Sentinel-2 provides ocean colour data which is useful to understand the trophic status of the marine environment and other pollutants like turbidity, suspended matters, organic matter, etc. Monitoring of the marine environment in terms of marine safety, climate and seasonal forecasting, human intervention in the aquatic ecosystem, etc. could be studied using Sentinel-2 data (https://sentinel.esa.int/web/success-stories/-/copernicus-sentinel-2-brings-students-together-for-an-online-remote-sensing-course). Researchers across the globe highly recommended the Sentinel 2 data for water quality assessment. Multispectral imaging (MSI) data are used by the Polytechnic Institute of Beja, Portugal, and AERES University of Netherland for the assessment of water qualities in inland waterbodies. Sentinel products are used for monitoring of harmful algae in the water environment. Time series analysis of cyanobacteria could also be done using Sentinel data. Sentinel-3 Ocean and Land Colour Instrument (OLCI) is another satellite data product that is specially designed to monitor the aquatic environment, sea surface topography, climate, and ocean forecasting. The spatiotemporal variability in estuarine water is highly dynamic that could be assessed through Sentinel data (Hommersom et al., 2009; Nechad et al., 2015). The radiometric matchup between satellite products and in-situ data can address the accuracy of the water quality monitoring from space (Salama et al., 2022). Table 3 is showing the available parameters that could be assessed through Sentinel data.

4.3. Satellite Pour l'Observation De La Terre

The satellite pour i'observation de la terre (SPOT) is a series of optical remote sensing satellites of the European space agency that provides high-resolution images with wide ground coverage. The major objective of this mission is to monitor the earth's resources, human activities, forecast the climate, land environment as well as ocean ecosystem. The recent SPOT 7 satellite provides very high spatial resolution (pan band 1.5 m, visible and near-infrared band 6 m) and near real-time imageries that are useful to assess the rapid response of earth surface features. SPOT satellite data are recognized for assessment of the water quality. Different parameters like chlorophyll (Yang et al., 2011), Secchi disk depth (Lathrop et al., 1991), turbidity, suspended solids (Mohd and Norsaliza, 2010), and total phosphorus (Yang et al., 2011) that expressed the quality of the waterbody, could be assessed using SPOT satellite data. The utility of SPOT data to assess the different water quality parameters along with methodology is represented in Table 4.

4.4. Moderate Resolution Imaging Spectrometer

The MODIS instrument is available in terra and aqua spacecraft and provides moderate resolution data which are very useful for monitoring natural resources (https://modis.gsfc.nasa.gov/data/). It also provides ocean colour products that are produced by the ocean colour data processing system (OCDPS) and used for monitoring of the ocean environment. ocean colour data has wide application areas like SST, SSS, ocean colour (https://oceancolor.gsfc.nasa.gov/). MODIS data are also useful for the assessment, monitoring, and modeling of chlorophyll, suspended solids, turbidity, CDOM, etc (Wong et al., 2008; Schaeffer et al., 2015). The application of MODIS data on water quality parameters has been summarised in Table 5.

4.5. Medium Resolution Imaging Spectrometer

The Medium Resolution Imaging Spectrometer (MERIS) is associated with the Envisat mission of the European space agency. Although, this spectrometer was specially designed for ocean colour monitoring now expanded its applicability to land and atmosphere (https://earth.esa.int/eogateway/instruments/meris). MERIS data provides high spectral and radiometric resolution images that are useful for monitoring of open ocean and estuarine areas. Like other satellite/instruments, MERIS data are also useful to assess different water quality parameters (Martinez et al., 2005) that are prescribed in Table 6.

4.6. Indian Remote Sensing Satellites

Indian remote sensing (IRS) series satellites were developed and built by the Indian Space Research Organization (ISRO) to monitor natural resources (Chauhan et al., 1996). Initially, the aim of the IRS series was to monitor land resources but IRS P4 or OceanSat-1 was designed to fulfill the data requirement of from marine environment (Das and Mohanty, 2006). IRS series carries moderate to high resolution (Linear Imaging Self-Scanning Censors or LISS-I, II, III, IV; Wide-Field Sensor or WiFS; Advanced Wide-Field Sensor or AWiFS and Panchromatic or PAN sensors (https://www.ioccg.org/reports/ocm/ocm.html) that are useful to monitor and analyse the natural resources at the different sale (regional, country-level, etc.). The LISS IV is one of the high-resolution sensors having applicability in the assessment of the water environment (Satapathy et al., 2010). Shirke et al. (2016) used IRS LISS IV product to assess the sewage pollution in Malad creek. Vijay et al. (2015) reported that extent of sewage pollution in marine environment can be identified and analysed using LISS IV data. The IRS P4 carries Ocean Colour Monitor (OCM) sensor and Multi-frequency Scanning Microwave Radiometer (MSMR) sensors that provide information related to several oceanographic parameters like SST, wind speed, and atmospheric water vapour (Subrahmanyam et al., 2002; Parmar et al., 2006; Kumar et al., 2012; Sathiyamoorthy et al., 2012; Modi et al., 2021). The OCM also provides the water quality data namely chlorophyll, inorganic suspended matter and yellow substance, and oil spill, etc. (https://directory.eoportal.org/web/eoportal/satellite-missions/i/irs). The OceanSat-2 is the second oceanographic satellite of the IRS series to continue the oceano- graphic study using satellite data. OceanSat-2 is applicable to study sediment dynamics, monitoring of algal bloom, sea ice, monsoon, and cyclone fore-cast (https://directory.eoportal.org /web/eoportal/satellite-missions/o/oceansat-2). The application of OCM data has been summarised in Table 7.

There are some other sensors namely IKONOS, Cartosat, SARAL-AltiKa, Advanced Space-borne Thermal Emission and

Table 5. MODIS Data and Water Quality Parameters with the Method

Dataset	Parameter	Method	Band/Index/Equation	Reference
MODIS	CDOM	R_{rs} ratio and absorption algorithm, ratio	$R_{rs}(667)/R_{rs}(488)$, blue and green, green and red	Schaeffer et al., 2015; Wang et al., 2005; Menken et al., 2006
	Temperature		TIR	Wang et al., 2005; Handcock et al., 2006; Morozov et al., 2015; Bierman, 2010
	SDD	Blue, green	Blue, green	Menken et al., 2006
	Turbidity and SS	Ratio	NIR and red	Wu and Murray, 2003
	Chlorophyll	Ratio	NIR and red	Menken et al., 2006; Hunter et al., 2010

Table 6. MERIS Data and Water Quality Parameters with the Method

Dataset	Parameter	Method	Band/Index/Equation	Reference
MERIS	Chlorophyll	Neural network (NN), non-linear regression, PCA + MLR, ratio	NA, $[R_{rs}(670) - 1 - R_{rs}(710) - 1] \times R_{rs}(750)$; PC1, PC2, PC3, PC4; blue and green band	Giardino et al., 2010; Gitelson et al., 2014; Flink et al., 2020; Ruiz-Verdú et al., 2008
	Suspended particulate matter	NN	NA	Giardino et al., 2010
	CDOM	NN	NA	Giardino et al., 2014

Reflection Radiometer (ASTER), hyperspectral, spectroradiometer also available and used for monitoring and management of inland estuarine, and marine waterbody. Satapathy et al. (2010) showed the effectiveness of IKONOS data for the assessment of water turbidity. SARAL data sets are very useful for sea-level assessment for the world ocean (https://www.mosdac.gov.in/saral-altika). ASTER data is also used for the assessment of water quality for the global waterbodies. It's also used to calculate the water quality index (WQI) with the association of field observations (Abdelaty, 2018).

Table 7. IRS Data and Water Quality Parameters

Spectral band	Application
Band1	Yellow substance/organic matter
Band2	Chlorophyll
Band3	Chlorophyll and other pigments
Band4	Turbidity and suspended solids
Band5	Chlorophyll references
Band6	Total suspended matter
Band7	Atmospheric correction
Band8	Atmospheric correction/Aerosol optical thickness

5. Limitations of Remote Sensing

Although, several satellite data are available to monitor the water pollution from the space, optically non-active parameters are still challenging to assess with this technique. Even assessment of optical parameters during monsoon is quite difficult. Unavailability of high-resolution data for every region, clouds on the image, high cost, etc. can reduce the acceptability of this technique. Processing of data like atmospheric correction, ortho-rectification, etc., is quite complex. Highly configured computers, advanced software, and trained people are also required in this field, which may be an issue at different places. The available equations/algorithms are restricted to places, seasons, and parameters. Interrelated/overlapping parameters are problematic to identify using moderate resolution data. Though, there are some limitations, remote sensing technology provides an adequate way to evaluate and monitor water quality parameters.

6. Discussion

The literature review narrates that several satellites are there for the estimation of selected water quality parameters. Based on the appearance of water spectral reflectance is different and this difference can measure by different spectral bands of the electromagnetic spectrum. Spectral, spatial, and temporal resolution is the critical component for the selection of a particular sensor. High-resolution satellite data are always preferable, but the combined resolutions (spatial, spectral, and temporal) are mostly used for water quality monitoring (Hellweger et al., 2004). High-resolution satellites, namely QuickBird, Ikonos, WorldView-2, etc., are recommended for their heterogeneous spatial properties (Giardino et al., 2014). Due to wide spatial coverage, short time of repetivity, and low cost, Landsat series satellites are (Thematic mapper, multispectral) widely used for water quality estimation of surface water (Dekker et al., 1996; Hellweger et al., 2004; Brezonik et al., 2005; Sudheer et al., 2006; Hadjimitsis et al., 2009). Landsat TM has been recognised as the oldest sensor for assessment of water quality. Sentinel data have huge potential to monitor the water quality in a significant way. Sentinel data are open source high resolution therefore there is wide applicability of this data for water quality study. Similarly, SPOT, MODIS, MERIS, and IRS satellites are also applicable for water quality determination at different scales (regional, country, global).

Satellite-based monitoring of the surface waterbodies is not adequate to display pollution status or mapping of aquatic environs. The empirical method should also be applicable for validation of the spectral response of the sensor by making a statistical relationship between the result get from the conventional procedure and spectral reflectance captured by satellite bands. The empirical methods are suitable for data analysis, validation, and easy to apply for accuracy assessment. This approach should be helpful for large-scale water quality assessment, and the health of rivers, and waterbodies. It will minimize the ground-based laborious work, save the human resource, and will support avoiding financial issues for water quality survey.

7. Conclusions

The review study addressed the significance of remote sensing techniques to study water pollution. The availability of open-source data can reduce the project cost and save time. Different satellites and sensors have been reviewed to describe the water quality parameters, which can be assessed efficiently through this technique. The study reveals that optical parameters can be evaluated and monitored with this technique, but there is some limitation for non-optically active parameters. The Landsat data have wide application in the field of inland as well marine water quality assessment. Other satellite data like Sentinel, and SPOT can assess water quality with minor details. MODIS and MERIS have little boundation for small waterbody but have a significant application in the marine environment. IRS satellite data are also very useful for water quality assessment as well as ocean forecasting. Several methods, equations, and algorithms are already developed that might be helpful for future research work. Image analysis along with ground truthing is a key procedure for the assessment of water quality in an inland waterbody or marine environment. The review study suggests future innovation and development of sensors to assess the non-optically active constituents, high-resolution data, and uniform methods for a particular water quality parameter, new methods or algorithms to assess water pollution more efficiently.

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