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State-of-the-Art Review of Assessing Water Quality from Space

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Abstract. Water acts as the medium which helps supply seafood and freshwater food for human consumption and drinking water. It is thus imperative that such a precious resource should be well monitored to safeguard human health and survival. Conventionally water quality can be monitored through manual laboratory-based methods which are time-consuming. Ground-based sensors are helping in expediting this task, though it involves the use of multiple sensors at various locations and requires regular maintenance and replacement. Satellite technology provides a good alternative method as it can scan large areas at a relatively low cost. Measurements of parameters such as sea surface temperature, total suspended solids (turbidity), primary food production (chlorophyll A), abnormal movement of aquatic animal, disease occurrence, water oxygen deficiency, growth monitoring of aquatic life and many others have been successfully reported in the literature. With the advent of micro-satellites that can transmit higher resolution images with a finer spectral resolution, greater advancements can be made for the detection of a greater number of critical water quality parameters. This paper reviewed the existing status of the water quality monitoring from space technology and covered published research done in various parts of the globe, including the problems, solutions, algorithm used, the advantages of the study, research region, water bodies, water quality variable, and satellites data.

Keywords: Satellite, space imaging, image processing, remote sensing, water quality monitoring.

1. Introduction

Since water quality has a substantial impact on human health and the general quality of life of the people, water quality has been a major cause of concern in recent years, especially in industrialised countries. When reduced to its most basic definition, water quality is an evaluation of the suitability of water for a certain purpose based on specified criteria. Satellite images, in this period of the Industrial Revolution 4.0 are a good source to show the overall picture and are full of important and intriguing information. The Industrial Revolution 4.0 envisions a new ultra-paradigm that allows the industry to adapt in real-time to alterations in the ecosystem. Leveraging these new transitions and comprehending their revolutionary potential with regard to technology, altering demography and global connectivity is vital for the satellite sector [1]. They provide a wealth of data that can be used to produce scientific results and provide advantages in decision-making. Using satellite images, we can see how much a place has changed, just how well our plants, fish are flourishing, where a fire burns, and when a storm is on its way [2].

The majority of the world's water is used for farming, commerce, energy generation, water supply production, and domestic uses [3]. Water contamination is occurring as a result of anthropogenic activities, excessive pollution, agriculture, and a variety of other factors, all of which are affecting the development and survival of aquatic organisms. Water physio-chemical characteristics such as temperature, dissolved oxygen, and pH all degrade the water's ability to maintain its optimal quality. In certain cases, changes in physio-chemical parameters might render the pond unfit for agriculture, resulting in the death of fish and other aquatic animals. There are certain species that are known to be very sensitive to these changes in water quality parameters, which may cause their development to be stunted or even cause them to die prematurely. One of the options is to continuously monitor the water parameters in a reservoir in order to identify any changes in water quality that may occur. Many nations still rely on manual collection of water samples and laboratory testing to determine the properties of the water being studied. This strategy is time-consuming and inefficient. In addition, the parameters properties and resulting measurements may change over time during transit from the bodies of water to the labs, and the absence of real-time analysis affects the precision of the data obtained from the experiments. As a result, it is tough to keep up with study results that can be used to warn people about worsening water conditions that are emerging in bodies of water. When it comes to the physical, chemical, and biological characteristics of water, those that are good for human consumption vary from those that are ideal for irrigating a crop [4]. In many parts of the globe, polluting elements that cause degradation in water quality harm the majority of freshwater, estuarine, and coastal ecosystems [5]. In order to evaluate and detect any changes in water quality over a time period and to be capable of responding to evolving water quality issues such as the tracking of primary food production (chlorophyll A), harmful algal blooms, contamination, red tides, and aquatic disease; water quality assessment is essential. When it comes to determining the status of a waterbody's water quality, surveying it and accurately describing its attributes are the very first steps.

In addressing the above issues, it is proposed to have real-time or near real-time visual information to provide improved assessment of water quality parameters such as Chlorophyll-a (CHL-a), suspended particulate matter (SPM), coloured dissolved organic matter (CDOM), temperature, turbidity, and the availability of underground water in order to provide effective details on these parameters [6]. Manually collecting ground data may be time-consuming and inconvenient at times. Again, instruments such as sensors and machines may be costly sometimes and need the use of human resources for long-term upkeep.

The purpose of this study is to assess the current status of recent geospatial research on water quality monitoring. To get an understanding of the many research studies in this subject, the challenges, solutions, and conclusions, as well as the study nations, water bodies, water quality metrics, kinds of satellites employed, and spaceborne sensors used in those studies throughout the time period 2011 to 2021.

2. Methodology

The process of writing this review article started with reviewing the published papers in the field of geospatial research on water quality monitoring. The steps of reviewing literature are complex. The steps used in this review are shown in the flow chart in Figure 1. This review study maintained a flow chart for the systematic study. The data of published research papers were extracted from many databases using the Universiti Putra Malaysia online library. In its optimal form, the literature review represents a formal data collection process wherein information is gathered comprehensively. As a data collection tool, this literature review involved activities such as identifying, recording, understanding, meaning making and transmitting the information. The detailed processes are described below:

- **Identification of queries:** After finalizing the title, some queries were developed to make a structure to search from databases. The queries are:
    - Search 01: Water Quality Monitoring from space,

- Search 02: Water Quality Monitoring by satellite image,
- Search 03: Satellite-based water quality monitoring,
- Search 04: *Aquaculture* water quality *analysis using satellite*.

- **Developing keywords:** For making a specific, algorithm-oriented, organized search some keywords were chosen such as water quality monitoring, geospatial, satellite, aquaculture, spatial data analysis etc.
- **An initial online search using keywords:** The databases of IEEE, Scopus, Science Direct, Elsevier, Academia, Google Scholar, Springer and Wiley were used for the initial online paper hunt. From the search, a total of 78,560 published research papers were found and only 30 papers based on the queries downloaded. These 30 papers were downloaded based on the relevance regarding keywords and review questions. Another 8 papers were dropped as they did not focus on water quality monitoring; thus 22 papers were finally used for this review.
- **Database refinement based on indexing:** The database was refined based on the availability of papers on a particular database. For example, Elsevier and Scopus showed more results which were easier to select specific papers for this review interest.
- **Inclusion and exclusion of articles based on title and abstract:** The criteria for inclusion were only the papers that represented data on water quality monitoring using satellite data, water quality parameters, and satellite sensors in the research.
- **Information extraction and evaluation:** Google excel sheet was used to categorize the extracted data and evaluated by co-authors. The evaluation criteria include the background of the study, the reliability of the information, the source etc.
- **Analysis and interpretation of findings:** The analysis was done using google excel software and interpretation was completed by measuring the significance of the research.

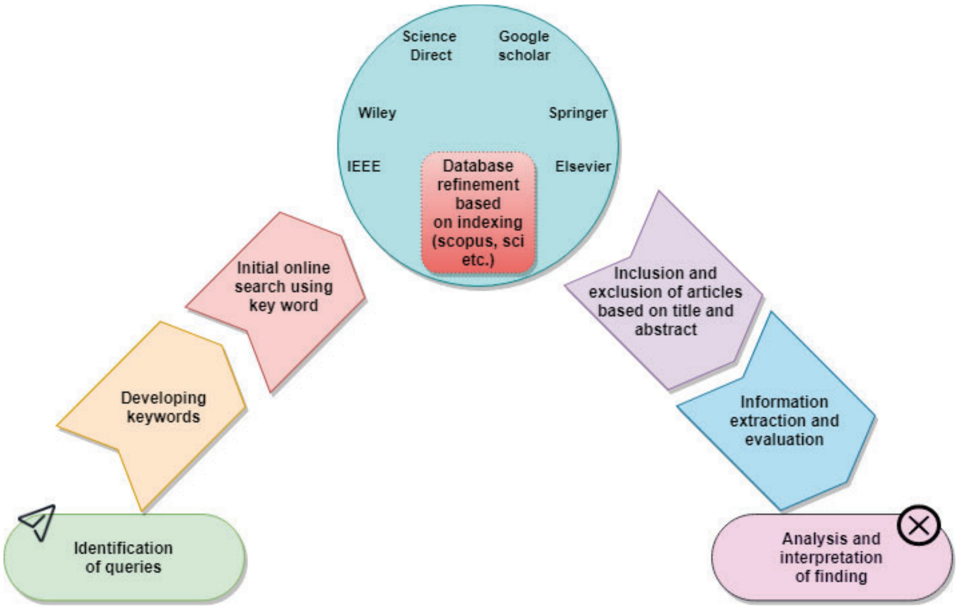

Figure 1. Methodological diagram of the whole review process.

3. Findings and discussion

The purpose of this section to demonstrate in a logical and methodical manner the conclusions of the literature analysis, which included findings from 22 research publications. Table 01 compares different research done in various parts of the world, as well as the issues, solutions proposed, algorithm used, observations made by the authors, and benefits derived from the research.

Table 1. State-of-art of water quality monitoring from space.

No.	Ref	Issues	Solution	Algorithm/ Model	Observations	Benefits/Accuracy
1	[7]	Change in water quality.	Remote sensing.	Time series.	Time series MERIS data is an appropriate and affordable technology.	Low-cost technology.
2	[8]	1. Theoretically based algorithms. 2. Inadequate reparameterization.	Chrorophyll-a concentration estimation in turbid productive waters.	MERIS-based NIR-red algorithms.	The two-band and three-band NIR-red algorithms gave consistently highly accurate estimates of chl-a concentration	The mean absolute error of 4.32 mg m−3 and 4.71 mg m−3, and a root mean square error as low as 5.92 mg m−3
3	[9]	Absence of SICF (chl-ab30mgm3) causes inappropriate signal.	Estimating trophic status in coastlines and inland waterways using satellite data (MERIS).	Algorithm for MPH (maximum peak.	Using top-of-atmosphere properties like fluorescence and backscatter/absorption in the red/NIR wavelengths of MERIS delivers great precision.	The MPH algorithm is the most efficient.
4	[10]	The optical complexity of turbid waters makes accurate remote retrieval of Chl-a difficult.	An adaptive GA-PLS model was created using a genetic algorithm.	Maximum peak-height algorithm (MPH)	Due to the coarser and discontinuous spectral design, simulated OLCI datasets deteriorate both GA-PLS and three-band model performance.	The GA-PLS model can accurately estimate Chl-a.
5	[11]	Humans heavily impact the world's coastal zones, causing eutrophication.	Compares MERIS chlorophyll-a concentrations with ship-based monitoring during the Baltic Sea's productive seasons.	GA-PLS model with three-band NIR-red algorithm.	The RMSE was 64% and the MNB was 17% for satellite-derived chlorophyll-a measurements compared to in situ observations made within 3 days.	MERIS captures spatial dynamics and phytoplankton bloom extent better than ship-based monitoring.
6	[12]	High salinity and poor water quality in marshlands.	Proposing equations using Landsat-8 data, salinity, and minerals.	Optical algorithms	Winter and fall have the lowest SO4 and CaCO3 levels. The salinity indicators fell in the winter and rose in the fall.	This method produces more realistic results.
7	[13]	Dams and hydropower production reduced and deteriorated water quality in wetlands. Salinity affects	Develop a novel differential equation approach to recover salinity and NDVI from optical remote sensing Landsat-	Algorithms OC-2, Morel-3	The combination of Landsat-8 data, GIS, and salinity algorithms might be a useful tool for marsh salinity retrieval.	The exponential algorithm's standard error and correlation coefficients are (51.25) and (0.8524).

		agricultural yields and food supply.	8 (OLI/TIRS) data.			
8	[14]	Desalination facilities treat saltwater and release waste into the sea, increasing salinity and temperature.	Comparison of two sources: space-based sea surface temperature (SST) and ground measured temperature.	Linear, power and exponential algorithm.	MODIS SST data indicate increasing temperature along the coast owing to land-water mixing and declining sea depth. MODIS thermal images have low resolution (1 km). Thus, MODIS spatial resolution cannot identify desalination plant effects.	The confusion using MODIS ill impair the precision of plant monitoring. Adding DS-1 data at greater resolution reduces such misunderstanding.
9	[15]	The C2RCC (Case-2 Regional/ Coast Colour (C2RCC) was only verified utilizing OLCI/Sentinel-3 images for coastal regions. Therefore, is of enormous significance to know about their exactitude for inland waters.	Evaluation of the C2RCC exactness in valuing the water quality factors from OLCI/Sentinel-3 images in inland waters dictated by CDOM.	---	The C2RCC fails. This research will help enhance C2RCC for optically complicated waters.	The findings demonstrated that C2RCC-estimated PW, IOPs, and OSS concentrations had little association within situ data.
10	[16]	This study used BOMBER (Bio-Optical Model-Based Tool for Estimating Water Quality and Bottom Properties from Remote Sensing Images) as an analytical tool.	Remote sensing of the water column and bottom optical characteristics.	----	BOMBER is written in IDL (Interactive Data Language) and utilises IDL widgets for its GUI. It is offered as an add-on for the ENVI+IDL image processing programme.	However, its basic design may be adapted to any other aquatic settings (e.g., coastal zones, estuaries, lagoons) where remote sensing reflectance values are available.
11	[17]	Modern remote sensing technologies cannot objectively depict the spatial change of water environment.	The quick and objective space monitoring of RS	Bio-optical Model	They advocated three techniques. Obtaining data through satellite pictures, aerial photos, and weather. Second, integrated laboratory testing methodologies.	The quick and objective space monitoring of RS provides a scientific solution for surface water quality monitoring.

					Third, by using online harmful chemical monitoring.	
12	[18]	Water contamination from industrial and residential runoff is a serious worldwide issue. And conventional sampling is time consuming and costly.	The novel technique for water quality mapping based on the optical model of water was developed to get the water quality across Straits using remote sensing imaging data.	Data fusion, remote sensing data inversion model	The algorithm used achieved high R and low RMS.	Using Landsat TM data technique may be used to multi-date data and other satellite data.
13	[19]	Microphytobenthos (MPB) is not presently employed as a bioindicator of water quality.	1. Evaluates the potential of MPB metrics. 2. Identify intertidal vegetation.	--	When compared to field validation data, the MPB detection performance was typically high.	User and Producer accuracies were 94% and 84% respectively.
14	[20]	The current water quality factor measurements are pricey and time-ingesting.	Proposed using Sentinel-2 data to estimate chl-a levels in the upper water column.	A Random Forest machine learning classification	This technology would offer near-real-time data on the Menor sea's water quality. The suggested approach delivers high spatial resolution data (60 m).	Rf, svmRadial and DNN functioned well.
15	[21]	20 years chl-a data was studied.	The OC5 Ifremer method was used to estimate Chl-a using merged satellites (SeaWiFS-MODIS/Aqua-MERIS-VIIRS).	Random forest (rf), support vector machine (svmRadial), Artificial Neural Network (ANN) and Deep Neural Network (DNN) algorithms.	As a result of improved water quality in the surrounding river catchments, this trend in phytoplankton biomass has been connected with decreased river discharges towards the conclusion of the period.	--
16	[22]	Recently, major efforts have been made to integrate in situ and satellite data for efficient coastal monitoring.	A 15-year diurnal fluctuation of Water Constituent Concentrations (WCCs) was recovered from multi-sensor satellite pictures and in situ hyperspectral	OC5 Ifremer	For 15 years, the WCCs obtained by 2SeaColor at the ocean surface correspond well with those returned by the associated MOD2SEA model at the TOA level.	This research uses spatial and temporal WCC data from in-situ measurements and satellite pictures to discover anomalies and alert managers in the Wadden Sea's complicated coastal waterways.

			data in the Dutch Wadden Sea using Radiative Transfer (RT) models.			
17	[23]	Laguna Lake is permanently eutrophicated and polluted by nutrients (cyanoHABs).	In 2020 Pacific typhoon season (September–November), assess Sentinel-2 images for lake monitoring.	RT model 2SeaColor & MOD2SEA	The results suggest that Super Typhoon Goni and Typhoon Vamco delivered higher suspended sediment loads to the reservoir than pre-storm (0–35 g/m3). Pre- and post-typhoon concentrations of Chl-a were 10 mg/m3 and 30 mg/m3, respectively.	The Sentinel-2 mission enhances cyanoHAB synoptic mapping and documents changes in their distribution and severity.
18	[24]	Water quality characteristics are challenging to forecast in time and place.	Ecological-hydrodynamic modelling is difficult and requires effective prediction techniques.	--	They can predict chl-a and SST. Deeper, less murky water.	The NN outperformed SARIMA in forecasting Chl-a concentrations in turbid and shallow waters (>2 mg m 3).
19	[25]	The ability to reliably establish a lake's average condition from standard in situ sampling is severely hampered by horizontal water quality patchiness.	Spatial variability must also be included in monitoring systems that attempt to assess ecosystem features.	Seasonal Auto-Regressive Integrated Moving Average (SARIMA) and nonlinear neural network (NN).	Using 93 match-up samples, researchers re-fitted C2RCC's absorption coefficient partitioning to increase prediction accuracy for Chl (r 2 = 0.79, RMSE = 5.4 mg m3).	Because satellite observations give unique insights into near-surface variability, they may be used to develop in situ monitoring programmes.
20	[26]	Surface water quality estimation and mapping are critical for planning and managing inland reservoirs.	Spatial forecast and mapping	Optically complex.	S2 was better predicted by all three models than L8.	S2 outscored L8 by 67% in recovering WQPs from the Owabi Dam reservoir.

3.1 Research countries

Sections should be numbered with a dot following the number and then separated by a single space.

No.	Continent	Research area	Reference
1.	Europe	European perialpine region	Bresciani. 2011
2.		Sweden	E. Therese Harvey. 2014
3.		France	Simon Oiry 2020
4.		Spain	Diego Gomez 2021
5.		Europe	Francis Gohin 2019
6.		Netherlands	Behnaz Arabi 2020
7.		New Zealand	Moritz K Lehmann 2021
8.	Asia	Malaysia	Syazwani Mohd Yusop.2011
9.		Philippines	Isabel Caballero 2021
10.		China	Rei LIU. 2010, Kaishan Song. 2013
11.	Asia (gulf)	Iraq	Hashim Ali Hasab. 2020, Hashim Ali Hasab 2015
12.		THE UAE	Ammar Al Muhairi. 2010
13.		Arabian Gulf region	Maryam R. Al Shehhi 2021
14.	Africa	South Africa	Mark William Matthews. 2012
15.		Ghana	Yvonne Yeboah Adusei. 2021
16.	North America	USA	Kaishan Song. 2013
17.	South America	Brazil	Enner Alcântara. 2018
18.	Australia	Australia	Kaishan Song. 2013
19.	Asia and Europe	Russia	Wesley J. Moses. 2012

The chart depicts that research on water quality monitoring from space is being carried out in various locations of the globe across six continents, as shown in the table. Most of the work is done in Europe, with Asia coming in second place for space-based water quality monitoring. This table shows that nations such as European countries, the United States, the United Arab Emirates, China, Malaysia, and other emerging but least developed countries have published relatively more papers on water quality geospatial research than other countries.

3.2 Water bodies

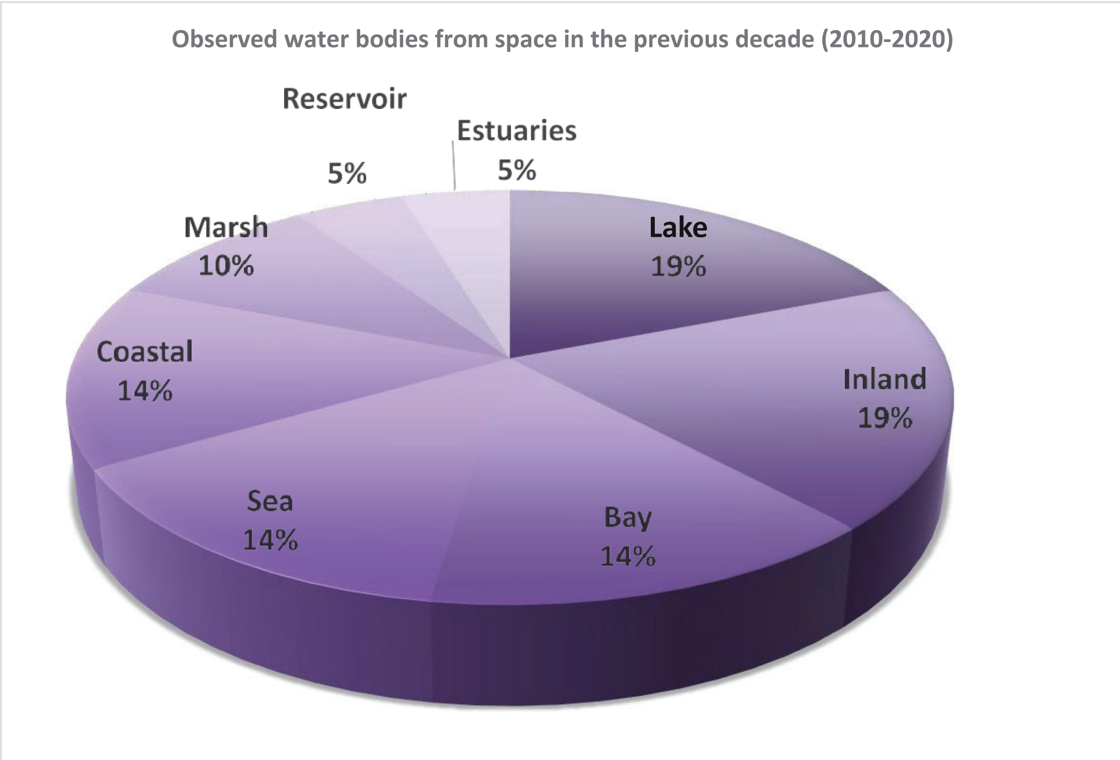

Figure 2. Water bodies that were monitored from space in the last decade (2010-2020)

The pie chart above highlights which water bodies were observed by satellite over the previous 10 years of 2011-2021, and which water bodies were not. Throughout the 22-research papers that was utilised to compile this review article, the search technique is referred to as the many sorts of water bodies are being observed. According to the pie chart percentile, it is obvious that the bulk of the geospatial research was conducted on lakes [27] [28] [29] [29] [30], and inland water bodies [31], [32] [15][33] with no distinction made between the two types of water bodies. Again, according to this review study, 14 percent of the research articles were focused on the bay [19] [33][34] , sea[14], [35] [36], and coastal environment [31] [11] [20], whereas marsh (10%) [13][12], reservoir (5%) [37], and estuaries (5%) [19] were found to be at the bottom of the priority list.

3.3 Water quality parameters

Table 03. Water quality parameters are monitored from space in the last decade (2010-2020).

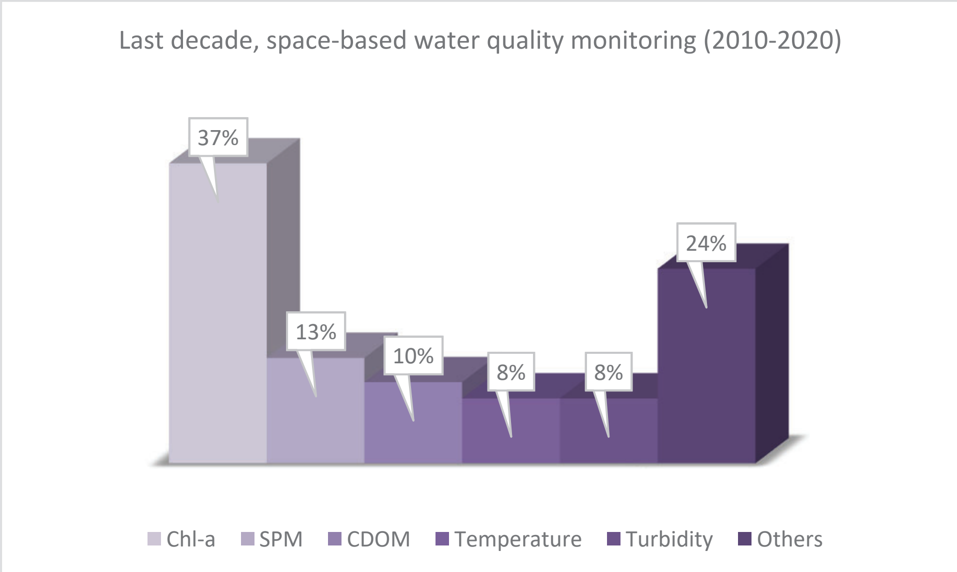

Figure 3. Water quality parameters are monitored from space in the last decade (2010-2020). Acronyms are Chlorophyll-a (chl-a), Suspended Particulate Matter (SPM), Colored Dissolved Organic Matter (CDOM), Temperature, Turbidity.

The information in the chart above pertains to the criteria of water quality that have been examined in various research studies conducted throughout the world during the previous decade. The presence of chlorophyll-a (chl-a), which indicates the presence of phytoplankton biomass in water, is the most important parameter to monitor from space [27] [34][31] [32] [20] [33] [35] [29] [38] [36] [15] [28] [13] [30]. Second, Suspended Particulate Matter (SPM) contributes to the second highest percentile of the total proportion recorded using satellite data. [11] [15] [35] [30] [28]. The downward trend is showing that the Colored Dissolved Organic Matter (CDOM) ([11] [15] [27] [35], Sea surface temperature (SST) ([14] [36] [28], and Turbidity [13] [28] [37] were consecutively used to a lesser extent in the geospatial study.

Finally, researchers found that other parameters were employed in 24 percent of study publications that were ascribed less relevance by the researchers. Those are related to one's water-leaving reflectance (pw) Remote sensing reflectance (Rrs) [15], chlorophytes [19], total suspended matter (TSM)[38], total suspended solids, thermal pollution[28], pH, alkalinity, total dissolved solids and dissolved oxygen [37], Suspended sediment (SS), Secchi disk depth (SDD) [12], Water salinity and SO4 and CaCO3 levels [13], Cyanobacterial-dominance, surface scums and floating vegetation [31].

3.4 Types of satellite image

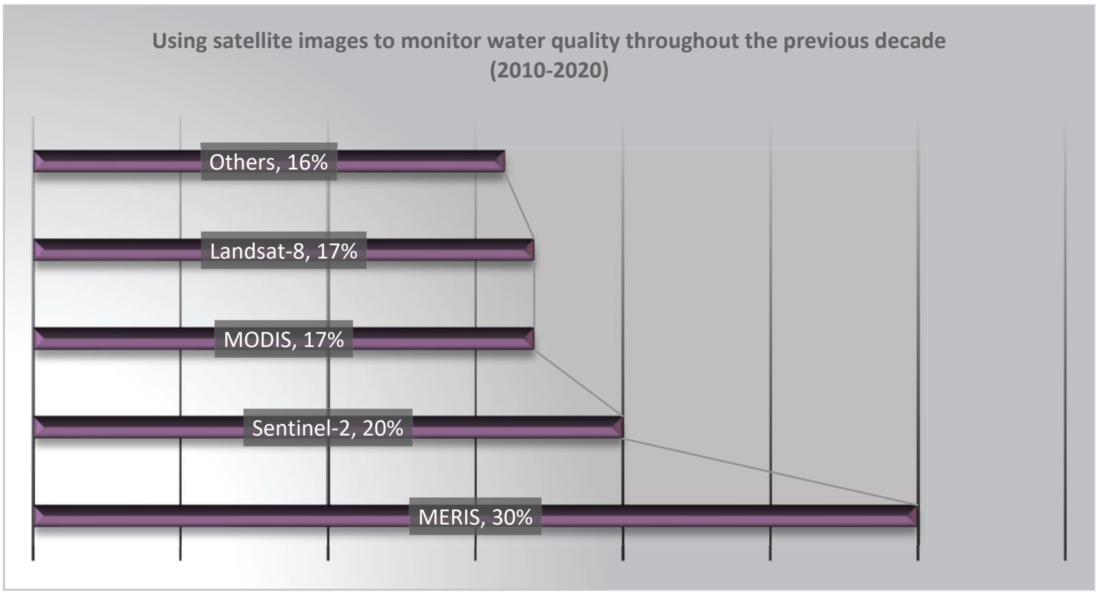

Figure 4. Types of satellite images used in water quality monitoring in the last decade (2010-2020).

The bar chart depicts a comparison of the most frequently used satellite photos for monitoring water quality from space, as shown in the table. According to the data at the bottom of the graph, MERIS (MEdium Resolution Imaging Spectrometer) satellite photos are the most often used by researchers to determine water conditions [27] [34] [31] [32] [11] [15] [28] [33][35]. Sentinel-2 comes after MERIS that contributes 20% [19] [20] [35] [38] [29] [37]. Thirdly, Moderate Resolution Imaging Spectroradiometer (MODIS) [32] [14] [28] [33] [36] and Landsat-8 (Optical remote sensing data) [12] [28] [13] [18] [37] is being used 17% of the researcher. Analytical software used in geospatial research needs image information that has been atmospherically adjusted for remote sensing in order to function properly. The other categories refer to DubaiSat-1 (DS-1) [14] SPOT, AVHRR, CASI sensors [28], and Sentinel-3 [35]. Often, the distinguishing properties of water in conjunction with non-water components, such as reflections of superstructures, are not reflected in satellite photos acquired at high resolution. Clouds, a mirror image of high-rise structures, or tower blocks may all be readily mistaken for a calm sea surface at times, especially in low light. As a result, thorough validation as well as the usage of advanced algorithms are essential in order to get credible data from satellites[11].

3.5 Spaceborne sensors

Table 2: COMMONLY USED SPACEBORNE SENSORS IN WATER QUALITY ASSESSMENTS [39][40],

	Satellite (S)	Sensor (S)	No. 0f spectral bands	Resolution Spatial (m)	Resolution Temporal (days)	Repeat Cycle (days)
High Resolution	ALOS	AVNR-2	4	2.5-10	2	46
	Digital Globe	Quickbird	5	0.7-2.9	3-4	3-4
	Digital Globe	WorldView-1	Pan	0.5	1.7	14
	Digital Globe	WorldView-1	8	0.5-1.9	1-3	1.1
	GeoEye	IKONOS	5	0.8-3.2	3	14
	GeoEye	Geoeye-1	5	0.5-1.8	3-4	8.3
	Otroview-3	OHRIS	5	4	4-5	~3
	SPOT5	HRG,HRS	5	5-20	~3	26

Moderate Resolution	EO-1	Hypenion, ALI	9	10-30	16	16
	ISS	HCO	128	100	3	10
	Landsat 1-5	MSS	5	60	16	16
	Landsat 4-5	TM	7	30	16	16
	Landsat 7	ETM+	8	30	16	16
	Landsat 8	OLI	11	30	16	16
	PROBA-1	OHRIS	19	18-38	7	7
	Sentinel-2A and Sentinel-2B	MSI	13	10-60	5	5
	Terra	ASTER	14	15-80	16	16
Regional-Global Resolution	ENVISAT	MERIS	15	300-1200	1	35
	ENVISAT	AATSR	7	1000	3-6	35
	ERS-1	ATSR-1	4	1000	3-6	35
	ERS-2	ATSR-2	7	1000	3-6	35
	NMBUS-7	CZCS	6	825	6	6
	NOAA-16	AVHRR	6	1100-4000	9	
	Orboview-2/Sea star	SeaWFSTM	8	1100	1	16
	Suomi NPP	VIIRS	22	375-750	1-2 times a day	16
	Sentinel-3	SLSTR,OLCI, SRAL, & MWR	21	300	<2	27
	Terms and Aqua	MODIS	36	250-1000	1-2	16

In terms of the platforms on which they are installed, observation sensors may be categorised into two broad categories: passive and active. Airborne sensors are those that are mounted on a platform within the Earth's atmosphere, whereas spaceborne sensors are those that are outside of the Earth's atmosphere (for example, a satellite). It is vital to understand the qualities of these sensors in order to choose the most suitable sensor for the study's aims. The sensors that are sent into orbit are the subject of this section. The numerous remote sensing satellites that are often employed in water quality studies are listed in the table to the right. Many features of remote sensing satellites are included in the table, including their spectral qualities, which include spatial resolution, spectral bands, and repetition cycle, among other things. It is useful to have this tabular information when planning water quality assessment studies, and it may also be used to identify the most relevant sensors from among the many different sensors that are now available on the market.

4 Conclusion:

From 2011 to 2021, this review study examined the state of recent geospatial research on water quality monitoring by investigating the various research fields, research problems and solutions, and research findings, as well as the countries involved, water bodies involved, water quality parameters involved, types of satellites involved, and spaceborne sensors involved in that research during the time period under consideration. The findings show that most of the study was carried out in the European region. Second, as compared to other water bodies, lakes and inland water bodies (19 percent) are the ones that are most closely monitored in the studies reviewed in this article. Thirdly of the several water quality metrics measured from space, Chl-a (37 percent) was found to be the most prevalent. Finally, MERIS (30 percent) space-based data has been the most broadly available among academics who want to examine water quality from space. This review article also covered some published research done in various parts of the globe, including the problems, solutions, algorithm used, and the advantages of the study. Future study will cover the accuracy of algorithm used and role of microsatellites in the real time water quality parameter observation.

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