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The role of remote sensing in the evolution of water pollution detection and monitoring: A comprehensive review

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ABSTRACT

This comprehensive review explores the transformative role of remote sensing technologies in the detection and monitoring of water pollution. Remote sensing provides dynamic, large-scale, and cost-effective solutions for continuous assessment of water quality. The review covers the application of remote sensing for detecting a range of pollutants, including chemical contaminants, physical parameters, and biological pollutants. The review systematically analyzed 132 studies selected from the Web of Science database using the keywords "remote sensing" and "water pollution," covering publications from the 1990s to December 2023. The analysis highlights the use of multispectral and hyperspectral imaging, machine learning algorithms, and statistical models for precise pollutant detection and quantification.

Key findings demonstrate the efficacy of remote sensing in providing timely and detailed information on water quality, which is essential for environmental monitoring and management. However, several challenges persist, including limitations in the spatial and temporal resolution of satellite sensors, the complexity of water body optical properties, and the need for advanced data processing algorithms. Future research should address these challenges by focusing on enhancing sensor technology, developing sophisticated algorithms for data analysis, and integrating remote sensing with in-situ measurements to achieve more comprehensive water quality monitoring. This review underscores the significant advancements in remote sensing technologies and their crucial role in sustainable water resource management and environmental protection. It emphasizes the need for ongoing innovation and interdisciplinary collaboration to further enhance our understanding and management of water pollution.

1. Introduction

1.1. The dangers water resources face

Industrialization has played an important role in fostering economic growth and promoting urbanisation over generations. However, this has contributed to environmental degradation, mostly owing to the emission of unfavorable chemical and biological contaminants - in gaseous and solid phases - into our soil, air, and water (A. et al., 2018). Environmental contamination, caused by natural and anthropogenic activity, has become a significant concern in modern-day society (Walczykowski et al., 2013).

Water makes up around 70% of the Earth's surface and 50–95% of the mass of all living organisms (A. et al., 2018; Boyd, 2020; Dargaville

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and Hutmacher, 2022), however it is unevenly available, causing global stresses, along with increased consumption and pollution (Boyd, 2020). Flooding in some areas, droughts in others, and a constantly increased demand for cleaner water results in pollution, limited availability and a risk to the ecosystem (Ingrao et al., 2023; Altıok et al., 2023).

1.2. Water pollution

Water pollution is the direct or indirect discharge of contaminants into natural water bodies, such as lakes, rivers, oceans, aquifers, reservoirs and groundwater, without prior proper management, affecting ecosystems, such as aquatic organisms and plants (Walczykowski et al., 2013). There are two main sources of water contamination: (1) Point source which is the entry of contaminants from a single, discrete source such as a ditch or pipe; and (2) nonpoint distributed contamination. Nonpoint source contamination usually is a cumulative outcome of low quantities of contaminants from the leaching out of fertilized, and pesticide-loaded agricultural lands due to nitrogen and xenobiotic compounds or nutrient/phosphate runoff into stormwater ending in water bodies (Walczykowski et al., 2013) or sediment, respectively. Water-polluting substances can be categorized into four distinct classes such as organic pollutants, inorganic pollutants, radioactive pollutants, and pathogens. Certain components can have significant detrimental effects even when present in very low quantities (J. Singh et al., 2020).

1.3. Types and sources of water pollution

Water pollution can be classified into various types based on the nature of pollutants, including chemical, physical, and biological pollution. Chemical pollution involves contaminants like heavy metals, pesticides, and industrial chemicals. Physical pollution includes changes in water temperature, turbidity, and sediment load. Biological pollution refers to the presence of harmful microorganisms, such as bacteria and viruses. The sources of water pollution are diverse and include industrial discharges, agricultural runoff, untreated sewage, and urban stormwater. Identifying and monitoring these sources are crucial for effective water management and pollution control.

1.4. Water quality

There are standards for water quality control that have been established to serve as guides for selecting water supplies for a variety of applications and for preserving water bodies from contamination. The assessment of water quality is crucial in several sectors, including household, agricultural, and industrial water supplies, fisheries and aquaculture, leisure, and the overall well-being of ecological systems (Boyd, 2020). The characteristics that determine the quality of water are classified as biological, physical, and chemical pollutants, and each of these categories involves a range of associated parameters (Akhtar et al., 2021). Bacteria, algae, viruses, and protozoa are examples of biological water quality metrics, whereas physical water quality parameters include turbidity, temperature, colour, taste, odour, particulates, and Electrical Conductivity (EC). The factors indicative of chemical water quality include pH levels, inorganic and organic compounds, heavy metal concentrations, hardness, dissolved oxygen (DO) levels, Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), and radioactive substances (Omer, 2019). However, these methods can be complicated and sometimes fail to accurately represent water quality. Furthermore, these techniques can result in significant costs, be labour-intensive, require a considerable amount of time, include additional risks, and may only detect some contaminants present in the water. The results of these methods are compared with established regulations to estimate and categorize the water quality. However, this conventional comparison approach may need to be revised and subjective (Alvizuri-Tintaya et al., 2022). Therefore, it is necessary to advance the robustness and reliability of traditional *in-situ* monitoring of water quality, linking physicochemical and biological analysis with remote assessment.

The concept of water quality has a long history, spanning over hundreds of years. For example, faecal indicator bacteria (FiB) have been utilized for over 150 years ago as indicators of water contamination and associated with health risks. This tradition traces back to significant events in the late 19th century, including John Snow's investigation of the 1854 London cholera outbreak and Robert Koch's discovery of *Vibrio cholerae* in 1884, originally observed by Filippo Pacini in 1854 (Burian et al., 2000; Holcomb and Stewart, 2020; Teaf et al., 2018). However, the faecal indicator technique suffers from limitations, including inconsistent associations between faecal indicator bacteria occurrence, enteric pathogens, as well as being time-consuming, costly, and posing health risks (Field and Samadpour, 2007; Sclar et al., 2016).

Water quality is complex spatiotemporal parameter. Water quality differences are also dependent on the intended purpose of the water. While the fundamental regulations associated with this issue cover the quality standards for drinking water, irrigation water, and wastewater disposal, it is also feasible to establish a distinct quality standard tailored to the specific requirements. While water quality standards are laboriously monitored using the stated parameters, additionally, desired water quality can be accomplished with the assistance of suitable treatment techniques when it is required (Omer, 2019). Furthermore, measuring water quality of wastewater to identify its pollutants is crucial for choosing the most appropriate wastewater treatment method.

1.5. Optical mechanisms of water pollution

Understanding the optical mechanisms of water pollution is essential for remote sensing applications. Pollutants can alter the optical properties of water by changing its color, turbidity, and reflectance characteristics. For instance, dissolved organic matter and chlorophyll can absorb specific wavelengths of light, while suspended sediments can scatter light. Remote sensing technologies utilize these changes in optical properties to detect and quantify various pollutants in water bodies. Advanced sensors can capture data across multiple spectral bands, enabling detailed analysis of water quality parameters.

1.6. Remote sensing for water quality detection and monitoring

Remote sensing technologies, along with Geographic Information Systems (GIS), offer enormous potential for detecting events in nature. Among these are detection and monitoring of water body condition, quality and contamination level (Walczykowski et al., 2013). Since the successful launch of Landsat-1 in 1972, remote sensing technologies have revolutionized water quality monitoring by leveraging the spectral, spatial, and temporal properties of light reflected from water bodies (S. K. Singh et al., 2015). These technologies use a variety of sensors mounted on satellites and aircraft to measure radiation across different wavelengths, enabling the detection of chemical, biological, and physical pollutants in water (Cantini et al., 2019).

Remote monitoring of water resources enables dynamic observation, is endorsed with high adaptability and efficiency and can include big volumes of data (Zang et al., 2012) while being cost and time-effective. Therefore, as remote sensing technologies evolve (Ardila et al., 2022; Buriti, 2022), their application in water pollution monitoring promises to become more refined, offering comprehensive and dynamic insights into water quality (Sagan et al., 2020). The integration of remote sensing with traditional water quality monitoring methods can enhance the accuracy and comprehensiveness of water pollution assessments.

Therefore, this review aims to describe the transformative role of remote sensing technologies in detecting and analyzing water pollution through specific pollutant detection and monitoring, marking a pivotal shift in how environmental data are collected and interpreted. Furthermore, the current gaps and challenges are discussed pointing towards future directions.

2. Methods

Web of Science database (WOS) has been employed for the purposes of this study. We have noticed a big difference in the number of papers on Water quality – 731 articles (27 review articles) – and Water pollution. Exploring the WOS database using the keywords "remote sensing" and "water pollution" revealed a collection of 120 papers starting from the 1990s to December 2023 (Fig. 1). This disproportion suggests a higher focus on broader aspects of water quality, with comparatively less attention dedicated to the challenges and methodologies specific to detecting and analyzing water pollution (see Fig. 2).

Thus, the central objective of this paper is to gather most of the knowledge on remote sensing applications in detecting **specific pollutants** within water environments to assess water quality. The investigative process was structured and embraced a dual-phase assessment methodology.

Initially, each paper underwent a preliminary screening to assess its relevance to the targeted theme. This phase allowed for a quick elimination of studies that did not align with the primary focus. Following this, we conducted a more comprehensive review. The comprehensive review involved systematically noting critical elements, including the types of pollutants, specific remote sensing instruments, sensor specifications, geographical contexts of the studies, diverse water body classifications under investigation, temporal and spatial resolution of data collection, methodologies used for data analysis, calibration and validation techniques, sources of ancillary data (e.g., meteorological, hydrological), statistical methods applied, outcomes and key findings, limitations and challenges identified in the studies, and recommendations for future research.

During this extensive review, a notable trend emerged, with several studies specifically addressing pollutants around mining areas. Recognizing the significance of this subtheme, we did additional research using the keywords "remote sensing," "mine," and "water pollution," resulting in additional studies in the literature review.

Out of the 132 studies examined, we found 67 of them to be directly related to the investigated topic, providing substantial insights into remote sensing applications for water pollutant detection and, subsequently, the assessment of water quality. An additional 13 studies, while not directly related, held relevance and were retained for further readings. The remaining studies, which were not aligned with the primary focus, predominantly addressed general water quality parameters (such as temperature, pH, turbidity) rather than **specific water pollutants** (like heavy metals, nitrates, phosphates). One of the related studies offered a short review of remote sensing technologies in water monitoring, where twelve scientific studies were reviewed. However, all of the mentioned studies were published in Chinese and therefore not included in this review (Liu, 2023).

We have grouped the results into three sections, chemical, physical, and biological, and complex matrix water pollutants.

3. Results

3.1. Remote sensing and chemical water pollutants

Chemical water pollutants, predominantly emitted into natural water bodies through anthropogenic activities, include substances such as nitrogen compounds and nutrients from agriculture, heavy metals from mining, acids from manufacturing, and chlorinated organic compounds from sewage systems and industrial activities (Walczykowski et al., 2013). Additional pollutants include oils, fats, hydrocarbons from wastewater effluents, oil spills, pesticides and herbicides like glyphosate, atrazine, and chlorpyrifos (Choudri et al., 2020; Geissen et al., 2015; Mahmood et al., 2016; Rashid et al., 2010; Sousa et al., 2018). Monitoring these pollutants involves measuring parameters such as pH, inorganic and organic compounds, heavy metal concentrations, water hardness, DO levels, BOD, chemical oxygen COD, and radioactive substances (Omer, 2019).

Chemical pollutants, such as heavy metals, nutrients, and industrial chemicals, typically affect the water's optical properties by absorbing specific wavelengths of light. For instance, dissolved organic matter and chlorophyll absorb light in the ultraviolet and visible spectra, respectively. These absorptive characteristics lead to changes in the water's color and decrease its clarity.

Chemical pollutants can alter the overall spectral signature of water bodies. The presence of these chemicals can be detected through remote sensing by identifying specific absorption features in the spectral data. Chemical changes often result in color changes in the water, which are detectable with multispectral and hyperspectral imaging techniques.

Several studies have utilized remote sensing to investigate these chemical pollutants. For instance, El-Zeiny et al. (2019) used Landsat imagery to assess water quality in Qaroun Lake, Egypt, measuring pH, EC, turbidity, ammonia, nitrate, phosphate, organic matter, and heavy

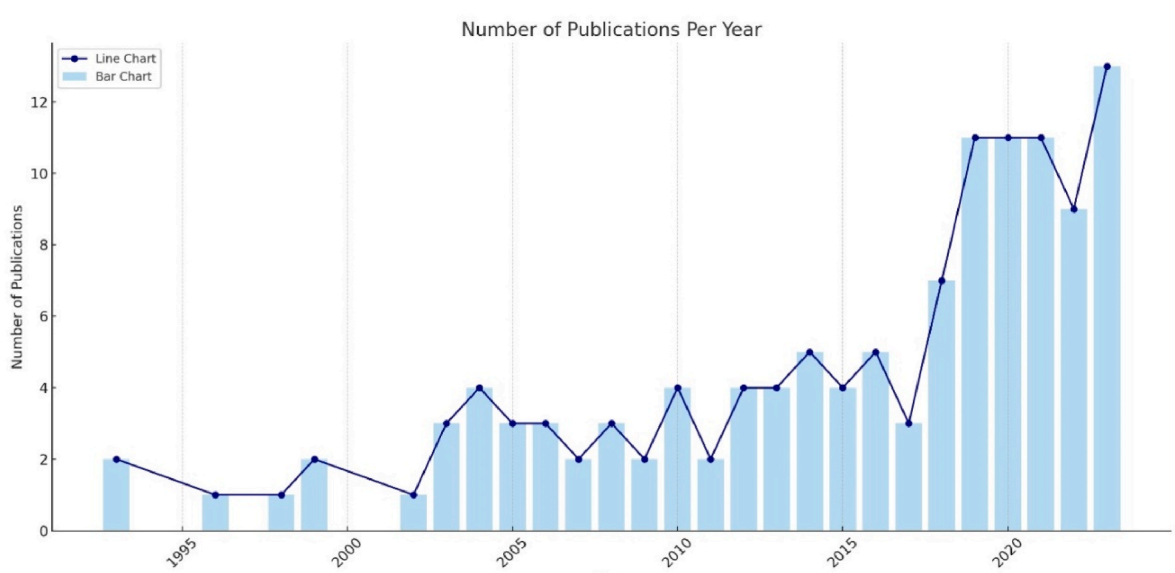

Fig. 1. Number of publications per year within the WOS database using the keywords "remote sensing" and "water pollution."

metals like Pb, Cd, Ni, and Cr. Correlating 24 water samples with Landsat data, the study found Pb and Ni levels exceeding EPA limits and toxic ammonia levels. Similarly, Fouladi Osgouei et al. (2022) used Sentinel-2 imagery and Artificial Neural Networks (ANN) to model water quality in the Aras River, focusing on sodium ($Na+$), magnesium ($Mg2+$), chloride ($Cl-$), sulphate ($SO42-$), calcium ($Ca2+$) ions, and EC. The results highlighted significant pollution from the Armenian tailing dam, corroborating findings from the World Bank.

In another study, González-Márquez et al. (2023) also used Landsat-8 multispectral images to model nitrate concentrations in Playa Colorada Bay, Mexico. By correlating nitrate with optically active parameters from visible and infrared spectra, the study provided a spatio-temporal understanding of nitrate dynamics, revealing concentrations exceeding recommended values for marine life protection according to Mexican pollution control criteria. Do et al. (2023) investigated water pollution in Hanoi, Vietnam, using machine learning with Sentinel-2A and Sentinel-1A data to estimate Total Suspended Sediments (TSS), COD, and BOD, demonstrating high predictive accuracy.

Studies by Shukla et al. (2020) and Alparslan et al. (2009) examined the intersection of land use changes and water quality. Shukla et al. used IRS 1C and Landsat 7 imagery to assess water quality in the Upper Bhima river subbasins, measuring parameters like hardness, Total Dissolved Solids (TDS), BOD, chlorides, pH, color, and turbidity. Alparslan et al. used satellite imagery to map water quality in Turkey, investigating chlorophyll *a* (Chl-a), total phosphorus (TP), total nitrogen (TN), turbidity, BOD, and COD. Similarly, Zeng et al. (2009) studied TN and TP levels in a Chinese lake using Landsat-5 and SPOT-5 imagery, highlighting the negative impact of land use on water quality.

Pollution risk in the Hebei Yuecheng Reservoir, China, has been assessed using a dual NPS model with remote sensing and GIS data to understand phosphorus pollution from different land uses (S. Wang et al., 2014). On the other hand, Liang et al. (2016) developed a technique using remote sensing to measure cadmium (Cd) content in water by analyzing the extinction coefficient and reflectance spectra of Cd compounds.

The effects of pollutants like colza oil, crude oil, and gas oil on radar cross-sections of seawater surfaces have been investigated in a controlled environment, concluding that all pollutants reduced the radar cross-section compared to clean seawater (Mainvis et al., 2018). Chen et al. (2012) used a spectrometer to measure remote sensing reflectance and develop algorithms for estimating heavy metal concentrations (Cu, Pb, Zn) in a Chinese river (Chen et al., 2010) (Fig. 3).

Additional studies have investigated heavy metal pollutants in broader contexts. Jiji et al. (2020) analyzed 17 heavy metal pollutants in Tiruppur District, India, using Landsat data and ICP-OES measurements. Trivero et al. (2013) investigated eight heavy metals in an Italian river using QuickBird 2 imagery, highlighting temporal changes in pollution levels. Other studies have used satellite imagery to investigate water

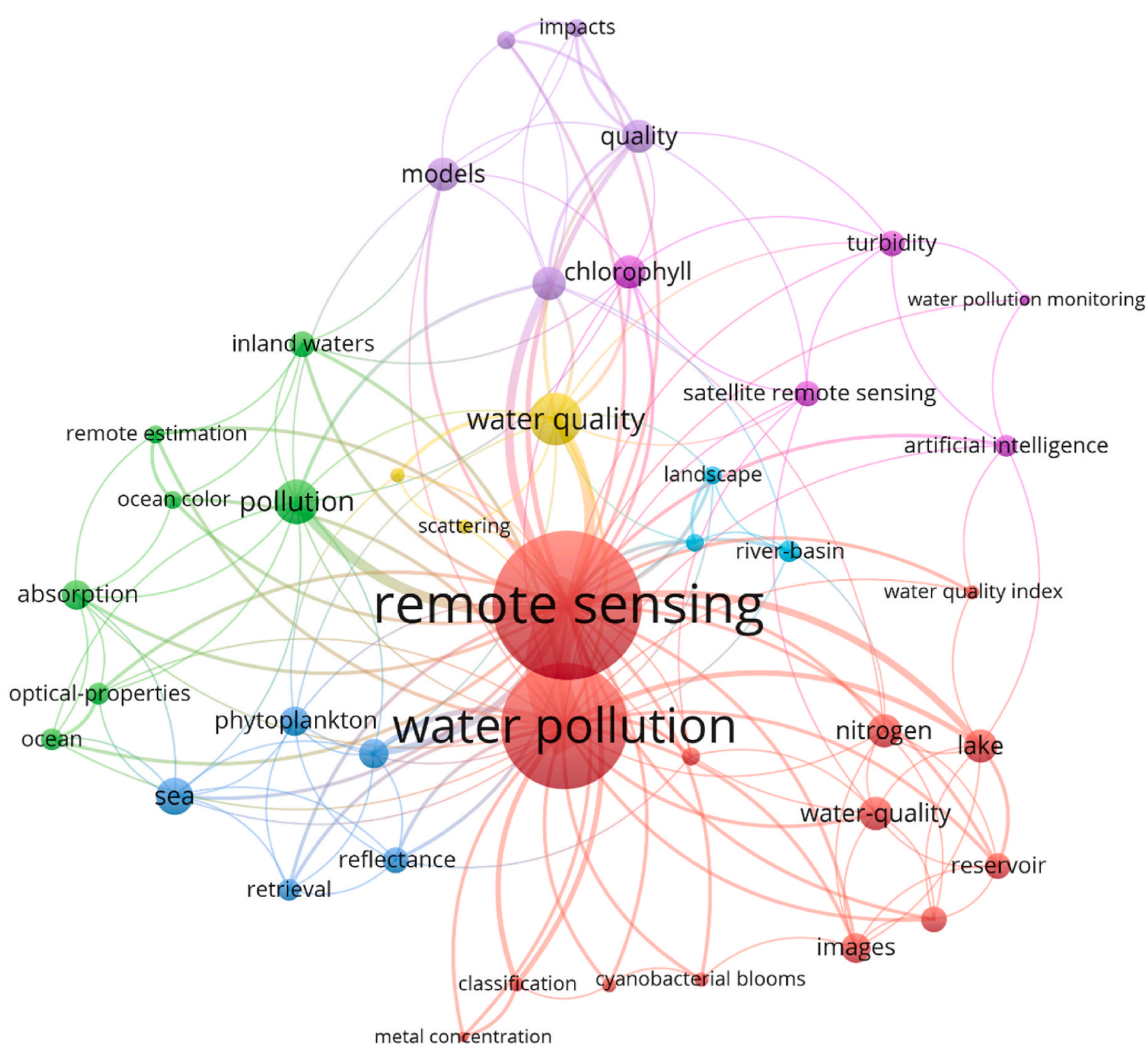

Fig. 2. Keywords network visualization (each colour denotes a distinct group of keywords that frequently appear together in the literature). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

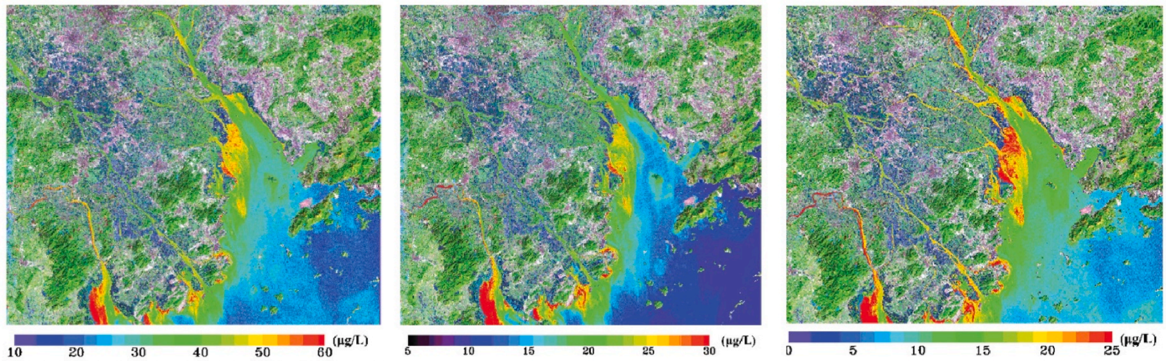

Fig. 3. Heavy metals distribution (Zn, Pb and Cu, left to right) (Chen et al., 2010).

pollution in general contexts, employing indices like the Normalized Difference Water Index (NDWI) to classify pollution levels (Alvizuri-Tintaya et al., 2022), or to support ex-situ findings (Arentsen et al., 2004).

3.2. Remote sensing and physical water pollutants

Physical pollutants, such as suspended sediments, turbidity, and temperature changes, primarily affect the scattering properties of water. Suspended particles increase the scattering of light, which can make the water appear murkier and affect its transparency. Temperature changes can alter the refractive index of water, influencing how light propagates through it. Although not inherently toxic, excessive levels can have harmful effects on aquatic ecosystems. These pollutants include sediment loads from intensive land use, and discarded garbage, such as plastic bottles, bags, rubber, masks, gloves, and wood. Physical pollutants are the most visible among water pollutants and significantly impact aquatic flora and fauna (Walczykowski et al., 2013).

Table 1
Chemical, physical and biological pollutants and parameters investigated with remote sensing.

No	Analysis	Parameters and pollutants investigated	Study area	RS sensor	Water body type	Reference
1	Chemical:	Pb, Cd, Ni, Cr, NH_3., NO_3^-, PO_4^{3-}, OM	Egypt	Landsat	lake	El-Zeiny et al. (2019)
	Physical:	EC, turbidity, TSS				
2	Chemical:	Na^+, Mg^{2+}, Cl^-, SO_4^{2-}, Ca^{2+}	Iran	Sentinel-2	river	Fouladi Osgouei et al. (2022)
	Physical:	EC				
3	Chemical:	NO_3–N	Mexico	Landsat-8	coast	González-Márquez et al. (2023)
4	Chemical:	COD, BOD	Vietnam	Sentinel-1/2	river	Do et al. (2023)
	Physical:	TSS				
5	Chemical:	Hardness, Chlorides, BOD, pH	India	1C Linear imaging Self Scanner III, Landsat 7	river	Shukla et al. (2020)
	Physical:	TDS, Color, and Turbidity				
6	Chemical:	TN, COD, BOD, TP	Turkey	Landsat-5 TM + SPOT-Pan, IRS-1C/D	lake	Alparslan et al. (2009)
	Physical:	Turbidity				
	Biological:	Chl-a				
7	Chemical:	TN, TP	China	Landsat-5, SPOT-5	lake	Zeng et al. (2009)
8	Chemical:	P	China	NPS model with RS and GIS	lake	(S. Wang et al., 2014)
9	Chemical:	CdS, CdO	lab	ASD	lab	Liang et al. (2016)
10	Chemical:	Colza, crude, gas oil	pool	radar	pool	Mainvis et al. (2018)
11	Chemical:	Cu, Pb, Zn	China	spectrometer	river	(Chen et al., 2010, 2012)
12	Chemical:	As, Cd, Cr, Cu, Fe, Pb, Ni, Zn, Al, Co, Mg, Be, B, Li, Mo, Se, V and Hg	India	Landsat	water bodies in a broad area	Jiji et al. (2020)
13	Chemical:	Cr, Ni, Cu, Zn, As, Cd, Hg, Pb	Italy	QuickBird 2	river	Trivero et al. (2013)
14	Chemical:	B, Cu, Pb, Zn,TP, TN, orthophosphate, oil and grease	Utah	Landsat 7	stormwater runoff events	Arentsen et al. (2004)
	Physical:	TSS, turbidity				
	Biological:	Fecal coliforms				
15	Chemical:	As, Cd, Fe, Zn, Mn, Ni, and Al, pH, DO	Bolivia	Sentinel-2	central water bodies	Alvizuri-Tintaya et al. (2022)
	Physical:	Turbidity, conductivity				
16	Physical:	TSS	China	MODIS-Aqua,	lake	(M. Wang et al., 2013)
17	Physical:	Sediment and thermal pollution	China	UAV	water bodies of SW China	Zang et al. (2012)
	Chemical:	oil spills and red tide				
18	Physical:	Suspended matter	Russia	Sentinel MSI S2, MODIS	coastal zone	Shul'ga et al. (2022)
19	Physical:	Turbidity and suspended sediments, transparency	New Zealand	Landsat, ERS satellite	bay	Lounis et al. (2006)
	Biological:	Chl-a				
20	Biological:	Microbial contamination	Canada	various	beaches	Kotchi et al. (2015)
21	Biological:	Chl-a	China	MODIS	lake	(Li et al., 2019a)
22	Biological:	algal blooms	China	MODIS	lake	(M. Zhang et al., 2014)
23	Biological:	Chl-a, phytoplankton biomass	Russia	Various (MODIS?)	lake	Gbagir and Colpaert (2020)
24	Biological	*E. coli*	India	LISS III sensor	groundwater bodies in an area	Dandge and Patil (2022)
	Chemical:	pH, K, NO_3^-, SO_4^{2-}, Cl^-, F^-, TA, and TH				
	Physical:	Turbidity, TDS, EC				

The presence of physical pollutants can also be detected through remote sensing by examining changes in the water's reflectance patterns. For example, high turbidity levels cause increased backscattering of light, which can be measured by remote sensors. Both chemical and physical pollutants contribute to the overall optical complexity of water bodies, and advanced remote sensing techniques can be used to differentiate and quantify these pollutants by analyzing their unique spectral and scattering signatures.

3.2.1. Detection and monitoring methods

Wang et al. (2013) demonstrated this in their study on Lake Taihu in China, using MODIS-Aqua measurements to emphasize the significance of Shortwave Infrared (SWIR) bands in detecting TSS and improving atmospheric correction algorithms for water colour products. Similarly, El-Zeiny et al. (2019) investigated Qaroun Lake in Egypt, revealing the impacts of untreated pollutants, including turbidity and TSS, alongside various chemical pollutants, using Landsat and Sentinel-2 imagery. Their findings highlighted the urgent need for measures to mitigate contamination levels and safeguard water quality.

Do et al. (2023) also studied TSS in combination with BOD and COD, highlighting the ability of remote sensing to monitor both physical and chemical pollutants concurrently. This integrated approach is further supported by studies that evaluate chemical and physical pollutants together, sometimes including biological parameters for a comprehensive understanding of water pollution (Table 1).

The flexibility of remote sensing is showcased by Zang et al. (2012), who used Unmanned Aerial Vehicle (UAV) imagery to investigate small-scale water pollution in Southwest China. They focused on sediment and thermal pollution, oil spills, and red tide, demonstrating how high-resolution UAV imagery can enhance pollution monitoring accuracy and efficiency.

Shul'ga et al. (2022) examined suspended matter in coastal waters near Crimea, identifying both natural and anthropogenic sources of suspended matter. Their approach to mapping suspended matter dynamics offers crucial insights for environmental monitoring, particularly in coastal regions where hydrometeorological factors influence pollutant distribution.

Lounis et al. (2006) studied water quality in Algiers's Bay, focusing on physical pollutants such as turbidity, suspended sediment concentration (SSC), and water transparency, using Secchi Disk Depth (SDD) measurements alongside Chl-a concentration, a biological parameter. They integrated Landsat and ERS satellite imagery with in-situ measurements and neural network modelling to construct Pollution Signature Draw (PSD) and map key water quality parameters across the bay.

3.2.2. Remote sensing and mine tailings

Mine tailings, comprising waste materials from mining operations, are stored in containment structures called tailings dams. These tailings can contain hazardous substances like heavy metals and chemicals. However, failures in these containment structures can lead to tailings spills, releasing contaminated water and sediment into the environment. These spills pose significant environmental risks, including water pollution and habitat destruction. Remote sensing technologies play a crucial role in monitoring tailings storage facilities and detecting potential risks of spills. By providing detailed spatial and temporal information, remote sensing helps assess the integrity of tailings dams and identify areas that are prone to failure. Moreover, remote sensing facilitates rapid response and assessment during a spill, enabling effective mitigation measures to minimize environmental damage. Therefore, remote sensing data can be used for long-term reclamation and rehabilitation monitoring and effective environmental management of mining areas (Charou et al., 2010).

Several studies have investigated the use of remote sensing to monitor chemical pollutants released from mining activities (Table 2). Tesfamichael and Ndlovu (2018) utilized middle-resolution satellite imagery to investigate concentrations of various chemical constituents (major anions, cations, trace elements) in water areas affected by abandoned gold mines. Their results highlight the potential of moderate spatial resolution remote sensing for quantifying hydrochemical properties in mining environments and advocate for further studies with larger sample sizes to enhance accuracy and reliability.

Karan and Samadder (2016) used remote sensing and GIS technologies to assess the environmental impact of coal mining activities, focusing on surface and groundwater quality. They introduced a novel Risk Potential Index (RPI) model, which integrates remote sensing data from sources like Landsat and MODIS to forecast surface water contamination due to coal mining. The RPI model, based on the Source/Vector/Target framework, considers factors such as the proximity of mining activities to surface watercourses, transportation pathways of contaminants, and areas at risk of pollution. Their study identifies critical areas susceptible to contamination, aiding decision-making for pollution mitigation strategies.

Charou et al. (2010) utilized multi-temporal imagery from Landsat-5, Landsat-7, SPOT Panchromatic, and ASTER satellites to assess the impact of mining activities on land and water resources. By synergistically using remote sensing and GIS, they created a comprehensive database for storing, processing, and retrieving environmental data, essential for environmental impact assessment and monitoring in mining areas even after mining activities have ceased.

Crioni et al. (2023) focused on monitoring river turbidity following a mine tailing dam failure using Sentinel-2 imagery. Their research developed an empirical model based on satellite-derived data to predict turbidity levels, showing a strong correlation between turbidity and near-infrared band (NIR) data from Sentinel-2 imagery. This study highlights the efficacy of remote sensing in assessing the spatiotemporal dynamics of river turbidity, particularly after industrial accidents like mine tailing dam failures.

Ruppen et al. (2023) also used Sentinel-2 to evaluate the impacts of tailings spills on water quality following the Catoca mine tailings spill in Angola. By analyzing satellite imagery, the study tracked the pollution plume resulting from the tailings spill over considerable distances, providing insights into the spatiotemporal dynamics of the pollution event (Fig. 4). Similarly, Pyankov et al. (2021) used Sentinel-2 for water pollution monitoring near abandoned mines, correlating high levels of

Table 2
Physicochemical analysis combined with remote sensing for mine tailings detection and monitoring.

No	Mine type	Analysis	Parameters and pollutants investigated	Study area	RS sensor	Water body type	Reference
1	Gold	Chemical: Physical:	- several - EC	Africa/ India	Landsat, Aster	open pit/surface and groundwater	(Tesfamichael and Ndlovu, 2018; Karan and Samadder, 2016)
2	Diamond	Physical:	Turbidity, TSS	Angola	Sentinel-2	river	Ruppen et al. (2023)
3	Iron ore	Physical:	Turbidity	Brazil	Sentinel-2	river	Crioni et al. (2023)
4	Mainly lignite	Physical:	Temperature	Greece	Landsat, SPOT Panchromatic, and ASTER	one lake and two land areas	(Charou et al., 2010),
5	Coal	Chemical:	pH, sulphate, NO_3–N, total hardness, Pb, As	India	Landsat and MODIS	surface and goundwater bodies	Karan and Samadder (2016)
6	Coal	Chemical:	Fe	Russia	Sentinel-2	river	Pyankov et al. (2021)

Fig. 4. High resolution images of rivers and sediments contaminated by acidic mine water in the Kizel coal basin (left – Kos'va; right – South Vil'va; modifed from (Pyankov et al., 2021).

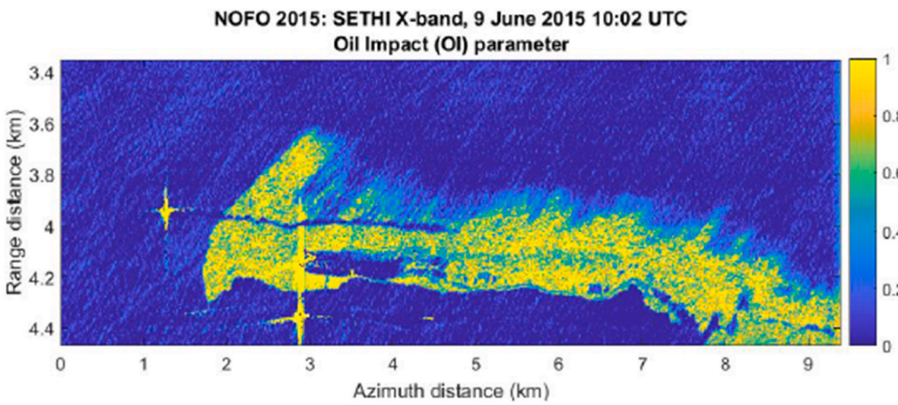

Fig. 5. OI parameter computed with SETHI (the ONERA airborne sensor dedicated to the exploration of scientific applications of remote sensing) X-band SAR data (modified from Viallefont-Robinet et al., 2019).

iron (Fe) contamination with changes in water colour to a 'rusty' shade in the Kizel coal basin, highlighting the severe impact of acid mine drainage (see Fig. 5).

3.2.3. *Remote sensing and oil spills in water bodies*

Our systematic search identified limited studies on oil spills in water bodies using remote sensing. However, broader literature extensively covers remote sensing applications for oil spill detection and monitoring, providing valuable insights into methodologies and advancements in this field (Fingas and Brown, 2014; Vasconcelos et al., 2023).

3.2.3.1. Radar satellite imagery studies. Gade and Alpers (1999) used Synthetic Aperture Radar (SAR) imagery from the European Remote Sensing Satellite ERS-2 to monitor oil spills in European coastal waters, analyzing over 660 SAR images. They identified oil spills ranging from 0.1 km^2 to over 56 km^2, with a higher detection frequency during morning satellite passes due to oil pollution occurring predominantly at night. Seasonal variations, such as increased wind speeds in winter, affected the visibility of oil on SAR images.

Liao et al. (2023) combined Polarimetric Synthetic Aperture Radar (PolSAR) images with deep learning to monitor oil spills. Using a semantic segmentation model based on DeepLabv3+ and trained with Sentinel-1 images, they detected oil films on the sea surface, showing a decrease in oil spill frequency in Jiaozhou Bay, China, from 2017 to 2019, indicating effective marine management.

Mainvis et al. (2018) analyzed the effects of oil slicks on radar backscattering from sea surfaces, using the first-order small slope approximation (SSA1) model to differentiate between contaminated and clean sea surfaces. Their statistical approach improved oil spill detection capabilities, crucial for environmental monitoring and response.

3.2.3.2. Field experiments and reflectance studies. Haule et al. (2021) conducted a field experiment in the Baltic Sea to assess dispersed oil's impact on remote sensing reflectance. Their findings highlighted the challenges of detecting dispersed oil forms and emphasized the sensitivity of upwelling radiance to subtle changes in oil pollution levels.

Viallefont-Robinet et al. (2019) conducted a controlled experiment, releasing a mineral oil emulsion into the sea to enhance satellite remote sensing methodologies. Using dual-frequency radar sensors, they developed an operational workflow integrating radar and optical branches for detecting, characterizing, and quantifying oil slicks, providing insights for effective intervention strategies.

3.3. *Remote sensing and biological and complex matrix water pollutants*

Biological water pollutants, including pathogenic microorganisms (e.g., *E. coli*) (Wu et al., 2021), protozoa, viruses, algae (e.g., algal blooms, cyanobacteria, and phytoplankton), pose significant ecological and environmental challenges to humans and aquatic ecosystems (Amorim and Moura, 2021). These pollutants can proliferate due to elevated nutrient concentrations from agricultural activities, leading to eutrophication. Microorganisms can enter water through rainfall carrying dust or from soil polluted by animal and human waste. Raw sewage is a common contaminant source (Walczykowski et al., 2013).

Remote sensing technologies offer valuable tools for monitoring and understanding the dynamics of these pollutants over large spatial scales and extended periods. Studies have demonstrated the effectiveness of remote sensing in detecting and quantifying biological pollutants, providing critical insights into their distribution, extent, and ecological impacts.

Kotchi et al. (2015) investigated microbial contamination of recreational waters in southern Quebec, Canada, using various EO images from satellites like WorldView-2, GeoEye-1, SPOT-5/HRG, Landsat-5/TM, Envisat/MERIS, Terra/MODIS, NOAA/AVHRR, and Radarsat-2. The study employed supervised classification and logistic regression models to link faecal contamination levels with environmental determinants derived from satellite images, aiming to understand the complex relationships between satellite-derived environmental data and microbial contamination risks.

Li et al. (2019) and Zhang et al. (2014) focused on estimating Chl-a concentrations and monitoring algal blooms in Taihu Lake, China, using MODIS imagery. Li et al. developed a classification-based algorithm to improve Chl-a estimation in turbid and eutrophic waters, while Zhang et al. tracked algal bloom development over time, providing valuable insights for managing their ecological impacts.

Gbagir and Colpaert (2020) analyzed water quality and ecological status in Lake Ladoga, Russia, using remote sensing data to monitor phytoplankton biomass and Chl-a concentrations, contributing to understanding the lake's ecological health and biological pollutant impacts.

Dandge and Patil (2022) assessed groundwater quality in the Bhokardan area of India using toposheets, and LISS III sensor imagery. They identified *E. coli* as the primary biological pollutant, followed by turbidity, providing insights into water resources quality for drinking purposes.

3.3.1. Complex matrix pollutants in water bodies

Klemas (2012) highlighted the role of remote sensing in monitoring coastal plumes, using sensors like multispectral and hyperspectral imagers and thermal infrared radiometers. These tools track coastal plumes by detecting differences in colour, turbidity, salinity, or temperature, explaining how plumes accumulate biological and physicochemical materials, including pollutants.

Wu et al. (2021) utilized high-resolution remote sensing imagery from the Chinese satellite Gaofen-2 (GF-2) to detect urban black-odour water (BOW), a result of pollutant discharge and water stagnation. Their method achieved an 85.7% accuracy rate in detecting BOW, demonstrating the practical application of remote sensing for managing urban water pollution.

Shao-Meng et al. (2003) used remote sensing to monitor water pollution from urban and rural waste discharges into Dianchi Lake, China, employing pixel unmixing techniques to enhance monitoring accuracy in this severely polluted and eutrophic lake. Similarly, Cai et al. (2023) used UAV hyperspectral data to identify urban water pollution sources, analyzing fluorescent components and spectral indices from dissolved organic matter in polluted water samples. Their method achieved over 70% recognition accuracy for different pollution sources, demonstrating UAVs' potential in environmental monitoring.

Industrial sewage outfalls have been monitored using combined web crawler technology and remote sensing to monitor in the Luan River Basin Zhang et al. (2021). By integrating internet-sourced industrial data with remote sensing images, they accurately identified sewage outfall locations and modelled sewage inflow distribution, achieving an 89% accuracy rate.

Bondur et al. (2020) monitored deep wastewater outfalls in the Black Sea, using spectral indices to identify the rupture location, discharge amount, and temporal changes, demonstrating remote sensing's capability to track industrial wastewater pollution.

The ecological status of the Mokra Sura river in Ukraine (Kharytonov et al., 2019) and monitoring algal blooms and hydrocarbon pollution from an oil spill (Laneve et al., 2022) have been done using Sentinel-2 data, integrating environmental water quality indices with satellite data to track pollutants like sulphate, magnesium, zinc, chromium, and oil contaminants.

UAV-mounted hyperspectral was also used to evaluate water quality indicators in Suzhou City, China, optimizing models with a differential evolution algorithm Zhang et al. (2022).

4. Discussion-challenges, gaps of knowledge and future directions

Remote sensing technologies have revolutionized the monitoring and analysis of water pollution, offering comprehensive insights across physical, chemical, and optical dimensions. By leveraging advanced sensors and integrating multisensor data, remote sensing has enabled the detection and quantification of various pollutants with greater accuracy and efficiency. The integration of remote sensing data with advanced processing techniques such as machine learning and spectral analysis further enhances our capability to monitor water pollutants. For instance, machine learning models applied to satellite data have improved predictions of Chl-a levels, providing insights into algal bloom dynamics and their environmental impacts (Binding et al., 2018). Similarly, advanced algorithms and models are essential for accurately interpreting complex optical signals from various water bodies (Cai et al., 2023).

This section discusses the current state and future prospects of remote sensing in water pollution monitoring, focusing on physical, chemical, optical, detection aspects, and accuracy validation.

4.1. Chemical aspects of water pollution monitoring

The detection of chemical pollutants, such as heavy metals, nutrients, and industrial chemicals, has been effectively conducted using hyperspectral imaging and specific spectral bands that capture unique absorption features (El-Zeiny et al., 2019; Chen et al., 2012). Remote sensing has proven particularly instrumental in detecting chemical pollutants, which often originate from industrial discharges and agricultural runoff. Sentinel-2 satellites, part of the European Copernicus program, have been invaluable in detecting chemical pollutants, combining high spatial resolution with increased spectral and temporal resolution necessary for comprehensive water resources remote sensing (Laneve et al., 2022). Multispectral and hyperspectral imaging, which involve capturing data across broad and narrow wavelength bands respectively, play crucial roles in effectively monitoring these pollutants. For instance, hyperspectral imaging has enabled detailed mapping of heavy metals like Pb and Cd in aquatic environments by distinguishing their unique spectral signatures. The development of new spectral indices and machine learning algorithms will enhance the detection capabilities of chemical pollutants. Establishing long-term remote sensing programs will help in understanding the temporal dynamics of chemical pollution and its long-term impacts on water quality.

4.2. Physical aspects of water pollution monitoring

Monitoring physical pollutants such as suspended sediments and turbidity demonstrates the importance of remote sensing technologies in water quality assessment. Remote sensing technologies, such as MODIS and Sentinel-2, have been effective in mapping turbidity levels across large water bodies. Thermal sensors on satellites like Landsat and MODIS are used to detect temperature variations in water bodies, which can indicate thermal pollution and its effects on aquatic life. The capacity to monitor these parameters over large areas and frequent temporal updates provides a powerful tool for environmental engineers, managers, and policymakers (D. Zhang et al., 2022). Future remote sensing missions should aim to provide higher spatial resolution to better capture localized physical pollution events. Combining remote sensing data with ground-based measurements will improve the accuracy and reliability of physical pollution monitoring.

On the other hand, UAV imagery, offering significantly higher resolution than satellites and piloted aircraft, has also been noted for monitoring water quality in smaller-scale water bodies. UAVs are cost-effective, flexible in flight path planning, and can capture high-resolution data close to the target, making them ideal for detailed pollution monitoring (Zang et al., 2012). However, their limited spatial scale of observation requires frequent flights to ensure comprehensive data acquisition.

4.3. Biological aspects of water pollution monitoring

Remote sensing of biological pollutants, particularly algal blooms, represents a vital application of these technologies. Algal blooms can severely degrade water quality and harm aquatic life and human health. Reflectance data gathered via satellite or aerial imagery provides a comprehensive view of water bodies, enabling the detection of Chl-a concentrations, a key indicator of algal biomass and eutrophication potential (Li et al., 2019). The integration of remote sensing data with in-situ biological sampling has improved the understanding of the spatial and temporal distribution of biological pollutants. Advances in sensor technology and data processing techniques continue to enhance our ability to monitor and manage algal blooms and related biological pollutants (Zimba and Gitelson, 2006). Future research should focus on enhancing the resolution and sensitivity of remote sensing technologies to detect a wider range of biological pollutants and integrating these technologies with automated in-situ sensors for real-time monitoring.

4.4. Accuracy validation of remote sensing in water quality monitoring

Accuracy validation is crucial for ensuring the reliability of remote sensing technologies in monitoring water quality indicators. Various methods have been employed to validate the accuracy of remote sensing data, including the comparison of satellite-derived measurements with in-situ observations. For example, Wang et al. (2013) demonstrated the use of MODIS-Aqua measurements to detect TSS in Lake Taihu, China, and validated their results with ground-based data, achieving a correlation coefficient of 0.89. Similarly, El-Zeiny et al. (2019) validated their findings on nutrient runoff in Qaroun Lake, Egypt, using in-situ measurements, reporting a high level of agreement with an R^2 value of 0.91.

Statistical methods, such as root mean square error (RMSE) and mean absolute error (MAE), are commonly used to quantify the accuracy of remote sensing models. For instance, Do et al. (2023) used these metrics to validate their remote sensing model for monitoring TSS, BOD, and COD, achieving RMSE values of less than 10%. Furthermore, integrating remote sensing data with machine learning algorithms has improved the accuracy of pollutant detection. Studies by Zang et al. (2012) and Shul'ga et al. (2022) have shown that using neural networks and other advanced algorithms can enhance the precision of remote sensing data, with validation results indicating significant improvements in model performance.

4.5. Optical aspects of water pollution monitoring

Understanding the optical properties of water affected by various pollutants is fundamental for remote sensing. Pollutants can alter the absorption and scattering of light, which is detectable through multispectral and hyperspectral sensors (Cantini et al., 2019). Remote sensing has been used to monitor changes in water color due to pollutants like dissolved organic matter and chlorophyll (Pyankov et al., 2021). Developing more sophisticated algorithms to differentiate between various optical signatures of pollutants will improve the accuracy of remote sensing data interpretation. Collaboration between optical scientists and remote sensing experts will lead to better models and tools for monitoring water quality.

4.6. Challenges and future directions

Despite these advancements, challenges persist in applying remote sensing for water pollution monitoring. Current satellite sensor limitations in spatial and temporal resolution can hinder the detection of localized or ephemeral pollution events. Moreover, the complexity of water body optical and physical properties necessitates sophisticated models to accurately interpret remote sensing data, requiring ongoing refinement of algorithms and models. The integration of remote sensing data with *in-situ* measurements can improve the accuracy and reliability of water pollution assessments. On-site measurements, including water quality indices that combine physical, chemical, and biological parameters, should be integrated into remote sensing technologies for comprehensive detection and monitoring (Dandge and Patil, 2022; Dandge and Patil, 2022).

The concept of "living" sensors, such as those based on Bioelectrochemical Systems (BES), offers an exciting complement to remote sensing technologies. BES devices use live microbial communities to convert biochemical energy from organic matter into electricity, responding sensitively to environmental perturbations. These biosensors can enhance the detection of environmental events, providing real-time data that complements satellite observations like those from Sentinel-2. Integrating BES with remote sensing could significantly improve the accuracy and responsiveness of water quality monitoring systems, offering a new dimension to biomarking and biological parameter monitoring.

By providing timely and detailed information on pollutant distributions, remote sensing tools enable targeted interventions and support sustainable management of water resources. Collaborations across disciplines—such as modellers, environmental scientists, and remote sensing specialists—will be crucial in leveraging the full potential of remote sensing for water pollution monitoring. Future research should focus on enhancing the spectral, spatial, and temporal resolution of remote sensing data, developing more sophisticated data processing algorithms, and integrating remote sensing with *in-situ* measurements for a comprehensive understanding of water pollution dynamics. Additionally, advancing remote sensing technology to detect and monitor chemicals such as pesticides, fertilizers, and emerging pollutants like microplastics will be vital.

5. Conclusions

Our review has critically evaluated studies on the application of remote sensing technologies for monitoring water pollution, covering chemical, biological, and physical domains. Key findings indicate that remote sensing, through multispectral and hyperspectral imaging, is highly effective in detecting and quantifying pollutants over large spatial areas and temporal scales. Integrating advanced data processing techniques, such as machine learning and deep learning, has significantly enhanced the accuracy and efficiency of remote sensing applications, enabling more precise identification and quantification of water pollutants.

Remote sensing stands as a pivotal tool in ongoing efforts to monitor and mitigate water pollution. With sustained advancements and collaborative efforts, the potential of remote sensing to contribute to the sustainable management of water resources and the protection of aquatic environments is immense. However, challenges persist, including technical limitations of sensors, atmospheric and aquatic interferences, and the need for comprehensive data analysis frameworks. Continuous innovation in sensor technology, algorithm development, and interdisciplinary collaboration is essential to overcome these hurdles.

Remote sensing technologies have proven indispensable in the global effort to monitor and mitigate water pollution. By continuously advancing these technologies and integrating them with continuous, real-time biosensor measurements, we can develop more effective water management strategies and decision-making policies, leading to improved environmental outcomes and the sustainable management of water resources.

CRediT authorship contribution statement

Gordana Kaplan: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fatma Yalcinkaya:** Writing – review & editing, Validation, Investigation, Formal analysis, Conceptualization. **Esra**

Altıok: Writing – original draft, Methodology, Formal analysis. **Andrea Pietrelli:** Writing – original draft, Validation, Supervision, Conceptualization. **Rosa Anna Nastro:** Writing – original draft, Visualization, Validation, Data curation. **Nicola Lovecchio:** Writing – review & editing, Investigation. **Ioannis A. Ieropoulos:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition. **Argyro Tsipa:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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