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REVIEW

Transforming water quality monitoring for advancements in sustainable resource management

Mahendra Aryal

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Abstract Water quality monitoring is a fundamental component of sustainable management of water resources. This review outlines the progression of water quality assessment, transitioning from traditional methodologies to advanced technologies such as remote sensing, nanotechnology, sensor networks, and artificial intelligence. It emphasizes the transformative potential of integrating big data analytics to enhance accuracy, transparency, and decision-making processes. The study addresses critical global issues, including transboundary water conflicts, complexities in data management and the emergence of contaminants. Additionally, the study employs case studies to illustrate the practical application of these technologies, offering actionable recommendations for their integration into sustainability governance frameworks. This review highlights the interconnectedness of advanced technologies, community engagement, and regulatory frameworks in pursuing sustainable water resource management, serving as a guide for researchers, policymakers, practitioners and communities dedicated to preserving water resources.

Keywords Water Quality . Contaminants . Advanced Technologies . Community Engagement . Sampling Techniques . Environmental Sustainability

Introduction

Water, regarded as the essence of life, is crucial for sustaining ecosystems, supporting agriculture practices, and fulfilling the needs of an expanding global population. The assurance of availability of clean and safe water is fundamental to public health, economic development, and environmental sustainability (UN-Water 2016). Rapid urbanization, industrialization, modern agricultural practices, and climate change have significantly contributed to the degradation of WQ. Timely monitoring is important for identifying potential threats and safeguarding water resources (Aryal 2022). In light of these challenges, the establishment of effective WQM systems is imperative to detect and mitigate contamination, thereby protecting both human health and the environment.

Water pollution poses serious risks to both ecosystems and human health, serving as a primary contributor to the proliferation of waterborne diseases like cholera and dysentery, which can lead to severe illness and mortality (Bashir et al. 2020). The quality of water resources is perpetually threatened by a variety of anthropogenic activities, including industrial discharges, agricultural runoff, urbanization, climate change, and population growth. Industrial pollution, characterized by the discharge of harmful pollutants from manufacturing facilities, has a profound impact on WQ (Chathuranika et al. 2023). Agricultural runoff introduces pesticides, fertilizers, and sediments into aquatic systems, resulting in nutrient pollution and increased turbidity. Urbanization alters land use patterns, heightens stormwater runoff, and contributes to contamination from residential areas (Kaur and Sinha 2019). Climate change exacerbates WQ issues through transformed precipitation patterns, rising temperatures, and extreme weather events. Additionally,

Mahendra Aryal
Department of Chemistry, Tribhuvan University, Kathmandu, Nepal
e-mail: mahendraaryalnp@yahoo.com

population growth amplifies the demand for water resources and intensifies WQ challenges due to insufficient sanitation infrastructure.

Although traditional WQM methods are recognized for their accuracy, they often fall short in addressing widespread and complex challenges due to their labor-intensive and time-consuming nature, as well as their limited spatial and temporal coverage (Essamlali et al. 2024). The last few decades have seen a surge in technological innovations designed to revolutionize WQM. Advanced technologies and methodologies now present real-time, high-resolution data collection and analysis. Innovations such as RS, automated sensors, biosensors, and advanced data analytics, including AI and ML, are transforming water resource management (Zainurin et al. 2022). This advanced system is capable of detecting contamination, monitoring environmental changes, and predicting risks, while also incorporating stakeholder input for community-based monitoring. It effectively addresses global water challenges, including scarcity and contamination, by emphasizing cost-effective and scalable solutions that enhance proactive resource management (Essamlali et al. 2024).

Despite facing challenges such as high costs, inadequate infrastructure, and complex policy barriers, the researchers have successfully integrated theoretical advancements with practical solutions, particularly in developing regions where WQ issues are pressing. These countries frequently encounter significant WQ challenges due to limited resources and outdated monitoring systems (Kirschke et al. 2020). The adaptive governance framework proposed in this research offers a flexible, context-specific approach to water management that can be tailored to diverse ecological, economic, and social conditions (Akamani 2023). By promoting collaborative decision-making among stakeholders, including local governments, communities, and international organizations, the framework ensures equitable access to clean water. Engaging multiple parties enhances accountability and aligns water management strategies with the specific needs of affected populations.

This review aims to provide an overview of the recent innovations and techniques in WQM. It investigates technological advancements in monitoring tools and methods, evaluates their applications and effectiveness, and identifies the challenges and opportunities associated with the implementation of these technologies for sustainable water resource management. Through the analysis of case studies and recent research, this article presents a comprehensive perspective on the current status of WQM and suggests future directions for improving the sustainability of water resources. These objectives are intended to assist researchers, policymakers, and practitioners in advancing WQM to protect our planet's most vital resource.

Water quality parameters

WQ is predominantly evaluated through an analysis of its physical, chemical, biological, and radiological characteristics. These parameters provide comprehensive insights into the health and usability of aquatic environments. Each category encompasses specific parameters that are crucial for the assessment of WQ. The interactions among these parameters highlights the intricate nature of aquatic ecosystems.

Water temperature plays a significant role in influencing biological, chemical, and physical processes within aquatic systems. It affects gas solubility, the metabolic rates of aquatic organisms, and the distribution of species. Generally, warmer water holds less DO, which is vital for the survival of aquatic life, hence rendering extreme temperatures potentially harmful to these organisms (EPA 2012). Elevated temperatures are detrimental to aquatic organisms compared to lower temperatures, as they lead to a substantial reduction in DO levels.

The coloration of water serves as a visual indicator of its quality, which is influenced by the presence of organic materials, pollutants, and minerals. Natural factors, such as DOM, as well as human activities, industrial discharges, can alter the color of water (Goerlitz and Brown 1972). Turbidity, defined as the clarity or cloudiness of water resulting from suspended particles, can affect light penetration, photosynthesis, oxygen production, and the feeding behavior of aquatic organisms (Omer 2019). Conductivity, which measures the ability of water to conduct electrical current, is correlated with the concentration of dissolved salts and minerals. It serves as an important indicator of WQ by revealing the presence of pollutants or changes in salinity levels (Tutmez et al. 2006). TDS, which include both inorganic and organic substances such as minerals, salts, and metals, significantly influence the taste of water and its suitability for drinking, irrigation, or industrial applications, consequently making it a critical parameter for monitoring.

Chemical parameters are utilized to quantify various substances present in water, thereby indicating its chemical composition. These parameters, which include pH, DO, nutrients, heavy metals, and other contaminants, are important for evaluating the suitability of water for diverse applications and for identifying potential health risks (Chapman 1996). The pH level serves as an indicator of the water's acidity or alkalinity, which in turn influences mineral solubility and biological activities. Maintaining appropriate pH levels is essential for facilitating chemical reactions and ensuring effective water treatment processes (Saalidong et al. 2022). DO is crucial for the survival of aquatic organisms, as it reflects the water's capacity to sustain life. Low levels of DO, often resulting from organic pollution and eutrophication, can lead to the mortality of aquatic organisms (Chapman 1996). Research has demonstrated that colder lakes and streams are capable of retaining higher levels of DO compared to warmer waters, which is vital for maintaining aquatic health (Omer 2019).

Nutrients such as nitrogen and phosphorus are required for plant growth; however, their excessive presence can lead to eutrophication, resulting in algal blooms and subsequent oxygen depletion (Rodríguez-López et al. 2023). Heavy metals, including lead, mercury, and cadmium, present significant health risks due to bioaccumulation and direct toxicity, often entering aquatic environments through industrial discharges and mining activities (Zhang et al. 2023). The radiological characteristics of water are associated with the presence of radioactive elements and substances, which can occur naturally, like those from geological formations, or result from human activities such as nuclear power generation (NAP 1997). Monitoring these parameters is important for ensuring public safety, as radioactive contamination can have long-term health consequences. Moreover, chlorine and chloramines are frequently employed as disinfectants in water treatment processes. Regular monitoring of their concentrations is necessary to ensure their efficacy in eliminating harmful pathogens while preventing excessive levels that could lead to taste and odor issues or adverse health effects (Lanrewaju et al. 2022).

Khalik et al. (2022) reported that the pH values in the Bengkulu River ranged from 5.8 to 8.4, while in the Nelas River, Indonesia, the pH values ranged from 5.8 to 8.1. TDS levels were found to be between 32 and 352 mg/L in the Bengkulu River and between 15 and 492 mg/L in the Nelas River, all of which fall within established quality standards. The study indicated a significant variation in TSS in the Bengkulu River, with values ranging from 1 to 4,220 mg/L, suggesting the presence of pollution. In contrast, TSS in the Nelas River ranged from 1 to 249.5 mg/L, which complies with irrigation standards. In addition, oil and grease concentrations in the Bengkulu River were reported to range from 0.0 to 4,998 mg/L, while in the Nelas River, they ranged from 0.0 to 897 mg/L, both exceeding quality standards, likely attributable to domestic activities and industrial discharges. Das (2017) documented a considerable variation in EC values in Chimdi Lake, Sunsari District, Nepal, with measurements ranging from 312.2 to 377.8 µS/cm. Additionally, TDS values in Chimdi Lake were reported to range from 189.2 to 227.3 mg/L.

Khalik et al. (2022) reported that the DO levels in the Bengkulu River ranged from 3.1 to 8.4 mg/L, while in the Nelas River, they ranged from 2.7 to 12.9 mg/L. However, a declining trend in DO values suggests an increase in pollution and a deterioration in WQ. BOD levels were observed to range from 0.3 to 29 mg/L in the Bengkulu River and from 0.6 to 11.8 mg/L in the Nelas River, with elevated values downstream attributed to organic accumulation. COD values exceeded the established standard of 10-80 mg/L, with measurements ranging from 1 to 300 mg/L in the Bengkulu River and from 3.5 to 64 mg/L in the Nelas River, indicating pollution stemming from residential and industrial sources. Additionally, as a consequence of mining and industrial activities, SO_4^{-2} levels in the Bengkulu River varied from 1 to 290 mg/L, while the Nelas River recorded a peak of 1400 mg/L in 2019. NO_2^- levels were found to range from 0.0 to 0.02 mg/L in the Bengkulu River and from 0.0 to 0.04 mg/L in the Nelas River, which are close to the quality standard of 0.06 mg/L, underscoring the necessity for continuous monitoring.

Pandey and Shakya (2011) found that Fe concentrations in spring water varied between 0.15 and 5 mg/L, whereas Mn levels in groundwater ranged from 0.03 to 0.1 mg/L. Additionally, Das (2017) documented NO_3^- concentrations in Chimdi Lake, which were found to be between 0.045 and 0.0655 mg/L. These values are significantly lower than the concentrations of 5-25 mg/L observed in springs and 5-50 mg/L in groundwater, as reported by Pandey and Shakya (2011) in the central development region of Nepal.

There are various VOCs contaminants found in water, including 1,1,1,2-tetrachloroethane, 1,1,2,2-tetrachloroethane, styrene, and tetrachloroethylene. These substances pose significant risks to public health and raise environmental concerns due to their widespread use in industrialized nations. Among the most alarming organic contaminants are aromatic hydrocarbons and chlorinated hydrocarbons (Lin and Li 2010). Specific VOCs, including tetrachloroethylene and trichloroethylene, have been identified as contaminants of groundwater, while PAHs resulting from the combustion of organic materials have been detected in surface water. The occurrence of organic chemical pollution can be attributed to various mechanisms, including natural production by aquatic microorganisms (2-methylisoborneol, geosmin, microcystin) and the discharge of industrial waste. Common pollutants encompass VOCs, pesticides, phenolic compounds, phthalates, and nitrogen compounds, with chlorination by-products such as trihalomethanes and haloacetic acids also identified in drinking water (Tsuchiya 2010). In response to the health implications associated with these contaminants, the WHO has established guidelines for organic constituents, pesticides, and disinfectant by-products in drinking water. Moreover, the presence of pharmaceuticals, personal care products, and perfluoroalkyl substances has emerged as a significant environmental concern.

The biological characteristics of aquatic ecosystems are primarily characterized by the presence of microorganisms, algae, and various aquatic life forms. Pathogenic microorganisms, including bacteria, viruses, and parasites, have the potential to contaminate water sources and contribute to the spread of diseases. Algae, while naturally occurring, can experience excessive proliferation due to nutrient pollution, leading to harmful algal blooms. As well, the diversity and health of aquatic organisms, such as fish and invertebrates, serve as indicators of overall WQ, reflecting both physical and chemical conditions (WHO 2021). Phytoplankton, a type of algae that produces oxygen through photosynthesis, constitutes the foundational level of the aquatic food web, while zooplankton, which are small aquatic animals, provide a food source for larger organisms and play a significant role in nutrient cycling. Monitoring fish populations and macrophyte communities is essential for assessing the impacts of pollution, habitat degradation, and changes in nutrient levels on these organisms and their ecosystems (Naselli-Flores and Padisák 2023).

Microorganisms, including bacteria and viruses play an important role in aquatic ecosystems. Certain bacterial populations serve as indicators of fecal contamination and the presence of pathogens, while others contribute positively to water treatment processes (Cabral 2010). The monitoring of microbial populations is critical for assessing WQ and evaluating the effectiveness of treatment methods. The assessment of biodiversity within aquatic ecosystems is vital for understanding their ecological health and resilience. Variations in biodiversity patterns can signal disturbances in WQ and ecosystem functionality (Tampo et al. 2024). Benthic macroinvertebrates, such as mollusks, worms, and crustaceans, are used as bioindicators due to their differential tolerance to pollution and habitat degradation. Uprety et al. (2020) reported that the Terai region of Nepal exhibited the highest mean levels of *E. coli* at 153 CFU/100 ml, whereas the hilly region recorded the highest mean TC levels at 1411 CFU/100 ml. Additionally, Pandey and Shakya (2011) documented FC levels in the central area of Nepal ranging from 0 to 212 CFU/100 ml in spring water and from 0 to 354 CFU/100 ml in groundwater. Das (2017) indicated that the water from Chimdi Lake exceeded the bacterial contamination guidelines established by the WHO. In Indonesia, Khalik et al. (2022) identified elevated TC counts in the Bengkulu River (33-16,000 MPN/100 mL) and the Nelas River (95-18,980 MPN/100 ml), indicating persistent pollution.

Water quality index

The WQI is a comprehensive tool used to assess the overall quality of water in aquatic environments. This method incorporates multiple parameters, including pH, DO, turbidity, TDS, NO_3^-, PO_4^{-3}, and various other contaminants, into a single numerical value that reflects the health of the water resource. By condensing complex data into a more accessible format, the WQI facilitates understanding among stakeholders such as policymakers, environmentalists, and the general public regarding WQ. The WQI is imperative for identifying sources of pollution, monitoring temporal changes, and informing water management practices, thus enabling stakeholders to make informed decisions aimed at protecting and enhancing water resources.

The WQI was first introduced by Horton (1965), who assessed WQ using various parameters, including sewage treatment, DO, pH, coliforms, EC, CCE, alkalinity, Cl^-, temperature, and visible pollution. Subsequently, Brown et al. (1970) refined the index to encompass nine parameters such as pH, temperature, DO, BOD, PO_4^{-3}, NO_3^-, turbidity, solids content, and coliform bacteria. Steinhart et al. (1982) developed an EQI specifically for the Great Lakes, which included variables like specific conductance, Cl^-, TP, FC, Chl-a, SS, visible pollution, and toxic contaminants. In the mid-1990s, the British Columbia Ministry of Environment, Lands, and Parks created the BCWQI as a standardized tool for assessing WQ on a scale of 0 to 100, based on physical, chemical, and biological indicators, to facilitate decision-making and water management (Zandbergen and Hall 1998). The WQGTG of the CCME, which is responsible for developing and recommending WQ guidelines in Canada, subsequently developed the CCME WQI after reviewing and revising the BCWQI model, which had already received recognition from recognized by the CCME (Uddin et al. 2021). The WQI is classified into several categories based on its numerical value. A WQI score ranging from 0 to 44 is designated as deviations from natural WQ and necessitating treatment prior to making the water safe for consumption. A WQI of 45 to 64 indicates that the WQ is frequently at risk and often diverges from natural levels, thereby affecting its appropriateness for irrigation purposes. A score between 65 and 79 is deemed WQ is generally safeguarded, it is occasionally threatened, with some deviations that may impact irrigation. A WQI value of 80 to 94 is regarded as water is typically well-protected, with minimal threats and infrequent deviations from natural levels. Lastly, a WQI score of 95 to 100 is considered well-protected WQ that is suitable for drinking, irrigation, and industrial applications (CCMEWQI 1999).

Table 1 presents an evaluation of pollution control measures through the application of various WQIs. Cristable et al. (2020) used the NSFWQI to assess WQ in Saluran Tarum Barat, West Java. This assessment involved measuring parameters such as temperature, turbidity, TS, pH, DO, BOD_5, PO_4^{-3}, NO_3^-, and FC, revealing medium level of WQ, which was adversely affected by agricultural, industrial, and infrastructural activities in the region. Similarly, Xiao et al. (2020) employed the WAWQI to evaluate the Arid Beichuan River Basin in China, measuring parameters including pH, DO, TDS, K, Na, Ca, Mg, NO_3^-, NO_2^-, NH_4^+, Cl^-, SO_4^{-2}, TN, TP, COD, TOC, NH_4^+, Fe, Mn, and Pb. Their findings revealed a degradation of WQ degradation from upstream to downstream, primarily attributed to human activities and contaminant runoff during the wet season. Additionally, Stričević et al. (2021) conducted an assessment of the Nišava River in Serbia using the SWQI, evaluating parameters such as oxygen saturation, BOD_5, NH_4^+, pH, TON, orthophosphates, SS, temperature, EC, and TC, respectively. This study identified the Jerma River as having poor WQ, with a noted decline since 2013 due to the discharge of untreated wastewater. Furthermore, Sudhakaran et al. (2020) assessed the Netravati River Basin in India using both the WAWQI and IWQI, analyzing parameters including pH, DO, EC, TDS, HCO_3^-, Na, K, Ca, Mg, Cl^-, SO_4^{-2}, PO_4^{-3}, NO_3^-, Fe, and Pb. In their study, they found significant seasonal variations in WQI values influenced by salt deposits, sewage, industrial waste, and other anthropogenic activities.

Radeva and Seymenov (2021) employed the CCMEWQI to evaluate the WQ of the Maritsa River in Southern Bulgaria. Their analysis included parameters such as N-NH_3, N-NO_3^-, N-NO_2^-, TN, TP, PO_4^{-3}, NH_4^+, As, Fe, Cu, Mn, Ni, Pb, and Zn. The findings indicated that the majority of these parameters failed to meet established WQ standards, primarily due to unregulated discharges from mining activities, anthropogenic influences, and industrial sources. Similarly, Fu et al. (2022) applied the IWQI to evaluate the Tuo River in China, assessing parameters such as the permanganate index, F^-, TN, BOD_5, COD, N-NH_3, DO, TP, EC, NO_3^-, SO_4^{-2}, and Cl^-. Their results revealed that 67.8% of the samples were classified as medium, 29% as poor quality, and 3.2% as bad quality. Wang et al. (2022) applied the WAWQI to evaluate the WQ of Tolo Harbour and Channel in Hong Kong. They examined parameters including temperature, pH, turbidity, DO, BOD_5, COD, TKN, TP, TSS, NH_3-N, NO_2-N, NO_3-N, PO_4^{-3}, F^-, Cu, Zn, As, Chl-a, oil and grease. The study concluded that the overall WQ was generally rated as outstanding or good, although some regional variations were noted. Finally, Yılmaz et al. (2020) assessed the Büyük Menderes River in Turkey using the WAWQI, measuring parameters such as pH, EC, TDS, Cl^-, N-NO_3, N-NH_3, DO, COD, orthophosphates, SO_4^{-2}, Na, K, Ca, and Mg. They recommended the treatment of domestic and industrial wastewater prior to discharge, as well as the regulation of fertilizer and pesticide usage, to preserve WQ.

Traditional water monitoring methods

Historically, methods for assessing WQ have included visual inspections, basic chemical testing techniques (such as titrations and colorimetric assays), and biological monitoring utilizing bioindicators, including

Table 1 Assessment of effectiveness of pollution control measures using WQIs

WQI	Location	Study period	No. of sampling site	Parameters	Remark	Reference
WAWQI	Ithikkara, & Kallada river basins, India	2011-2012	57	pH, TDS, EC, turbidity, temperature, hardness, Ca, Mg, Na, K, CO_3^{-2}, HCO_3^-, F^-, Cl^-, SO_4^{-2}, NO_3^-, Fe, & SiO_2	Most samples fell into the excellent (90%), and good (10%) categories during the monsoon and pre-monsoon periods, making the water suitable for drinking. In pyrite-rich catchments, H_2SO_4 drainage contributed to acidity, while negative pH and DO loading resulted from anaerobic conditions and high DOM, forming NH_3 and organic acids that lowered pH.	Nair et al. (2020)
CCMEWQI	Quebec, Canada	2014-2016	3	SS, pH, EC, N-NH_3, Fe, Na, Ca, Cu, Fe, Mg, Mn, K, Na, Zn NO_3^-, NO_2^- & P	WQI values showed that pH guidelines were frequently not respected in harvested peatlands, with significant differences in NH_3, conductivity, pH, and suspended material concentrations between water from harvested peatlands and streams in two of the three regions studied.	Betis et al. (2020)
WWQI	Limoeiro River watershed, São Paulo State, Brazil	2018	11	DO, pH, BOD, temperature, TN, TP, turbidity, Chl-a, TS, & *E. coli*	The WQI was lowest during the water deficit season and highest during the water-sufficient season, with an improved trophic state index. Positive linearity between water balance and WQI was seen in areas with minimal surplus and deficit, but extreme conditions and water deficiency impaired surface WQ and increased interaction between rainwater and LULC.	Gomes (2020)
CCMEWQI	Agan River catchment, West Siberia	1993-2017	25	pH, NH_4^+, NO_3^-, PO_4^{3-}, BOD_{20}, Cl^-, SO_4^{2-}, TPH, Fe, Mn, Cu, Cr, Ni, Hg, Pb, & Zn	Ni, Hg, Pb, Zn, Cu, Mn, and Fe concentrations exceeded fisheries' standard limits in 10.8, 14.5, 22.3, 24.7, 54.7, 88.6, and 99.2% of samples. The catchment's WQ was classified as poor and marginal, and TPH values showed a significant positive correlation with good density and oil-contaminated lands.	Moskovchenko et al. (2020)
WAWQI	Jamalpur Sadar area, Bangladesh	-	42	pH, TDS, Cl^-, SO_4^{2-}, PO_4^{3-}, Ca, Mg, Na, K, Cu, Fe, Mn, Zn, Pb, Cd, & Cr	WQI indicated that 22.7% of samples had high metal mobility, with HMPI, HMEI, and EWQI results aligning with WQI findings; 95% of groundwater samples were unsuitable for drinking, while 18% of surface water and 25% of groundwater samples were suitable for irrigation, indicating higher non-carcinogenic health risks from surface water.	Zakir et al. (2020)
SWQI	Morača river basin, Montenegro	2010-2018	12	Oxygen saturation, BOD_5, NH_4^+, pH, TN, orthophosphates, SS, temperature, EC, & TC	SWQI values varied between 73 and 97, signifying an overall WQ classification ranging from good to excellent. However, the lower Morača River has been identified as the most polluted area within the basin, primarily due to the impacts of municipal wastewater, agricultural activities, and solid waste disposal. Despite the general improvement in WQ, the lower Morača River was classified as "poor" owing to these pollution sources, thereby underscoring the necessity for effective pollution control measures, particularly during periods of low flow.	Doderovic et al. (2020)
VWQI	Dong Thap province, Vietnam,	2019	58	Temperature, pH, turbidity, DO, BOD, COD, TSS, NH_4^+, NO_3^-, TN, orthophosphate, Cl^-, SO_4^{2-}, TC, & *E. coli*	TSS, BOD, COD, N-NH_4^+, N-NO_2^-, P-PO_4^{3-}, coliform, and *E. coli* were the main WQ constraints, with entropy weight calculations showing WQ deterioration in the order of microbiological > nutrients > organic matters.	Giao et al. (2021)
CCMEWQI	Chapala lake, Mexico	2015-2016	13	pH, DO, NO_2^-, N_2, NO_3^-, PO_4^{3-}, Alkalinity, TS, COD, SO_4^{3-}, Cl^-, F^-, & SiO_2	WQI indicated poor WQ due to high conductivity, TS, N_2, and PO_4^{3-} from industrial and agro-industrial effluents. Metal speciation showed low concentrations of dissolved metals interacting with fish gills, affecting WQ. Analyses revealed that pollutants from agricultural and tourist activities increased levels of agrochemicals, organic matter, and untreated water.	Murillo-Delgado et al. (2021)
WAWQI	Juan Diaz River, Panama	2002-2008	105	pH, temperature, EC, turbidity, DO, BOD_5, TS, SS, DS, NO_3^-, PO_4^{3-}, FC, & TC	WQI values across all sampled stations ranged from 17 to 88, with the Villalobos Bathing Site being slightly polluted and the Los Pueblos Mall ranging from highly polluted to slightly polluted; the South Bridge Corridor showed the lowest WQ levels due to domestic and industrial wastewater discharges and hydro-morphological pressures.	Ortega-Samaniego et al. (2021)

macroinvertebrates. These approaches have contributed significantly to the foundational understanding of WQ management (Omer 2019). Additionally, manual grab sampling has frequently been utilized to facilitate detailed laboratory analyses, enabling more accurate measurements (Aryal 2022).

While traditional methods have established a critical foundation for understanding WQ, their inherent limitations impede comprehensive and real-time monitoring. These methods typically provide only discrete snapshots of WQ at specific locations and times, thereby failing to capture dynamic changes (Park et al. 2020). They are labor-intensive and time-consuming, as they depend on manual sampling and laboratory analysis, which restricts their capacity to cover extensive areas or to respond promptly to emerging issues (Cassidy and Jordan 2011). Additionally, these methods often concentrate on a limited range of WQ parameters, which may result in the oversight of emerging contaminants and indicators of ecosystem health. Variability in sampling and laboratory procedures can also lead to inaccuracies, further complicating the reliable assessment of WQ (Harris et al. 2019).

Modern technologies, including high-resolution MS, LC-MS/MS, and IoT-enabled sensors, address existing limitations by facilitating continuous, real-time monitoring and enhancing precision (Borrull et al. 2020; Brack et al. 2019; Essamlali et al. 2024). These advancements allow the detection of trace contaminants and permit the simultaneous measurement of multiple WQ parameters. The integration of big data analytics and AI provides sophisticated analytical capabilities, allowing for the identification of complex patterns and trends that traditional methodologies may not readily reveal (Kamyab et al. 2023). Although modern systems necessitate higher initial investments, they ultimately reduce long-term costs through increased efficiency and labor savings, while delivering more accurate and timely data for effective water management.

Real-world case studies highlight the limitations of traditional WQ monitoring methods. For instance, in Lake Villarrica, conventional monitoring practices failed to anticipate an algal bloom, which resulted in significant ecological damage (Rodríguez-López et al. 2023). In African rivers, such as the Msimbazi and Mirongo, insufficient monitoring contributed to unchecked industrial pollution, leading to extensive contamination (Chen et al. 2022). Similarly, in Maros City, Indonesia, traditional assessments neglected to account for the cumulative effects of urban runoff, which adversely affected WQ (Syafri et al. 2020). In Nepal, the manual sampling techniques employed by Aryal et al. (2022) were found to be labor-intensive and inadequate for providing real-time responses to water contamination. These instances underscore the urgent need for modern, integrated WQ monitoring solutions that effectively and sustainably address the complexities of contemporary water challenges. Amrita and Babiyola (2018) conducted a comparative analysis of traditional and modern WQ assessment methods, revealing that modern techniques offer distinct advantages. Specifically, modern methods yield real-time results and facilitate rapid analysis of WQ parameters, enabling prompt identification of contaminants. In contrast, traditional methods, such as titration, are often time-consuming, frequently requiring more than a day to complete, and demand considerable effort. Consequently, Pasika and Gandla (2020) reported that traditional assessments in aquaculture produced inconsistent results and less valuable data due to variations in water sample composition during prolonged testing periods.

Advances in water quality monitoring technologies

In recent decades, advancements in RS and satellite technologies have significantly transformed WQM. Satellites equipped with sophisticated sensors now provide invaluable data concerning extensive water bodies and even remote areas. High-resolution spectral data obtained from satellite sensors facilitates the identification of specific WQ parameters, such as Chl-a concentration, turbidity, and TSS (Tesfaye 2024). For instance, Sentinel-2 MSI and Landsat OLI images employ multispectral imagery to detect variations in Chl-a concentration, which serve as indicators of algal blooms (Xu et al. 2021). This capability empowers comprehensive monitoring of WQ across vast areas, providing critical insights into the health of aquatic ecosystems. A summary of advancements in WQM are presented in Table 2.

In comparison to traditional methodologies, regular satellite observations provide valuable temporal insights into changes in WQ, facilitating the identification of trends and potential issues over time. By consistently monitoring aquatic environments, satellites are capable of tracking seasonal variations, pollution events, and long-term environmental changes (Naimaee et al. 2024). This temporal data is pivotal for

Table 2 Advancements in WQM technologies

Method	Location	Study period	Parameter	Remark	Reference
Satellite data	Gold Coast Broadwater, Australia	2016-2021	TSS, & Chl-a	The most significant adverse WQ event within the dataset was attributed to summer rainfall occurrences, which resulted in increased TSS concentrations originating from the northern rivers and gradually dispersing southward. In contrast, high Chl-a concentrations were first recorded in the southernmost regions of the Broadwater.	Bertone et al. (2024)
IRS LISS IV satellite data	Harike Wetland, Ramsar site, India	2006	DO, conductivity, pH, turbidity, TSS, COD, & SDT	The near-infrared band significantly correlated with WQ parameters, while the green and red reflectance bands, using SDT values, distinguished between the two rivers with different water qualities.	Mabwoga et al. (2010)
Sentinel-2 MSI data	Freshwater reservoirs, Northern California, USA,	2015-2020	Algal bloom	NDCI quantified the spatiotemporal heterogeneity of algal blooms in small reservoirs, while the GEE facilitated efficient time series analyses of these algal blooms.	Kislik et al. (2022)
Satellite imagery	Polyphytos Reservoir, Kozani, Greece	2014-2022	Chl-a, turbidity, hydrocarbon	Analyzing over 300 satellite images with NDWI, Se2WaQ, and OSI algorithms effectively detected potential formations and characterized WQ over nine years.	Lioumbas et al. (2023)
MODIS 250-m imagery	Adour River, South Bay of Biscay, France	2007	Turbidity, & TSS	MODIS-Aqua band 1 (620–670 nm) predicted turbidity and total suspended matter concentrations with polynomial regression models, contrasting band 2's unsuitability. Comparisons of 250-m and 1000-m resolution maps of suspended matter showed consistent results, alongside a strong correlation between in-situ turbidity measurements and MODIS-Aqua satellite data.	Petus et al. (2010)
Landsat-8 satellite images	Karun River, Iran	2019	Temperature	Downstream water temperatures were cooler in hot seasons than upstream of dams, with RS data effectively complementing ground-based sensors for temperature estimation and pollution area identification.	Naimaee et al. (2024)
Multispectral, & hyperspectral sensors on board satellites, aircraft, & drones	Natural reserve, Maspalomas, Canary island, Spain	2018-2019	Chl-a	The drone hyperspectral instrument had a RMSE of 3.45 and a bias of 2.96 when estimating Chl-a concentrations compared to in situ measurements.	Eugenio et al. (2020)
Satellite system based on MERIS data	Coastal area, Baltic Sea	2008 & 2010	Chl-a	The satellite-based monitoring system exhibited a high degree of reliability, as the estimates of Chl-a concentrations closely aligned with in situ measurements, demonstrating strong correlations (RMSE=64%, MNB=17%) for data collected within a 0–3 day timeframe. Monthly comparisons showed improved RMSE and MNB of 8%, highlighting MERIS' advantage over traditional ship-based methods in capturing the dynamics of phytoplankton blooms, owing to its synoptic perspective and superior temporal resolution.	Harvey et al. (2015)
Landsat 8-derived forel-ule index, & GEE platform	Inland water, China	2015	Color	Yellow (~49%) and green (~41%) were the most prevalent lake colors in China, showing a notable difference in color distribution between small lakes (areas < 1 km^2) and large lakes (areas ≥ 1 km^2) (50% versus 28%).	Chen et al. (2021)
Sentinel-2 MSI, & Landsat-8 OLI Sensors	Tres Marias Reservoir, Sao Francisco, Beazil	2019	Chl-a, SDT, turbidity, temperature, DO, pH, color, EC, & Ox-red potential	Both sensors performed in developing multiple regression models for three optically active components; Chl-a, SDT, and turbidity, with the MSI sensor demonstrating a slight advantage over the OLI sensor, while also showing a more significant advantage for optically inactive parameters.	Pizani et al. (2020)
Landsat 8 OLI Data	Mekong Delta, Vietnam	2017	Salinity	The spectral values of the Near Infrared band and VSSI showed high correlations with EC compared to other indices. The comparative results confirmed that soil salinity estimates derived from Landsat 8 data were consistent with in situ data, highlighting the potential of Landsat 8 OLI images for spatiotemporal monitoring of soil salinity in the topsoil layer.	Tran et al. (2020)

Table 2 Continued

Landsat-8/OLI, & Sentinel-2A/B Multispectral Instruments	Chesapeake bay, United States	2017-2018	DOC	The integration of data from three satellites highlighted the significant impact of marsh outwelling and seasonal variability on DOC dynamics. This phenomenon was further affected by various factors, including wind conditions, river discharge, and extreme weather events occurring at terrestrial-aquatic interfaces.	Cao and Tzortziou (2021)
Cloud-based Landsat images	Nhecolândia lakes, Brazil	2007-2017	pH	The pH values of 12,150 lakes were predicted using linear and symbolic regression techniques, achieving an R^2 of 0.81. The lakes were categorized as freshwater, oligosaline, or saline, with saline lakes making up 7.25%. A trend surface map created from the ALOS PRISM DSM indicated that saline lakes are located at lower elevations than freshwater lakes.	Pereira et al. (2020)
Landsat RS	Central North island lakes, New Zealand	2002	Chl-a	The comparison of 6sv model and the COST, and DOS atmospheric corrections showed that 6sv yielded more accurate reflectance values at a clear-water reference site, achieving the highest correlation coefficient ($r^2 = 0.954$) between ln(Band 3) water surface reflectance and ln(Chl-a). This highlighted Landsat imagery's ability to capture a wide range of Chl-a concentrations similar to traditional ground-based monitoring.	Allan et al. (2011)
RS Indices	Lake Mead, Colorado river, USA	-	Suspended sediments	High levels of suspended sediments were typically found at the entry points of Lake Mead, in contrast to the lower concentrations found within the lake's basins. The study demonstrated a robust exponential relationship ($R^2 \approx 0.96$) between SSC and NSMI values, illustrating that higher SSC levels correlated with increased NSMI values.	Adjovu et al. (2021)
RS, & GIS approach	Groundwater, Raipur, Chhattisgarh, India	2000-2018	EC, TDS, & NO_3^-	LULC changes primarily involved increased settlement and cultivation, along with expansions in anthropogenic activities such as roads and industrial areas. Spatiotemporal variations in the water table and quality parameters like EC, TDS, and NO_3^- showed significant alterations in groundwater quantity and quality due to human activities in the study area.	Mondal et al. (2020)
Landsat ETM+, & OLI sensors	Qaraoun Reservoir, Bekaa valley, Lebanon	2013-2015	Chl-a, TSM, & SDD	The ETM+-based models demonstrated superior performance over their OLI counterparts, achieving R^2 values of 0.70 for Chl-a, 0.81 for TSM, and 0.81 for SDD, compared to 0.50, 0.58, and 0.63 for OLI.	Deutsch et al. (2018)
Sentinel-2, & Landsat 8 images	Lake Chad, Africa	-	Chl-a	The 3BDA and NDCI Chl-a algorithms consistently achieved an average R^2 of 0.8 with S2 and L8 images, outperforming WV3 estimates in accuracy and performance.	Buma and Lee (2020)
MODIS medium-resolution bands	Tampa Bay, Florida, USA	2003	Salinity, Chl-a, CDOM, & TSS	In Tampa Bay, Case-II waters exhibited complex relationships among Chl-a concentration, CDOM absorption coefficient at 400 nm, and TSS across a salinity range of 24–32 PSU, with CDOM showing an inverse correlation with surface salinity that varied in slope by location. MODIS medium-resolution bands, initially for land use, were 4–5 times more sensitive than Landsat-7/ETM+ data and comparable to or higher than CZCS sensitivity.	Hu et al. (2004)
MODIS sensor products and multivariate statistical techniques	Jajrood River Watershed, North Tehran, Iran	2002-2007	COD, BOD_5, DO, PO_4^{-3}, Br^-, F^-, TDS, SO_4^{-2}, NH_3, NO_3^-, & No_2^-	The study used river water temperature, runoff, and two MODIS sensor products; monthly NDVI and land surface temperature as explanatory variables. NDVI and LST were tested by extracting their average values within 250 to 1500 m buffers around the streams.	Karami et al. (2012)
Microwave sensor array	New York, USA	-	No_3^-, PO_4^{-3}, NH_3, Hg, Pb, Cr, pH, NaCl, & DO.	Preliminary results indicated that using an array with elements operating at different frequencies was beneficial, as some sensors responded to certain contaminants while others did not, highlighting the importance of both frequency shift and response level change at the resonance frequency for detecting and evaluating water contaminants and parameters.	Zhang et al. (2019)

Table 2 Continued

IoT	Nepal	2019	pH, & EC	An IoT-based SWQM system was deployed to verify the accuracy of system measurements.	Pokhrel et al. (2020)
RS, & IoT	Nabukalou Creek, Fiji	-	Ox-red potential, & pH	The developed system proved effectiveness by providing precise and reliable real-time water monitoring data. This data was validated through hourly assessments of four water sources over a 12-hour period to ensure measurement accuracy.	Prasad et al. (2015)
FEEM	South Korea	-	Organic contents as COD in wastewater	Protein-like fluorescence exhibited peak excitation and emission wavelengths at 220/350 nm and 270/350 nm, whereas humic-like fluorescence demonstrated peaks at 240/450 nm and 340/450 nm. The correlation between protein-like fluorescence and COD was notably stronger than that of humic-like fluorescence, and the former was not influenced by the presence of SS. The application of multiple regression analysis, incorporating fluorescence intensities and light scattering measurements at 633 nm, significantly enhanced the correlation, resulting in an $R^2 >$ 0.9 for both the measured and predicted COD values.	Lee and Ahn (2004)
FT-IR-Attenuated total reflectance technique	California, USA	-	1,1,1,2-tetrachloroethane, 1,1,2,2-tetrachloroethane, styrene, & tetrachloroethylene	Flow rate optimization favored turbulent flow for VOC detection in water, though very high turbulence reduced the ATR signal as analytes exited too quickly. Optimal membrane thickness maximized the overlap between the IR evanescent wave and analyte diffusion depth. No universal optimal flow rate and membrane thickness were identified for all VOCs. Doubling IR reflection bounces enhanced detection sensitivity by a factor of 2, and detection limits decrease with VOC water solubility.	Lin and Li (2010)
FeO-NPs, & Quantum dots	Chandigarh, India	-	*E. coli*	*E. coli* presence was confirmed using standard techniques and CLSM with Aptamer II-conjugated CdTe-MPA QDs. An ATmega 328P biosensor demonstrated both quantitative and qualitative detection of *E. coli*, identifying low bacterial counts (up to 1×10^2 CFU/ml) using a photodiode and plano-convex lens. It provided high-resolution, sensitive on-spot detection of E. coli in water samples with a UV LED, LCD, and ATmega328P microcontroller.	Pandit et al. (2022)
Ag-NPs	Gujarat, India	-	*E. coli*	The developed biosensors showed a linear decrease in current intensity as *E. coli* concentration increased, with good reproducibility (RSD = 6.91%, n = 3) and high sensitivity (LOD = 150 CFU/ml). They exhibited excellent selectivity for *E. coli* over other bacteria, maintained stability for four weeks at room temperature, and achieved high recoveries (95.27 to 107%) during tap water sensitivity validation.	Dabhade et al. (2023)
Au-NPs	Jilin, China	-	*S. aureus*	AuNPs, aptamer, and vancomycin (Van) were combined to create dual-recognition molecules for visually detecting *S. aureus*, utilizing aptamer-coupled Fe_3O_4 for initial capture and enrichment, conjugating Van to S. aureus-Apt-Fe_3O_4 complexes, inducing AuNPs aggregation via freeze-thaw with stable results, enabling straightforward visual colorimetric detection of *S. aureus* from 10^1 to 10^4 CFU/ml with a low LOD of 0.2 CFU/ml.	Sun et al. (2022)

understanding the impacts of anthropogenic activities and natural processes on WQ. Additionally, satellite technology allows for the monitoring of water bodies on a global scale, thus contributing to a comprehensive understanding of large-scale environmental changes (Schaeffer et al. 2013). The Aqua satellite, which is part of the EOS, assesses global WQ by measuring parameters such as sea surface temperature, salinity, and Chl-a concentrations (Parkinson 2003). Such extensive data supports international initiatives aimed at the management and protection of water resources.

Using satellite data, Bonette et al. (2024) conducted an analysis of TSS and Chl-a concentrations in the Gold Coast Broadwater, Australia. Their findings indicated that summer rainfall events were responsible for the most significant WQ issues observed in the dataset. A high concentration of TSS originating from the northern rivers gradually dispersed southward, while elevated levels of Chl-a were initially detected in the southernmost region. In a separate study, Lioumbas et al. (2023) investigated Chl-a concentrations, turbidity values, and the presence of hydrocarbons in the Polyphytos Reservoir, West Macedonia, Greece. An analysis of over 300 satellite images and algorithms such as NDWI, Se2WaQ, and OSI was used to identify formations impacting surface WQ and provide a comprehensive characterization over a nine-year period. Additionally, Kislik et al. (2022) employed Sentinel-2 MSI data to examine algal blooms in two small freshwater reservoirs located in northern California, USA. They quantified the spatiotemporal heterogeneity of algal blooms using the NDCI and performed an efficient time series analysis using GEE. This research illustrated the potential of RS to furnish baseline data for aquatic studies, particularly in significant contexts like the largest dam removal in history. Guo et al. (2021) identified bands 3, 4, and 5 of Sentinel-2 imagery as the most influential for detecting TN, TP, and COD, noting that variations in TDS or salinity frequently coincided with changes in optically active WQ parameters, though not always to the same extent. Rokni et al. (2014) modeled the spatiotemporal changes of Lake Urmia, Iran, utilizing multiple Landsat sensors and various indices, and determined NDWI as the most effective for assessing alterations in the lake's surface area. Principal components analysis of multi-temporal NDWI data revealed a decreasing trend in the lake's surface area throughout the study period. Additionally, Chen et al. (2007) aimed to map the spatial distribution of WQ in the Gulf of Finland, specifically focusing on NO_3^- concentrations, which were found to be below 25 mg/L.

Sayler et al. (2022) used Landsat 9 OLI-2, which produced images that were consistent with those from Landsat 8 in terms of spectral, spatial, geometric, and radiometric characteristics. Landsat 9 features a 16-day revisit cycle and an 8-day offset relative to Landsat 8, facilitating the acquisition of over 700 scenes daily. This frequent and reliable data collection is crucial for effective monitoring and management of water resources. Vakili et al. (2020) utilized optically active parameters, including Chl-a, SDD, and TSS to estimate optically inactive parameters, such as TP and TN in the Geshlagh Reservoir located in western Iran, using Landsat 8 OLI images. They revealed the band ratio (B3/B2) and bands 3 and 4 as the most effective for determining Chl-a concentration and subsequently predicting TP and TN concentrations. Herrault et al. (2016) demonstrated the application of a CDOM algorithm for monitoring DOC fluxes in the Yenisei River, employing Landsat 8 OLI and SPOT5 images. Their model, based on the interaction of the green band and the green-red band, achieved high prediction accuracy with a model based on the green band and green-red band interaction (R^2 = 76%, RMSE = 1.21), and recommended extensive sampling along with synergies between Sentinel-2-3 and Landsat 8 for reproducible CDOM retrievals. Hossain et al. (2021) also employed a numerical model to estimate turbidity in the Tennessee River and its tributaries, applying Landsat 8 OLI imagery in conjunction with near real-time in situ measurements. They developed a nonlinear regression-based model using surface reflectance values (0.64–0.67 µm) from the red band (band 4) to estimate turbidity. Kutser et al. (2005) concluded that the 8-bit radiometric data from Landsat 7 were inadequate for estimating CDOM in southern Finnish lakes when the absorption coefficient exceeded 3 m^{-1} at 420 nm, suggesting that the ALI was more effective for mapping CDOM across a broader concentration range. Hellweger et al. (2004) investigated the use of satellite imagery for WQ studies in New York Harbor by comparing in situ data with images from Landsat 5 TM and MODIS sensors. They found a strong correlation between the reflectance of the Landsat 5 TM red bandwidth (0.63–0.69 µm) and turbidity (R^2 = 85%, n = 21), as well as Chl-a concentration (R^2 = 78%, n = 16), while indicating that Terra MODIS images were unsuitable for determining Chl-a concentration due to a lack of correlation with in situ measurements. Zhang et al. (2002) utilized an empirical neural network to estimate WQ parameters such as SSC, SDD, turbidity, and Chl-a concentration in the Gulf of Finland, integrating optical data from Landsat 5 TM with microwave data from ERS-2 SAR. This approach demonstrated a robust modeling capability that captured the nonlinear relationships between these sensors and surface water parameters, with thermal bands enhancing model performance to achieve R^2 values exceeding 91% for all measured WQ parameters. Notably, the exclusion of thermal bands resulted in a slight decrease in R^2, yet values remained above 85%.

Hu et al. (2004) employed MODIS medium-resolution bands to investigate salinity, Chl-a, CDOM, and total SSC in Tampa Bay, Florida, over a two day-period in October 2003. Their findings indicated that within the Case-II waters of Tampa Bay, the concentrations of Chl-a (11 to 23 mg/m^3), the CDOM absorption coefficient at 400 nm (0.9 to 2.5 m^{-1}), and total SSC (2 to 11 mg/L) often did consistently not co-vary across the salinity range of 24–32 PSU. Remarkably, CDOM demonstrated a linear, inverse relationship exhibiting surface salinity, with varying slopes at different locations. The authors further reported that MODIS medium-resolution bands were 4–5 times more sensitive than Landsat-7/ETM+ data and were comparable to or exceeded the sensitivity of the CZCS. Karami et al. (2012) used MODIS data alongside statistical methods to evaluate WQ parameters such as COD, BOD_5, DO, PO_4^{-3}, Br^-, F^-, TDS, SO_4^{-2}, NH_3, NO_3^-, and NO_2^- in the Jajrood River Watershed, located north of Tehran, Iran. Their discriminant analysis highlighted significant contributions from multiple parameters to class discrimination, particularly during the spring and summer months, with notable distinctions in April and September. The researchers utilized river water temperature, runoff data, and MODIS products, such as monthly NDVI and LST from 2002 to 2007, as explanatory variables, averaging NDVI and LST values within buffer zones ranging from 250 to 1500 meters around the streams. In contrast, Zhang et al. (2019) focused on the application of a microwave sensor array in New York to detect a wide range of water contaminants and parameters, including NO_3^-, PO_4^{-3}, NH_4^+, heavy metals (Hg, Pb, Cr), pH, conductivity (NaCl), and DO. Their research underscored the advantages of employing a multi-frequency sensor array, wherein different frequencies exhibited varying effectiveness in detecting contaminants, each demonstrating distinctive responses. The study highlighted the significance of frequency shifts and changes in resonance frequency in optimizing the detection and assessment of water contaminants, thereby emphasizing the versatility and specificity provided by such sensor arrays in the context of environmental monitoring.

Artlett and Pask (2017) demonstrated the utility of unpolarized Raman spectroscopy for determining salinity and temperature in natural water samples from Australia, achieving precise measurements with temperature RMSEs below 0.2°C and salinity RMSEs below 0.6 PSU. Their study applied a numerical model based on MLR to illustrate that both temperature and salinity similarly influenced the Raman spectra, with increases in either parameter resulting in a corresponding decrease in signal intensity. In contrast, Wei et al. (2016) investigated UV-visible RS reflectance to assess the spectral slopes of the absorption coefficient of CDM in various aquatic environments. They highlighted the sensitivity of UV wavelengths to variations in CDM spectral slope and advocated for their integration into future satellite ocean color sensors to enhance retrieval accuracy across coastal and open ocean regions, emphasizing the potential benefits of UV wavelengths in ocean color measurements. Lin and Li (2010) utilized the FT-IR-attenuated total reflectance technique to analyze VOCs in water samples from California, USA, optimizing flow rates and membrane thickness for VOC detection. They emphasized the impact of turbulent flow on detection effectiveness compared to laminar flow, highlighting the necessity to balance flow dynamics with ATR signal intensity, ensuring that the optimal membrane thickness aligned with the penetration depth of the infrared evanescent wave and the diffusion depth of the analyte for improved sensitivity. Lee and Ahn (2004) employed FEEM to analyze organic content, focusing on COD in wastewater samples from South Korea. Their study identified optimal excitation/emission wavelength pairs for protein-like and humic-like fluorescence, revealing strong correlations between protein-like fluorescence peaks and COD values. They achieved enhanced prediction accuracy through statistical regression methods by integrating fluorescence intensities and light scattering data as variables, resulting in high correlations ($r^2 > 0.9$) between measured and predicted COD values without the need for sample pre-treatment. This illustrates diverse spectroscopic techniques tailored for WQ assessment and their specific advantages and methodological nuances in detecting and quantifying environmental parameters.

Nanotechnology has significantly enhanced the analysis of WQ by improving sensitivity and precision of contaminant detection. Nanosensors are capable of identifying pollutants at extremely low concentrations, which facilitates early detection of pollution and the prevention of harmful exposures. Nanobiosensors, characterized by their small size and high sensitivity, are crucial for real-time monitoring of biomarkers at low concentrations, thereby playing an essential role in WQ assessment. These sensors can also detect microorganisms like bacteria and viruses, in water (Gupte and Pradeep 2021). One notable application in WQ analysis involves the use of Au-NPs, aptamer-vancomycin dual-recognition molecules, and magnetic enrichment techniques to visually detect *Staphylococcus aureus* in tap water. The methodology employed in this study involved the initial binding of *S. aureus* to aptamer-coupled Fe_3O_4 for separation and enrichment from complex sample matrices. This was followed by the conjugation of vancomycin to the *S. aureus*-Apt-Fe_3O_4 complex for a secondary recognition step, which supported straightforward colorimetric detection with a linear range from 10^1 to 10^4 CFU/ml and a detection limit of 0.2 CFU/ml (Sun et al. 2022). Researchers have advanced WQM by developing carbon nanotube-based sensors capable of detecting trace amounts of heavy metals such as Pb and Hg, which are important for ensuring the safe drinking water (Raju et al. 2023). Additionally, nanomaterials have been integrated into water treatment processes; for instance, TiO_2-NPs in photocatalytic processes to decompose organic pollutants, thereby enhancing the cleanliness and safety of water for consumption (Levchuk and Sillanpää 2019). The miniaturization of these devices has further facilitated the development of portable, nanotechnology-based tools for real-time WQ assessments, providing immediate feedback and enabling prompt remedial actions.

Bio-sensors have emerged as pivotal instruments in real-time WQM, utilizing biological components for the rapid and sensitive detection of contaminants. These devices employ biological recognition elements such as living organisms, enzymes, or antibodies, which significantly enhance the specificity and sensitivity of contaminant detection (Singh et al. 2020). The rapid response capabilities of bio-sensors facilitate immediate feedback regarding changes in WQ, rendering them indispensable for real-time monitoring. In addition, bio-sensors can be customized to detect specific contaminants, which provides a versatile and targeted approach to WQ assessment. This adaptability positions bio-sensors as powerful tools for the effective management and protection of water resources (Huang et al. 2023). On the other hand, Dabhade et al. (2023) developed Ag-NP biosensors for the detection of *E. coli* in water, demonstrating high sensitivity and selectivity with a low detection limit of 150 CFU/ml and excellent reproducibility (RSD = 6.91%, n = 3). Additionally, these biosensors exhibited stability for up to four weeks at room temperature and achieved high recovery rates in tap water, ranging from 95.27% to 107%.

The integration of sensor networks and IoT technologies has significantly transformed WQM into a real-time, interconnected system. Sensors strategically deployed throughout aquatic environments facilitate the continuous collection of high-resolution data, thereby enhancing the understanding of spatial and temporal variations in WQ. This innovative approach improves the ability to detect and respond promptly to pollution incidents (Essamlali et al. 2024). In contrast to traditional methods, Smart Water Networks employ sensor arrays to monitor critical parameters like pH, turbidity, and DO levels in real-time. The implementation of IoT technology enables seamless communication between sensors and centralized systems, which allows for timely responses to fluctuations in water conditions. Consequently, data from remote sensors can be rapidly analyzed and acted upon, thus improving water management practices (Pasika and Gandla 2020). Integrating data from various sensors improves the accuracy and reliability of WQ assessments by cross-verifying readings and providing a comprehensive overview of WQ.

Amruta and Satish (2013) proposed a solar-powered WQM system using a WSN that incorporated a UWSN powered by photovoltaic panels. They designed a system architecture that included a base station and distributed sensor nodes interconnected via Zigbee WSN technology, facilitating real-time WQM across various locations. Despite encountering challenges in the design and implementation of the prototype model, the data collected at each node, including turbidity, oxygen levels, and pH values, were transmitted to the base station through the WSN. This data was subsequently displayed in comprehensible format and analyzed using various simulation tools. The system offered several advantages, including low power consumption, zero carbon emissions, and flexibility for deployment in diverse locations. Sughapriyaa et al. (2018) developed a method for determining WQ using IoT and various sensor modules. This approach, in contrast to traditional methods that necessitate greater manual intervention and exhibit lower efficiency, aided rigorous monitoring of water pollution. The system employed sensors to monitor pH, turbidity, conductivity, and temperature, with an Arduino controller facilitating access to the sensor data.

Alerts and notifications regarding WQ were sent to individuals and relevant authorities, thereby enhancing WQM near water resources. The proposed model, which integrated various sensors, computed WQ parameters in real-time.

Gupta et al. (2021) proposed an IoT-based model designed to automatically evaluate WQ parameters such as turbidity, pH, and temperature using the ESP32 for underwater communication. This model integrates various communication modules, a turbidity meter, and a pH sensor, and employs a MLA using K-means clustering to analyze WQ data. The mobile model is capable of continuously monitoring WQ in both large and localized water bodies, with readings displayed on a website accessible to the central pollution control board. The low-cost robotic system capable of underwater communication via high-speed Wi-Fi, enhancing the project's self-sufficiency and efficiency. Anuradha et al. (2018) developed a cost-effective system for real-time WQM utilizing IoT. This system measures chemical and physical parameters, such as pH, temperature, turbidity, and TDS, with data processed by a Raspberry Pi controller and displayed on the internet through the ThingSpeak API. The sensor-based system is characterized by high mobility, frequency, and low power consumption, and it is capable of measuring additional quality parameters, including hardness, EC, F^-, Cl^-, NH_3, and Fe content, making it suitable for industrial and drinking water monitoring applications. Geetha and Gouthami (2016) developed a low-powered, simple IoT-based system for in-pipe WQM. This system tests water samples, uploads sensor data online, and issues alerts for deviations in turbidity, conductivity, and pH levels. The core controller is equipped with a built-in Wi-Fi module for remote monitoring, and the system's functionality could be enhanced through the integration of anomaly detection algorithms. Mukta et al. (2019) developed an IoT-based SWQM system that employs pH, temperature, turbidity, and electrical conductivity sensors connected to an Arduino Uno. This system transmits data to a NET desktop application for analysis against standard values. The model utilizes a fast forest binary classifier to assess water potability, thereby improving WQM and highlighting the role of technology in sustainable water resource management.

Emerging technologies

Advancements in DNA sequencing technologies have profoundly transformed the assessment of microbial WQ, providing enhanced insights into microbial communities and potential health risks. High-throughput sequencing methods, particularly NGS, facilitate the rapid and comprehensive profiling of microbial DNA in water samples (Tan et al. 2015). This capability allows for an in-depth understanding of the diversity and structure of microbial communities. Additionally, DNA sequencing aids in the identification of specific pathogens, thereby enabling the monitoring of waterborne disease risks and the formulation of timely interventions. Through microbial source tracking, DNA sequencing can also pinpoint contamination sources, whether of human, agricultural, or wildlife origin, thus supporting targeted and effective mitigation strategies (Chan et al. 2019). El-Chakhtoura et al. (2015) employed NGS to investigate the stability of microbial communities from a water treatment facility to its distribution endpoint. Their findings revealed significant disparities between the microbial populations at the treatment plant and the endpoint, suggesting considerable alterations within the distribution network. Notably, rare taxa such as *Nitrospirae, Acidobacteria,* and *Gemmatimonadetes* exhibited greater abundance at the endpoint compared to the treatment facility. Although these changes did not present a public health risk, the results of the 16S rDNA sequencing underscore the necessity for continuous WQ assessments throughout distribution systems.

Metabolomics and proteomics represent advanced analytical methodologies that facilitate a comprehensive understanding of the biochemical processes occurring within aquatic environments. By analyzing the distinct profiles of metabolites and proteins present in water samples, these techniques yield an in-depth perspective of the biochemical landscape (Lin et al. 2006). They are capable of identifying a diverse array of compounds, thereby enabling the identification of specific metabolites or proteins that function as biomarkers for contaminants. This integrative analysis supports the early detection of environmental stressors, which is crucial for proactive water resource management and helps shape strategies to maintain and restore water quality (López-Pedrouso et al. 2020).

The application of stable isotopes has emerged as a significant methodology for tracing water sources and comprehending hydrological processes. Stable isotopes demonstrate predictable fractionation patterns during both physical and chemical processes, promoting researchers to monitor the movement of water (Negev et al. 2017). Isotope analysis facilitates the differentiation among various water sources, including surface water, groundwater, and precipitation, thereby providing key information for the management and allocation of water resources. Also, stable isotopes contribute to the understanding of the cycling and transformation of water within ecosystems, offering valuable insights into intricate hydrological dynamics. This approach is particularly advantageous in research focused on assessing the impacts of climate change, pollution, and other factors on water resources (Nigro et al. 2024).

Innovative sampling techniques

Traditional methodologies such as spot sampling and in-situ measurements are often labor-intensive and constrained by accessibility issues. To address these challenges, the utilization of drones equipped with specialized sensors and sampling devices, in conjunction with IoT-based systems, presents innovative solutions. These advanced techniques facilitate real-time, continuous monitoring and yield more accurate and comprehensive data regarding WQ.

Microfluidics has emerged as an advanced technology in the collection of water samples, demonstrating precision and efficiency in the analysis of WQ parameters. A significant innovation within this domain is the development of lab-on-a-chip devices, which integrate various analytical functions onto a single chip. These devices facilitate the rapid and simultaneous analysis of multiple WQ parameters, streamlining the assessment process and reducing the time required for evaluations (Saez et al. 2021). Microfluidic systems are particularly noteworthy for their miniaturization, which allows for the creation of compact and portable sample collection devices that require smaller sample volumes. This technology supports real-time, on-site analysis, eliminating the necessity of transporting samples to laboratories and expediting WQ management decisions (Zhang et al. 2024).

Passive sampling methods signify a paradigm shift from traditional grab sampling techniques, enabling continuous and long-term monitoring of WQ. For instance, diffusive samplers employ passive diffusion to accumulate contaminants over time, thereby providing a more accurate representation of long-term exposure to pollutants (Vrana et al. 2005). Additionally, sorbent-based techniques are extensively used in passive sampling, incorporating materials that selectively absorb specific contaminants, which allows the concentration and detailed analysis of these pollutants (Godlewska et al. 2021). A primary advantage of passive sampling is its capacity to provide continuous monitoring, which captures fluctuations in WQ over prolonged periods and enhances the detection of trends and potential issues that may not be evident through intermittent sampling efforts (Zabiegała et al. 2010).

Drones have significantly transformed the process of water sample collection, particularly in areas that are difficult to access or pose safety risks. These unmanned aerial vehicles, equipped with high-resolution cameras and advanced sensors, facilitate the rapid and thorough assessment of extensive water bodies and remote locations. The integration of automated sampling devices on drones assists for precise collection from designated sites, thereby minimizing the necessity for manual intervention (Sibanda et al. 2021). This technological advancement is both cost-effective and efficient, improving access to challenging environments and enhancing WQM efforts (Zhang et al. 2023).

Data management and analysis

The rise of advanced monitoring technologies has significantly augmented the volume of data in WQ management, creating challenges in the management, processing, and extraction of insights from large datasets. Prominent issues include the necessity to address the substantial and rapid influx of data generated by numerous sensors, which necessitates the implementation of scalable processing solutions (Adamala 2017). Ensuring data quality and standardization across various sources is imperative for conducting reliable analyses. The interoperability of different data formats is also critical for achieving comprehensive integration and analysis (Kadadi et al. 2014). Additionally, protecting the security and privacy of WQ data is essential to prevent unauthorized access and to ensure compliance with relevant regulations.

Efficient data storage and retrieval systems are crucial for effective WQM. Cloud-based storage solutions provide scalable, secure, and accessible options for managing substantial volumes of WQ data, offering flexibility and reliability (Lakshmikantha et al. 2021). Robust database systems, including both relational and NoSQL databases, set up structured storage and rapid retrieval of WQ information (Schulz et al. 2016). The systems that support real-time data access are particularly valuable, as they facilitate immediate analysis and decision-making, enhancing the responsiveness and effectiveness of WQ management initiatives (Zainurin et al. 2022).

The integration of diverse datasets, coupled with the utilization of visualization tools, significantly enhances the interpretability and usability of WQ data. Integration platforms that amalgamate data from multiple sources provide a comprehensive perspective on WQ parameters and trends (Essamlali et al. 2024). Geospatial integration is particularly beneficial for improving spatial analysis and decision-making by merging WQ data with geographical information. Visualization tools, such as GIS-based maps, charts, and dashboards, provide intuitive and accessible insights into complex WQ datasets, thereby facilitating stakeholders' understanding and enabling informed action based on the information presented (Oseke et al. 2020).

Big data analytics is instrumental in the identification of emerging contaminants that may be overlooked by traditional methodologies. ML and AI have become essential tools for the prediction and assessment of WQ. ML algorithms analyze historical data to forecast future WQ conditions, aiding in proactive management and intervention (Essamlali et al. 2024). In contrast, AI models are capable of predicting algal blooms by analyzing historical data related to nutrient levels, temperature, and other factors. By examining complex datasets derived from diverse sources, such as industrial discharges and agricultural practices, AI can identify patterns that indicate the presence of new or unregulated pollutants. This enhances monitoring efforts and activates timely interventions to mitigate associated risks. Additionally, AI applications are adept at detecting patterns and anomalies within WQ data, improving the identification of contamination events or abnormal conditions (Sheik et al. 2023). This capability is crucial for the development of early warning systems that safeguard public health and protect aquatic ecosystems. The integration of AI and big data analytics with RS technologies, including satellite imagery and GIS, allows for large-scale monitoring of water bodies. This integration facilitates the detection of changes in WQ across extensive areas (Duan et al. 2024). Such an approach yields valuable insights into the impacts of land-use changes, urbanization, and climate variability on water resources, ultimately contributing to the formulation of more effective management strategies. Additionally, ML algorithms can be adapted to accommodate changing environmental conditions, providing dynamic and responsive WQ management (Ahmed et al. 2019). These algorithms continuously learn from new data, enhancing their predictive capabilities and recommendations over time.

Regulatory frameworks and policies

WQ management is of paramount importance for safeguarding public health, preserving ecosystems, and ensuring sustainable water resources. In light of increasing global challenges such as pollution and water scarcity, the establishment of international regulatory frameworks has become essential for effective management. Organizations such as WHO, the UNEP, and the EU have developed comprehensive guidelines and standards pertaining to WQ. These guidelines address a range of issues, from the provision of safe drinking water to the protection of ecosystems. The frameworks delineate contaminant limits and advocate for integrated approaches, thereby facilitating cooperation among nations to mitigate pollution and advance sustainable water resource management.

Global WQ standards are instrumental in harmonizing initiatives aimed at safeguarding water resources and public health. The WHO guidelines lead these initiatives by establishing thresholds for critical WQ parameters that are vital for both human and environmental health (WHO 2022). These guidelines present a universally acknowledged framework for WQ management, fostering consistency in policies among various nations. In a similar vein, organizations such as the ISO develop standardized methodologies for WQ analysis, which facilitate the comparability of data on a global scale. These standards provide a structured approach for laboratories and researchers, enhancing the reliability and accuracy of WQ assessments across diverse regions (ISO 2023).

Many regions adapt global standards to address local conditions. For instance, the WHO has established drinking-water guidelines that set permissible limits for various contaminants, including As (10 µg/L), NO_3^- (50 mg/L), and Pb (10 µg/L), as well as Bisphenol A (0.1 µg/L), Nonylphenol (0. 3 µg/L) and Beta-estradiol (1 ng/L), providing a foundational framework for national regulations (WHO 2017). UNEP's Global Programme of Action to address pollution originating from land-based sources, while the EU's WFD aims to maintain high WQ standards across Europe. The DWD enforces stringent standards for contaminant concentrations in drinking water to protect public health. For example, Pb concentrations are restricted to 10 µg/L, NO_3^- levels are limited to 50 mg/L, and As is capped at 10 µg/L. The microbiological parameters, such as *E. coli*, must be absent in a 100 mL sample of water (EU 2020). These standards are routinely updated in response to emerging scientific data and health risk assessments.

In the United States, the Safe Drinking Water Act establishes maximum contaminant levels for both chemical and biological substances present in drinking water, while the Clean Water Act governs discharges into the nation's water bodies. This legislation encompasses all water sources currently utilized or potentially usable for drinking purposes, which includes both surface water and groundwater (EPA 2024). The ISO 5667 series delineates standards for water sampling and monitoring, thereby promoting methodological consistency. It offers general principles and guidance for the design of sampling programs and techniques applicable to various aspects of water sampling, including drinking water, wastewater, sludges, effluents, SS, and sediments (ISO 2023). The Basel Convention is focused on regulating transboundary movements of hazardous wastes to ensure their safe disposal, while the Stockholm Convention addresses persistent organic pollutants that pose significant risks to WQ and ecosystems. Additionally, conventions pertaining to the Helsinki and Danube rivers emphasize the management of transboundary watercourses to safeguard shared water resources (Kiss and Shelton 2021).

International agreements and treaties provide essential frameworks for the collaborative management of shared water resources, thereby facilitating coordinated efforts to address transboundary WQ issues. A critical component of this collaboration is the exchange of WQ data and the harmonization of monitoring methodologies, which enhance consistency across different jurisdictions. Joint research initiatives contribute to a deeper understanding of WQ challenges and promote innovative solutions that transcend national borders. Through such collaboration, nations can effectively manage shared water bodies, advance sustainable development, and safeguard water resources for future generations. These frameworks establish protocols and guidelines for global WQ management, ensuring the availability of safe water for all.

Conclusion

This study examines the development of WQM from traditional methodologies to advanced technologies and innovative sampling techniques. Key themes include the transformative effects of technologies such as RS, nanotechnology, sensor networks, and AI, which facilitate real-time assessments and data-driven decision-making processes. Effective WQ management requires international cooperation, which can be achieved through cross-border collaboration, the establishment of global standards, and the sharing of information. Despite the ongoing challenges posed by limited access to technology, complexities in data management, and the emergence of new contaminants, these issues also present opportunities for innovation and the development of adaptive strategies. To attain sustainable water resource management, it is imperative to amalgamate scientific advancements with community engagement and comprehensive regulatory frameworks. This integration is crucial for ensuring access to clean water, protecting ecosystems, supporting economic development, and protecting public health. Ultimately, the modernization of WQ management enhances transparency and facilitates informed decision-making, thereby empowering communities to actively engage in the management of water resources. Collective efforts are essential for navigating the complexities associated with water management and for ensuring the sustainability of this vital resource.

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List of abbreviations

Abbreviation	Meaning
3BDA	Three-Band Algorithms
6SV	Satellite signal in the solar spectrum vector
16S rDNA	16S ribosomal Deoxyribonucleic Acid
AI	Artificial Intelligence
ALI	Advanced Land Imager
BCWQI	British Columbia Water Quality Index
BOD	Biochemical Oxygen Demand
BOD5	Biochemical Oxygen Demand after 5 days of incubation at 20°C
CCE	Carbon Chloroform Extract
CCME	Canadian Council of Ministers of the Environment
CCMEWQI	Canadian Council of Ministers of the Environment Water Quality Index
CDM	Colored Dissolved and Detrital Material
CDOM	Colored Dissolved Organic Matter
DOM	Dissolved Organic Matter
CFU	Colony Forming Unit
Chl-a	Chlorophyll-a
COD	Chemical Oxygen Demand
COST	Cosine of the Solar Zenith Angle
CZCS	Coastal Zone Color Scanner Experiment
DA	Discriminant Analysis
DNA	Deoxyribonucleic acid
DO	Dissolved Oxygen
DOC	Dissolved Organic Carbon
DOS	Dark Object Subtraction
DS	Dissolved Solids
DWD	Drinking Water Directive
E. coli	*Escherichia coli*
EC	Electrical Conductivity
EOS	Earth Observing System
EQI	Environmental Quality Index
EU	European Union
ERS-2 SAR	European Remote Sensing satellites (ERS–2) Synthetic Aperture Radar (SAR)
ETM+	Enhanced Thematic Mapper Plus
EWQI	Environmental Water Quality Index
FC	Fecal Coliforms
FEEM	Fluorescence Excitation-Emission Matrices
GEE	Google Earth Engine
GIS	Geographic Information Systems
HMEI	Heavy Metal Evaluation Index
HMPI	Heavy Metal Pollution Index
IoT	Internet of Things
IRS LISS IV	Indian Remote Sensing (IRS) Linear Imaging Self-Scanning Sensor-IV (LISS-4)
ISO	International Organization for Standardization
IWQI	Integrated Water Quality Index
Landsat 5 TM	Landsat 5 Thematic Mapper
Landsat OLI	Landsat Operational Land Imager
LC-MS/MS	Liquid Chromatography-Tandem Mass Spectrometry
LOD	Limit of Detection
LST	Land Surface Temperature
LULC	Land-Use Land-Cover
ML	Machine Learning
MLA	Machine Learning Algorithm

List of abbreviations continued

MLR	Multiple Linear Regressions
MODIS	Moderate Resolution Imaging Spectroradiometer
MPN	Most Probable Number
MS	Mass Spectrometry
NDCI	Normalized Difference Chlorophyll Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NGS	Next-Generation Sequencing
NPs	Nanoparticles
NSFWQI	National Sanitation Foundation Water Quality Index
NSMI	Normalized Soil Moisture Index
PAHs	Polycyclic Aromatic Hydrocarbons
PSU	Practical Salinity Units
RMSE	Root Mean Squared Error
RMSEs	Root Mean Square Errors
RS	Remote Sensing
RSD	Relative Standard Deviation
SDD	Secchi Disk Depth
Se2WaQ	Sentinel-2 Water Quality
Sentinel-2 MSI	Sentinel-2 Multispectral Instrument
SPOT5	Satellite pour l'Observation de la Terre 5
SS	Suspended Solids
SSC	Suspended Sediment Concentration
WFD	Water Framework Directive
SWQI	Serbian Water Quality Index
SWQM	Smart Water Quality Monitoring
TC	Total Coliforms
TDS	Total Dissolved Solids
TKN	Total Kjeldahl Nitrogen
TN	Total Nitrogen
TOC	Total Organic Carbon
TON	Total Oxidized Nitrogen
TP	Total Phosphorus
TSS	Total Suspended Solids
UNEP	United Nations Environment Programme
UWSN	Underwater Wireless Sensor Network
VOCs	Volatile Organic Contaminants
VWQI	Vietnamese Water Quality Index
WAWQI	Weighted Arithmetic Water Quality Index
WFD	Water Framework Directive
WHO	World Health Organization
WQ	Water Quality
WQGTG	Water Quality Guidelines Task Group
WQI	Water Quality Index
WQIs	Water Quality Indices
WQM	Water Quality Monitoring
WSN	Wireless Sensor Network
WV3	WorldView-3 Image
WWQI	Waste Water Quality Index

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