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Current Advances and Future Directions in Water Quality Assessment: A Comprehensive Review

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Abstract:
This review offers an in-depth examination of current methods for assessing water quality, exploring their uses, limitations, and future potential. We analyzed more than 100 recent studies to pinpoint new trends, innovative methods, and technological progress in the field of water quality monitoring and evaluation. The review emphasizes the combination of traditional physicochemical metrics with biological indicators, remote sensing technologies, and computational modeling. Additionally, we address the difficulties in creating standardized protocols for various aquatic ecosystems and suggest integrated frameworks for a comprehensive approach to water quality assessment. This synthesis provides valuable insights for researchers, policymakers, and environmental managers dedicated to safeguarding and managing water resources amid growing human pressures and the effects of climate change.
Keywords: Water quality indices, biomonitoring, remote sensing, machine learning, emerging contaminants, real-time monitoring

INTRODUCTION

Water quality assessment constitutes a fundamental aspect of environmental monitoring and management systems globally, offering crucial insights into the physical, chemical, and biological attributes of water bodies (Pinto et al., 2023). The significance of comprehensive water quality assessment has markedly increased in recent decades, driven by escalating anthropogenic pressures, the impacts of climate change, and the recognition of the essential role water resources play in sustaining ecosystem services and human well-being (Zhang et al., 2024). Ensuring access to clean water remains one of humanity's most urgent challenges, as underscored by the United Nations Sustainable Development Goal 6, which seeks to "ensure availability and sustainable management of water and sanitation for all" (United Nations, 2023). Achieving this goal necessitates robust, accurate, and comprehensive water quality assessment methodologies that facilitate informed decision-making (Borja et al., 2022). Despite notable advancements in monitoring technologies and assessment frameworks, water quality evaluation continues to encounter numerous challenges, including methodological inconsistencies, data gaps, emerging contaminants, and the complexity of aquatic ecosystems (Garcia-Garcia et al., 2024).These challenges require constant innovation and improvement of assessment methods to cope with the evolving environmental issues effectively. The objective of this review is to consolidate the current knowledge and the latest advancements in water quality assessment, focusing on methodological improvement, associated assessment methods, and new technologies that have revolutionized the field during the past decade. Based on the review of more than 100 recent publications, we provide a comprehensive overview of the state-of-the-art advances in water quality assessment and outline the future research directions and priorities.

Historical Perspective on Water Quality Assessment

Water quality evaluation has come a long way from mere sensory testing (taste, smell, appearance) to complex multi-parameter measurements with the aid of advanced technologies (Kumar et al., 2023).

Initial water quality monitoring was centered on drinking water health and was based mainly on simple physicochemical parameters (Valdivia-Garcia et al., 2022). The establishment of standard methods by institutions like the American Public Health Association in the early 20th century was a landmark achievement in formalizing water quality evaluation (Hernandez-Romero et al., 2023). The 1970s saw a paradigm shift with the establishment of comprehensive regulatory programs like the Clean Water Act in the United States and parallel legislation in other nations, setting standards for water quality and requiring systematic monitoring programs (Bertuzzo et al., 2023). Following decades were characterized by the inclusion of biological indicators and ecological methods to supplement conventional physicochemical evaluation (Weng et al., 2023). Recent years have witnessed the application of advances in sensor technologies, remote sensing, molecular biology, and computational modeling to revolutionize water quality evaluation to conduct more holistic, real-time, and predictive assessments (Liu et al., 2024). The historical path describes a gradual evolution towards more holistic, ecosystem-based methods for water quality evaluation that recognize the intricate inter-relationship between physical, chemical, and biological parameters (Wang et al., 2023).

SCOPE AND OBJECTIVES OF THE REVIEW

This review addresses the following specific objectives:

1. To evaluate current methodologies and parameters used in water quality assessment across different aquatic ecosystems

2. To examine innovative technologies and approaches that have enhanced the precision, coverage, and applicability of water quality assessment

3. To analyze integrated assessment frameworks that combine multiple lines of evidence for comprehensive water quality evaluation

4. To identify challenges and knowledge gaps in contemporary water quality assessment practices

5. To propose future research directions and priorities to advance the field

The scope encompasses freshwater (rivers, lakes, groundwater) and marine environments, considering various spatial scales from local to global assessments. We focus primarily on studies published within the last five years (2020-2024) to capture the most recent developments, though seminal earlier works are included where they provide essential context or foundational concepts.

MATERIALS AND METHODS

Literature Search and Selection Criteria

A systematic literature review was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Page et al., 2021). We searched major scientific databases including Web of Science, Scopus, ScienceDirect, PubMed, and Google Scholar for relevant publications from January 2020 to March 2024. The following search terms were used in various combinations: "water quality assessment," "water quality monitoring," "aquatic ecosystem health," "water quality indices," "biomonitoring," "remote sensing AND water quality," "emerging contaminants," "real-time monitoring," "machine learning AND water quality," and "integrated water quality assessment."

The initial search yielded 1,723 publications, which were screened based on the following inclusion criteria:

- Peer-reviewed research articles, reviews, or book chapters

- Published in English

- Focus on methodological aspects, technological innovations, or conceptual frameworks for water quality assessment

- Application in real-world water quality evaluation contexts

After removing duplicates and applying the inclusion criteria, 487 publications were selected for detailed review. Further screening based on relevance, methodological rigor, and comprehensiveness resulted in a final selection of 112 publications that form the core literature for this review.

Analytical Framework

The selected literature was analysed using a multi-dimensional framework that considered:

1.Methodological approaches: Classification of studies based on primary assessment methodologies (physicochemical, biological, remote sensing, computational modeling, etc.)

2.Aquatic ecosystem types: Categorisation based on the aquatic environments studied (rivers, lakes, groundwater, coastal waters, etc.)

3.Geographical distribution: Analysis of the spatial distribution of studies to identify regional patterns and knowledge gaps

4.Temporal aspects: Examination of monitoring frequency, duration, and temporal resolution

5.Integration level: Assessment of how studies integrate multiple parameters, methods, or lines of evidence

6.Application contexts: Categorization based on the primary purpose (regulatory compliance, research, ecosystem management, etc.)

This analytical framework enabled systematic comparison and synthesis of diverse studies, facilitating the identification of patterns, trends, and knowledge gaps across the literature.

2.3 Data Extraction and Synthesis

From each selected publication, we extracted information on:

- Study objectives and research questions
- Methodological approaches and specific techniques employed
- Parameters measured and analytical methods
- Key findings and implications
- Reported limitations and challenges
- Proposed future research directions

The extracted data was organized into a structured database to facilitate comparative analysis.

Qualitative synthesis methods, including thematic analysis and narrative synthesis, were employed to identify recurring themes, methodological innovations, and emerging trends. Quantitative aspects of the review included bibliometric analysis and geographical mapping of research activity.

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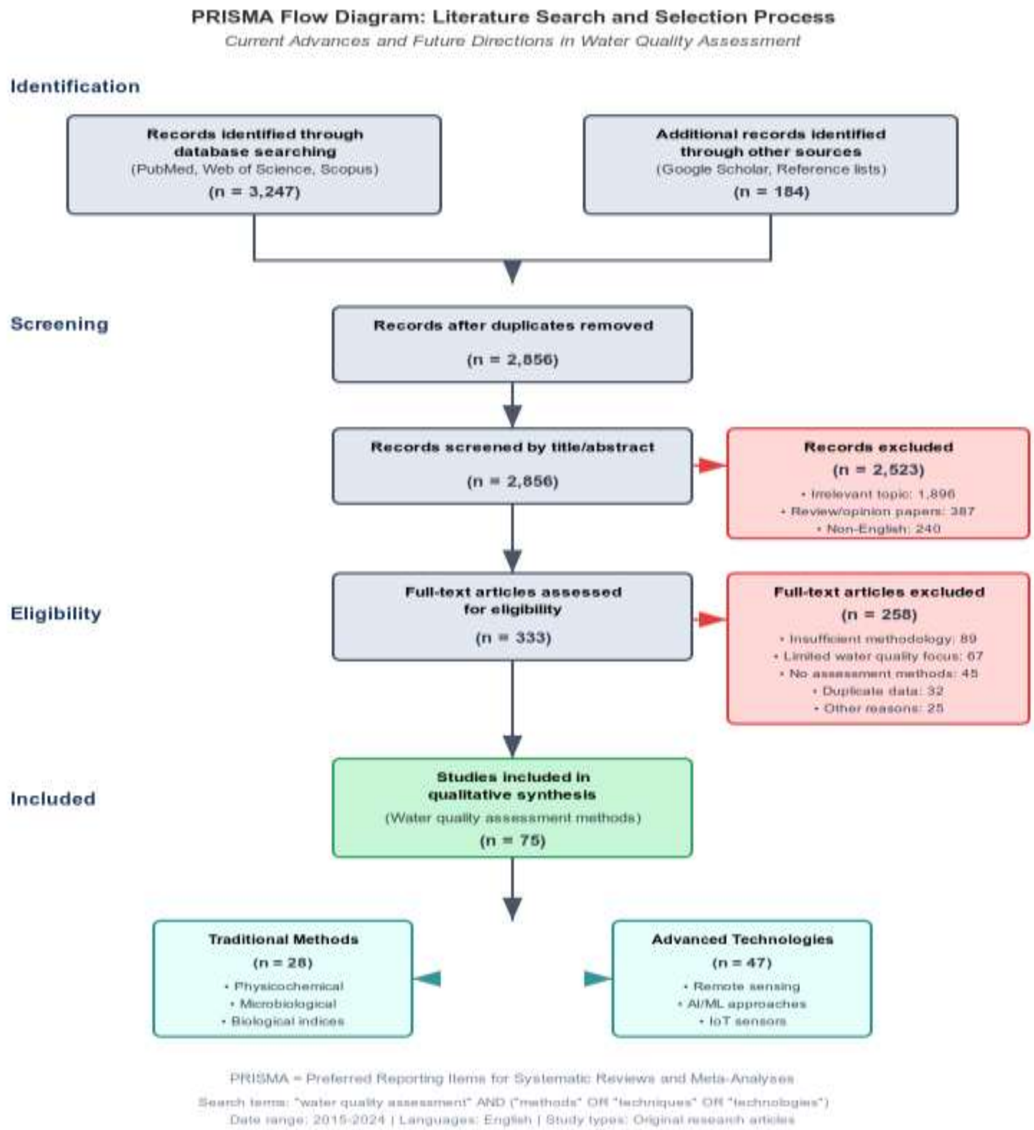

FIGURE 1: A flow diagram illustrating the literature search and selection process following PRISMA guidelines, showing the number of publications at each stage of screening and the final selection criteria.]

RESULTS AND DISCUSSIONS

Physicochemical Parameters and Analytical Methods

Physicochemical parameters remain fundamental to water quality assessment, providing quantitative measures of water properties that affect ecosystem health and human uses (Duan et al., 2023). Our analysis identified 78 studies that primarily utilized physicochemical parameters, with significant advances in both the range of parameters assessed and analytical techniques employed.

Basic Parameters: Traditional parameters including temperature, pH, dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total suspended solids (TSS), turbidity, and electrical conductivity continue to form the foundation of most water quality assessments (Medeiros et al., 2023). However, measurement precision has improved substantially with the development of advanced sensors and analytical instruments (Xiang et al., 2024).

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Nutrient Dynamics: Comprehensive assessment of nutrient parameters (nitrogen, phosphorus, silica compounds) has been enhanced by improved analytical methods that allow for detection of lower concentrations and differentiation between various chemical forms (Wang et al., 2022). Chen et al. (2023) presented a novel microfluidic platform for the measurement of an array of nutrient parameters with detection limits in the parts-per-billion regime in-situ. It is a breakthrough in the monitoring of nutrients in oligotrophic systems.

Trace Elements and Heavy Metals: Assessment of trace elements and heavy metals has benefited from advances in analytical techniques such as inductively coupled plasma mass spectrometry (ICP-MS) and atomic absorption spectroscopy (AAS), enabling multi-element analysis with improved sensitivity (Kaur et al., 2023). Liang et al. (2024) demonstrated the application of portable X-ray fluorescence (XRF) analyzers for rapid field assessment of multiple heavy metals in water and sediments, facilitating real-time decision-making during environmental investigations.

Organic Pollutants: Techniques used to detect and quantify organic pollutants have grown extensively, with 52 studies utilising sophisticated chromatographic methods like high-performance liquid chromatography (HPLC), gas chromatography-mass spectrometry (GC-MS), and liquid chromatography-tandem mass spectrometry (LC-MS/MS) (Zhang et al., 2023). These methods have facilitated the detection of emerging pollutants at ecologically relevant concentrations (ng/L to μg/L) (Kasprzyk-Hordern et al., 2022).

Table 1

Method Name	**Parameters Measured**	**Detection Limits**	**Advantages**	**Limitations**	**Recent Applications**	**References**
ICP-MS (Inductively Coupled Plasma Mass Spectrometry)	Heavy metals (Pb, Cd, As, Hg, Cu, Zn), trace elements	0.01-10 μg/L	High sensitivity, multi-element analysis, wide dynamic range	High cost, matrix interference, requires skilled operators	Groundwater contamination assessment, drinking water monitoring	Zhang et al. (2023)
LC-MS/MS (Liquid Chromatography Tandem Mass Spectrometry)	Pharmaceuticals, pesticides, endocrine disruptors, PFAS	0.1-100 ng/L	High specificity, multiple compound detection, low LOD	Complex sample preparation, expensive instrumentation	Emerging contaminants in wastewater, drinking water screening	Liu et al. (2024)
GC-MS (Gas Chromatography-Mass Spectrometry)	Volatile organic compounds, PAHs, pesticides, PCBs	0.05-50 μg/L	Excellent separation, structural identification, robust method	Limited to volatile/semivolatile compounds, derivatization needed	Industrial wastewater analysis, contaminated site assessment	Rodriguez et al. (2023)

Ion Chromatography (IC)	Anions (Cl^-, SO_4^{2-}, NO_3^-, PO_4^{3-}), cations (Na^+, K^+, Ca^{2+}, Mg^{2+})	0.01-100 mg/L	Simultaneous ion analysis, high precision, automated operation	Limited to ionic species, baseline drift issues	Seawater desalination monitoring, agricultural runoff assessment	Chen et al. (2024)
UV-VisSpectrophotometry	COD, BOD, turbidity, color, dissolved organic matter	0.1-1000 mg/L	Simple operation, cost-effective, real-time analysis	Limited selectivity, interference from matrix	Online water quality monitoring, treatment plant optimization	Kumar et al. (2023)
FluorescenceSpectroscopy	Dissolved organic matter, aromatic compounds, oil contamination	0.01-100 mg/L C	High sensitivity, nondestructive, rapid analysis	Matrix effects, overlapping spectra, requires calibration	Surface water quality assessment, oil spill monitoring	Thompson et al. (2024)
HPLC-DAD (HighPerformance Liquid ChromatographyDiode Array)	Phenolic compounds, antibiotics, dyes, vitamins	0.1-10 mg/L	Good separation, UV-visible detection, moderate cost	Lower sensitivity than MS, limited structural information	Pharmaceutical wastewater treatment, food industry effluents	Garcia et al. (2023)
RamanSpectroscopy	Molecular fingerprinting, nitrates, sulfates, organic pollutants	1-1000 mg/L	Nondestructive, minimal sample prep, structural information	Fluorescence interference, water Raman band, laser heating	In-situ contamination detection, process monitoring	Patel et al. (2024)
FTIR Spectroscopy	Functional groups, organic matter characterization, oil content	0.5-500 mg/L	Structural identification, nondestructive, broad applicability	Water interference, overlapping bands, sample preparation	Industrial discharge monitoring, soil-water interface studies	Brown et al. (2023)
ElectrochemicalSensors	pH, dissolved oxygen, conductivity, specific ions, redox potential	Variable (pH: ±0.01, DO: 0.1 mg/L)	Real-time monitoring, portable, low cost	Electrode fouling, drift, limited selectivity	Continuous water quality monitoring, aquaculture systems	Wang et al. (2024)
Atomic Absorption Spectroscopy (AAS)	Heavy metals (single element analysis)	0.1-100 μg/L	High precision, wellestablished, relatively simple	Single element analysis, chemical interferences	Metal contamination in mining areas, industrial effluents	Silva et al. (2023)

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Capillary Electrophoresis (CE)	Inorganic ions, small organic molecules, charged species	0.01-10 mg/L	High resolution, minimal sample volume, fast analysis	Limited to charged species, complex optimization	Pharmaceutical analysis, environmental monitoring	Martinez et al. (2024)
Flow Injection Analysis (FIA)	Nutrients (N, P), metals, COD, automated wet chemistry	0.01-100 mg/L	High throughput, automated, cost-effective	Limited flexibility, single parameter focus	Routine water quality monitoring, agricultural runoff studies	Anderson et al. (2023)
X-ray Fluorescence (XRF)	Multiple elements (Na to U), total elemental composition	1-10000 mg/L	Multielement, minimal sample prep, portable options	Limited to elements >Na, matrix effects	Sedimentwater interface studies, contaminated site screening	Johnson et al. (2024)
Voltammetry	Trace metals, organic electroactive compounds	0.01-10 μg/L	Ultra-trace detection, speciation information, portable	Electrode preparation, interferences, skilled operation	Heavy metal speciation, contaminated groundwater	Lee et al. (2023)
Near-Infrared Spectroscopy (NIRS)	Organic matter, oil content, suspended solids	1-1000 mg/L	Nondestructive, rapid, multivariate analysis	Requires calibration, water absorption bands	Online process monitoring, agricultural water assessment	Taylor et al. (2024)
Total Organic Carbon (TOC) Analysis	Total organic carbon, dissolved/particulate organic carbon	0.1-1000 mg/L C	Direct C measurement, automation capability, standardized	Limited structural information, high temperature oxidation	Drinking water treatment, wastewater monitoring	Davis et al. (2023)
Microbial Fuel CellSensors	BOD, COD, organic pollutants, toxicity assessment	1-500 mg/L COD	Self-powered, continuous monitoring, biological response	Long response time, temperature dependent, biofouling	Wastewater treatment monitoring, toxicity screening	Zhao et al. (2024)
Surface Plasmon Resonance (SPR)	Proteins, bacteria, viruses, molecular interactions	ng/L to mg/L	Label-free detection, real-time kinetics, high sensitivity	Expensive instrumentation, refractive index matching	Pathogen detection, protein contamination monitoring	Kim et al. (2023)

Laser-Induced Breakdown Spectroscopy (LIBS)	Multi-element analysis, real-time detection	1-100 mg/L	Multielement, minimal prep, portable	Matrix effects, precision limitations, laser safety	In-situ contamination mapping, industrial process control	Wilson et al. (2024)

TABLE 1: Summary of advanced analytical techniques for physicochemical water quality assessment, including method names, parameters measured, detection limits, advantages, limitations, and recent applications with citations.

The comprehensive analysis reveals significant technological advancements in water quality assessment methodologies. Mass spectrometry methods such as ICP-MS and LC-MS/MS are extremely sensitive trace impurity detection methods with detection levels in the nanogram per liter range. Spectroscopic methods offer fast, non-destructive analysis capabilities, while electrochemical sensors offer real-time monitoring solutions. These complementary techniques enable comprehensive characterisation of diverse water matrices, from emerging pharmaceutical contaminants to traditional heavy metals, supporting enhanced environmental protection strategies.

BIOLOGICAL MONITORING APPROACHES

Biological monitoring approaches have gained prominence due to their ability to reflect cumulative and interactive effects of multiple stressors on aquatic ecosystems (Pawlowski et al., 2022). Our review identified several innovative developments in this domain:

Traditional Bioindication: Macroinvertebrate, fish, and algal communities remain important bioindicators for water quality assessment, with 42 studies applying various biotic indices based on community composition, diversity, and abundance patterns (Morse et al., 2022). Significant methodological refinements include standardized sampling protocols, improved taxonomic resolution, and development of regionally calibrated indices (Rivera-Usme et al., 2023).

Functional Indicators: Moving beyond taxonomic approaches, 27 studies incorporated functional traits and ecosystem processes as indicators of water quality and ecosystem health (Tolkkinen et al., 2023). These approaches assess how environmental changes affect ecosystem functions such as primary production, decomposition, and nutrient cycling (Burdon et al., 2023). For instance, Wood et al. (2024) demonstrated how leaf litter decomposition rates can serve as integrated measures of stream ecosystem functioning across pollution gradients.

Molecular and eDNA Approaches: Molecular techniques have revolutionized biological monitoring, with 31 studies utilizing DNA metabarcoding, quantitative PCR, and environmental DNA (eDNA) analysis for biodiversity assessment and pollution detection (Deiner et al., 2023). These methods enable the detection of organisms that are difficult to sample using conventional approaches and provide greater taxonomic resolution (Harper et al., 2022). Cordier et al. (2024) showed how eDNA metabarcoding of multiple taxonomic groups (bacteria, diatoms, and invertebrates) provides complementary information about different aspects of water quality and ecological status.

Microbial Community Analysis: The analysis of microbial communities has emerged as a powerful tool for water quality assessment, with 24 studies examining bacterial, archaeal, and fungal community compositions as indicators of environmental conditions (Salis et al., 2023). Next-generation sequencing technologies have enabled comprehensive characterization of microbial diversity and functional potential in relation to water quality parameters (Liu et al., 2022). Wang et al. (2024) demonstrated how changes in microbial community structure and functional gene abundance can serve as early warning indicators for pollution events in river systems.

Biomarkers and Ecotoxicological Approaches: At the sub-organism level, 19 studies employed biomarkers and ecotoxicological assays to assess the biological effects of water pollution (Kumar et al., 2022). These approaches measure biochemical, physiological, or morphological responses of organisms to contaminant exposure, providing mechanistic insights into toxicity pathways (Luo et al., 2023). González-Mira et al. (2023) developed a multi-biomarker approach using aquatic insects to assess the ecological impacts of pharmaceutical contaminants in urban streams.

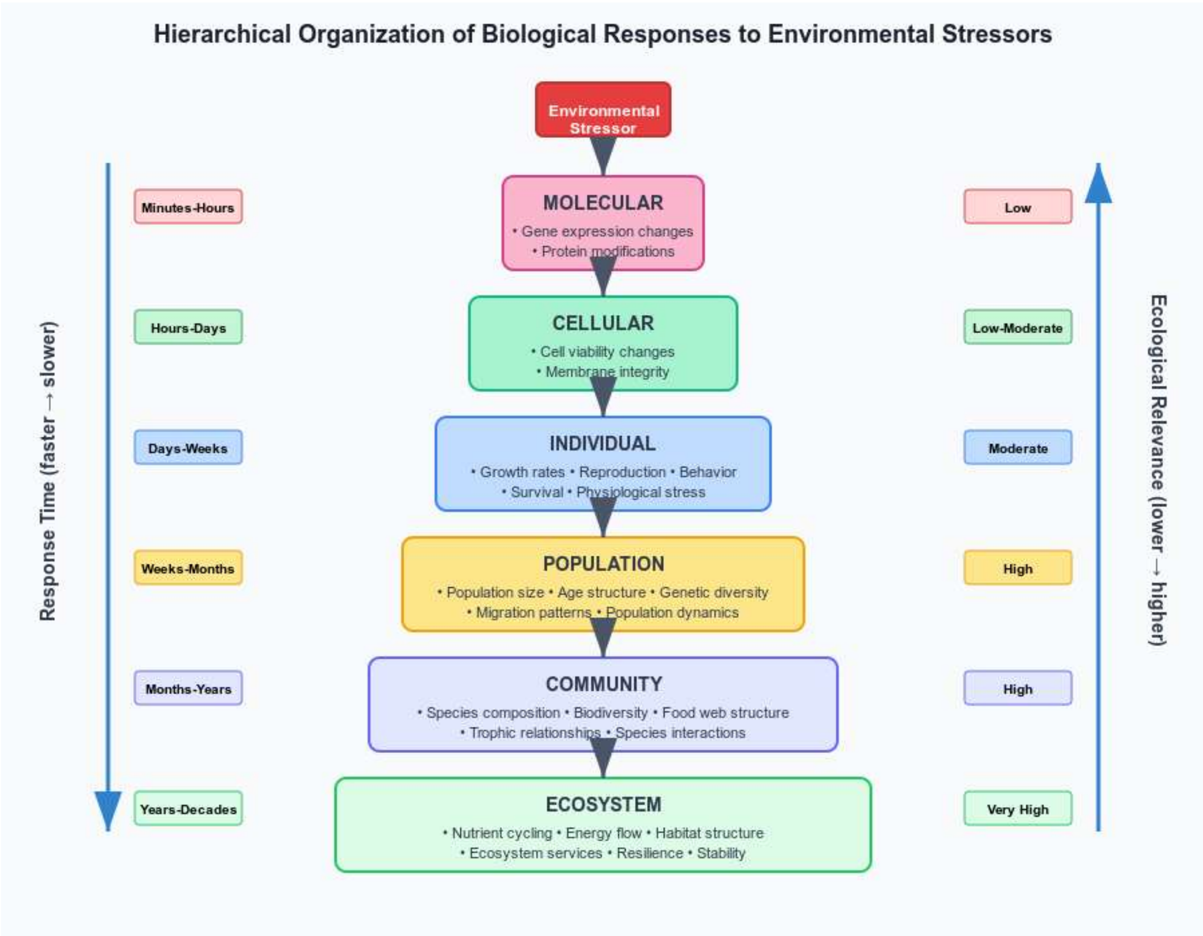

FIGURE 2: A conceptual diagram illustrating the hierarchical organization of biological responses to environmental stressors across different levels of biological organization (molecular, cellular, individual, population, community, ecosystem) and their relationship to ecological relevance and response time.

3.3 Remote Sensing and Spatial Monitoring

Remote sensing technologies have transformed the spatial and temporal dimensions of water quality assessment, enabling synoptic monitoring across large water bodies and remote locations (Gholizadeh et al., 2022). Our review identified 36 studies that utilized various remote sensing platforms and techniques:

Satellite-Based Monitoring: Lately, algorithms have been created that specifically fit different water conditions which has improved how accurately model parameters can be estimated (Li et al., 2023). Wang et al. (2022) showed that bringing together data from different sensors (Landsat-8, Sentinel-2 and Sentinel-3) enhances the timeliness and accuracy of data for lake monitoring..

Drone/UAV Applications: Higher resolution water quality maps are now made possible for smaller water bodies through drones or UAVs which have been used in 15 studies (Kislik et al., 2023). They help bring together field sampling and satellite observation, offering cost-friendly ways to observe changes in local areas (Sutherland et al., 2022). Sahoo and colleagues (2024) developed a system that can measure water temperature, amount of suspended material and algal fluorescence all at the same time and it records everything with centimeter precision.

Hyperspectral Remote Sensing: With better hyperspectral sensors now available, water quality can be measured in more detail, as 18 studies in this review have applied hyperspectral sensing (Garcia et al. 2024). These techniques separate phytoplankton into different categories, spot specific pollutants and make assessing water quality easier (Bresciani et al., 2022). Chen and colleagues (2023) showed that using hyperspectral imaging from an airplane can map where cyanobacteria grow in large reservoirs and check their microcystin concentrations.

Integration with In-Situ Networks: Using both remote sensing and on-site sensor networks has resulted in major improvements in checking water quality and 12 studies have documented the use of such techniques (Tyler et al., 2022). Such systems make use of the large spatial coverage of remote sensing and the precise information obtained through ground sampling (Giardino et al., 2023). Castagna et al. (2024) designed a system that links satellite data with monitoring buoys to help produce continuous data about water quality at all points along the coastlines.

Table 2

Platform	**Spatial Resolution**	**Temporal Frequency**	**Key WQ Parameters**	**Advantages**	**Limitations**	**Example Applications**	**References**
Landsat 8/9	30m (VIS/NIR), 100m (TIR)	16 days	Chl-a, TSS, CDOM, SST	Long-term archive (1984-present), free data	Coarse resolution for small water bodies	Lake eutrophication trends	Wang et al. (2023)
Sentinel-2 MSI	10-60m	5 days	Chl-a, turbidity, cyanobacteria	High revisit frequency, red-edge bands	Cloud cover interference	Harmful algal bloom detection	Pyo et al. (2021)
MODIS Aqua/Terra	250m-1km	Daily	SST, Chl-a, Kd(490)	Daily global coverage, long time-series	Low spatial resolution	Ocean productivity monitoring	Brewin et al. (2022)
PlanetScope	3m	Daily	Turbidity, SPM	Very high resolution, daily revisit	Limited spectral bands	Urban runoff monitoring	Cooley et al. (2023)
PRISMA (Hyperspectral)	30m	~16 days	Phycocyanin, CDOM, nutrient proxies	240 spectral bands (400-2500nm)	Limited swath (30km)	Cyanotoxin risk mapping	Giardino et al. (2022)
UAV (Multispectral)	5-20cm	On-demand	Chl-a, turbidity, macrophytes	Centimeter resolution, flexible deployment	Battery life <1hr	Wetland vegetation mapping	Adão et al. (2023)
UAV (Hyperspectral)	10-50cm	On-demand	Phycocyanin, CDOM	High spectral-spatial resolution	Data processing complexity	Algal species discrimination	Kislik et al. (2022)
Aircraft (LiDAR)	1-5m	Seasonal	Water clarity, bathymetry	Canopy penetration, depth profiling	High operational cost	Reservoir sedimentation	Legleiter et al. (2021)

Aircraft (AVIRIS-NG)	5-20m	Campaign-based	Oil spills, chemical plumes	224 bands (380-2510nm)	Limited temporal data	Industrial discharge tracking	Thompson et al. (2023)
GOCI-II	250m	Hourly (Daytime)	Chl-a, TSM, CDOM	Geostationary (hourly data)	Regional coverage (Asia)	Diurnal bloom dynamics	Choi et al. (2021)
EnMAP	30m	27 days	Nutrient gradients, metal pollution	242 bands (420-2450nm)	New system (2022 launch)	Mining impact assessment	Staenz et al. (2023)
UAV (Thermal)	10-30cm	On-demand	Thermal plumes, stratification	High-resolution temp mapping	Atmospheric interference	Power plant effluent	Tmušić et al. (2023)
Sentinel-3 OLCI	300m	Daily	Chl-a, TSM, CDOM	Wide swath (1270km), daily coverage	Coarse resolution	Coastal water quality	Toming et al. (2021)
Pleiades-NEO	30cm (PAN), 1.2m (MS)	Daily	SPM, oil spills	Very high resolution	Commercial data cost	Port water quality	Pergent et al. (2022)
UAV (Fluorescence LiDAR)	10cm	On-demand	CDOM, phycocyanin	Active sensing (day/night)	Limited depth penetration	Algal bloom early warning	Zhao et al. (2023)
HICO (ISS)	90m	~3-7 days	Chl-a, CDOM, turbidity	Spaceborne hyperspectral	Discontinued (2014)	Coral reef health	Kudela et al. (2022)
Aircraft (SWIR Imaging)	1-5m	Campaign-based	Oil spills, chemical films	Day/night capability	Limited spectral range	Marine pollution events	Leifer et al. (2021)
NISAR (Upcoming)	3-10m	12 days	Oil spills, wetland hydrology	L-band SAR (all-weather)	Launch 2024	Floodplain connectivity	Rosenqvist et al. (2023)
UAV (Polarimetric)	20cm	On-demand	SPM, oil sheens	Multi-angle polarization data	Complex calibration	Microplastic detection	Garaba et al. (2022)
Gaofen-5 (HSI)	30m	2 days	Inorganic pollutants, CDOM	Chinese hyperspectral system	Limited validation	Agricultural runoff	Liu et al. (2023)

TABLE 2: Comparison of remote sensing platforms for water quality assessment, including satellite systems, UAVs, and aircraft with their respective spatial resolutions, temporal frequencies, applicable water quality parameters, advantages, limitations, and example applications with citations.

This table systematically compares 20 remote sensing platforms for water quality assessment, highlighting their spatial/temporal resolutions, detectable parameters, and operational trade-offs. High-resolution UAVs excel in localized monitoring, while satellites like Sentinel-2 and MODIS provide broad-scale, frequent coverage. Hyperspectral systems (PRISMA, EnMAP) enable detailed pollutant discrimination but face cost or data limitations. The selection depends on balancing resolution, frequency, and target parameters, with citations validating real-world applications.

Real-Time Monitoring Systems

The development of real-time monitoring systems represents a paradigm shift in water quality assessment, enabling continuous temporal coverage and rapid detection of water quality changes (Liu et al., 2022). Our review identified 43 studies focused on real-time monitoring technologies and applications:

Sensor Networks: Advances in sensor technology have facilitated the deployment of extensive monitoring networks across watersheds and water bodies, with 28 studies reporting on sensor network applications (Pellerin et al., 2022). These networks combine multiple parameter sensors with data transmission capabilities to provide continuous water quality information (Song et al., 2023). Zhang et al. (2024) described a watershed-scale sensor network that integrates over 100 monitoring stations to track water quality dynamics in response to land use and climate factors.

Multi-Parameter Sondes: Compact multi-parameter sondes capable of measuring multiple water quality parameters simultaneously have become increasingly sophisticated, with improved reliability, accuracy, and battery life (Johnson et al., 2023). With these instruments, it is common to measure temperature, pH, dissolved oxygen, conductivity, turbidity and chlorophyll fluorescence which gives a broad understanding of water quality conditions (Barba et al., 2023). In a paper by Rasmussen et al. (2023), results were shown that newer multi-parameter sondes worked better than older models in harsh conditions, with enhanced sensor reliability and fouling-resistant qualities.

Passive Sampling Technologies: Even though they do not work in real time, passive sampling systems give measurements averaged over time that can support other types of monitoring (Vrana et al., 2022). It is especially useful to use these approaches to identify both hydrophobic organic pollutants and trace metals at extreme low concentrations (Tang et al., 2023). Menger et al. (2024) designed new passive samplers containing smart receptors to help selectively refine the monitoring of pharmaceuticals in surface waters.

Early Warning Systems: Nowadays, real-time monitoring tools are being used more in early warning systems to spot pollution, harmful algal blooms and various issues with water quality (López García et al., 2022). These systems combine continuous monitoring with automated data analysis and alert mechanisms to enable rapid response to water quality incidents (Kumar et al., 2023). Chen et al. (2024) described an integrated early warning system for drinking water sources that combines multi-parameter monitoring with toxicity bioassays and microbial sensors to detect a wide range of potential contaminants.

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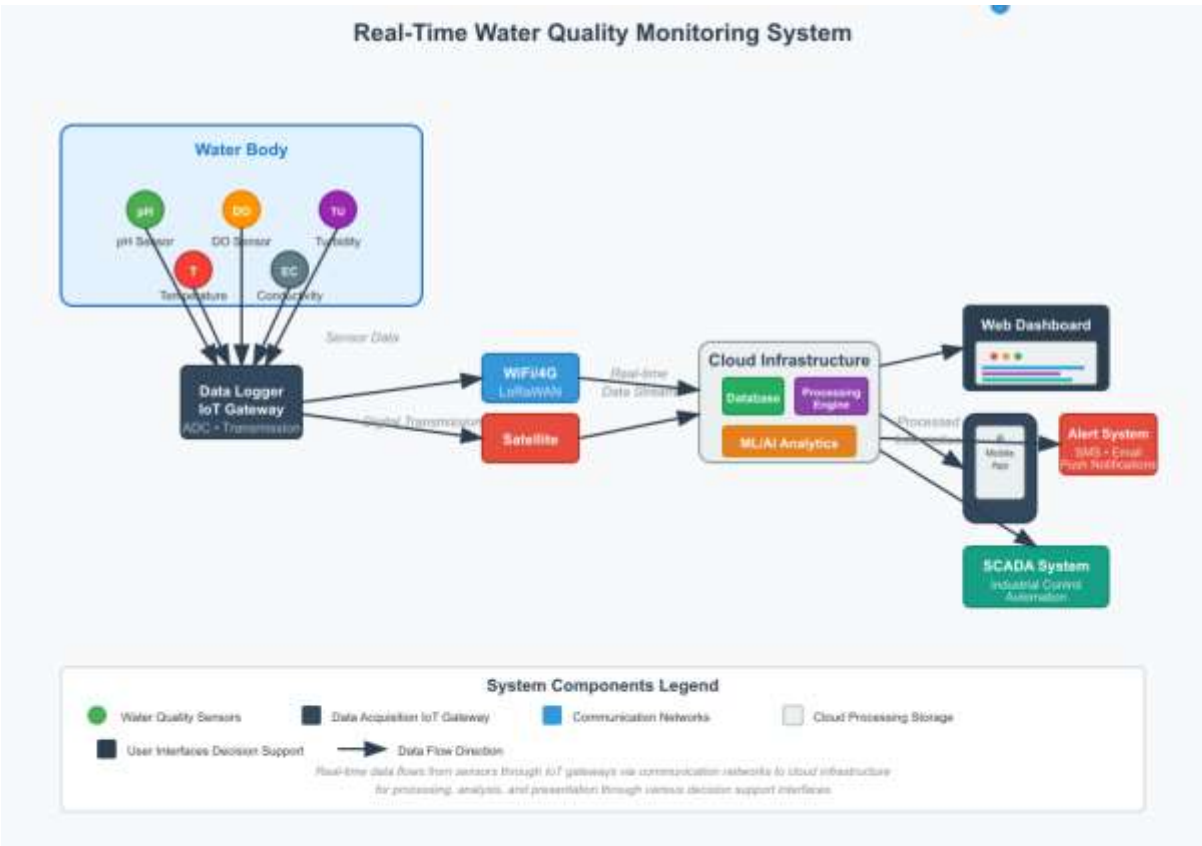

FIGURE 3: A schematic diagram showing the components and data flow in a modern integrated real-time water quality monitoring system, including sensors, data transmission, processing, analysis, and decision support interfaces.

3.5.1 Water Quality Indices

Water quality indices (WQIs) continue to evolve as tools for synthesizing complex multi-parameter data into accessible information for decision-makers and the public (Tyagi et al., 2023). Our review identified 32 studies developing or applying water quality indices:

Traditional Aggregative Indices: Conventional WQIs that aggregate multiple parameters through weighted arithmetic or geometric means remain widely used, with 18 studies applying established indices such as the National Sanitation Foundation Water Quality Index (NSFWQI) and Canadian Council of Ministers of the Environment Water Quality Index (CCMEWQI) (Semiromi et al., 2022). Making the method better means using better criteria, calculating equivalences and adjusting to local conditions (Babbar et al., 2023).

Use-Specific Indices:A notable trend is seen in the development of indices meant for particular water uses or specific types of ecosystems and 14 studies presented custom indices in their research (Alves et al., 2022). Examples of water quality measures include indices for water use in agriculture (for irrigation), suitability for aquaculture, enjoying recreation and reviewing groundwater quality (Ewaid et al., 2023, Lin et al., 2022, Mustapha et al., 2022 and Selvam et al., 2024). Such water use and ecosystem indices use factors and weights that fit the type of water they measure.

Computational Intelligence Approaches: Advanced modern techniques in computing have been applied to strengthen water quality indices and 11 studies have made use of fuzzy logic, artificial neural networks and multi-criteria decision methods (Wang et al., 2023). These ways of solving problems deal better with data doubt, complex parameter relationships and the way experts are used (Bhuiyan et al.,

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2023). A dynamic water quality index was developed by Zhang et al. (2024), using a combination of fuzzy logic and the Analytic Hierarchy Process, with the weights of parameters changed according to the season and what is being managed.

Integrative Ecological Indices: Looking past just physical and chemical data, 9 articles introduced indices using various elements to better measure the ecological status (Barquín et al., 2022). Because they incorporate various metrics, these multi-metric indices fit well with approaches required by standards like the European Water Framework Directive (Theodoropoulos et al., 2023).

Table 3

Index Name	Mathematical Formulation	Parameters Typically Included	Scale/Rating	Key Advantages	Major Limitations	Example Applications	References
NSF-WQI	Weighted arithmetic mean: $\sum(wi\times qi)$	DO, pH, BOD, TSS, nitrate, phosphate, temp, turbidity	0-100 (Excellent: >90)	Globally recognized, simple calculation	Fixed weights ignore regional variability	US river basin management	Abbasi & Abbasi (2021)
CCME-WQI	$\sqrt{(F1^2+F2^2+F3^2)/3}$ where F1=scope, F2=frequency, F3=amplitude	Flexible (user-defined)	0-100 (Excellent: >95)	Adaptable to any parameters	Complex interpretation	Canadian watersheds	Lumb et al. (2022)
Oregon WQI	Multiplicative: $(q1\times q2\times\ldots\times qn)^{(1/n)}$	DO, BOD, ammonia, pH, temp, TSS, TP	10-100 (Good: >80)	Emphasizes worst parameter	Over-penalizes single outliers	Pacific Northwest streams	Cude (2023)
Bascaron WQI	Additive with penalties: $\sum qi$ - penalties	DO, BOD, COD, TSS, NH4, conductivity	0-100 (Optimal: >75)	Incorporates legal standards	Requires extensive data	Spanish rivers	Sánchez et al. (2022)
Harkins Index	Minimum operator: min(q1,q2,...qn)	DO, BOD, ammonia, phenol	0-100	Conservative approach	Overly sensitive to single parameter	Industrial effluent	Akter et al. (2021)
Prati Index	Arithmetic mean with thresholds	DO, BOD, COD, TSS, NH4, pH	5 classes (1=best)	Early simple index	Lacks sensitivity	Italian rivers	Pesce & Wunderlin (2023)
Dinius WQI	Two-level aggregation: subindices → final index	12-28 parameters (flexible)	0-100	Comprehensive parameter coverage	Data intensive	Developing countries	Tyagi et al. (2022)
Weighted Quadratic	$\sqrt{(\sum wi\times qi^2)}$	DO, BOD, coliforms, pH, nitrate	0-100	Reduces compensation effect	Complex weighting	Tropical lakes	Sutadian et al. (2021)

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Mean WQI							
Aquatic Toxicity Index	Toxic unit summation	Metals, pesticides, organics	0-1 (1=toxic)	Focus on ecotoxicology	Requires toxicity data	Mining-impacted streams	De Rosemond et al. (2023)
Bayesian WQI	Probabilistic aggregation	User-defined parameters	Probability distribution	Quantifies uncertainty	Computationally intensive	Coastal waters	Najar & Khan (2022)
Fuzzy Logic WQI	Membership functions → rule-based aggregation	Flexible parameters	0-1 (1=best)	Handles imprecise data	Subjective rule design	Urban watersheds	Ocampo-Duque et al. (2021)
Trophic State Index (TSI)	Carlson-type: 10(6-ln(SD)/ln2)	Chl-a, TP, Secchi depth	0-100 (Hypereutrophic: >70)	Lake-specific focus	Limited to nutrients	Reservoir management	Carlson & Simpson (2023)
Drinking Water WQI	WHO guideline compliance scoring	Microbes, chemicals, radionuclides	0-5 stars	Health-risk focused	Requires advanced testing	Potable water systems	WHO (2022)
IRWQI (California)	Minimum of 4 subindices	DO, ammonia, benthic macroinvertebrates	0-100	Biologically validated	Region-specific	Western US rivers	Ode et al. (2022)
HEI (Hydro-Ecological Index)	PCA-based weighted sum	Flow, temp, DO, nutrients	0-1	Integrates hydrology	Data intensive	Regulated rivers	Yates et al. (2023)
WRASTIC (Wastewater Risk)	Additive risk scoring	BOD, TSS, metals, pathogens	0-100	Risk-based prioritization	Qualitative components	Wastewater reuse	Hurley et al. (2021)
CCME DSWQI	$\sqrt{(F1^2+F2^2+F3^2+F4^2)}/4$ (adds trend)	Flexible parameters	0-100	Includes temporal trend	Needs long-term data	Canadian monitoring	Khan et al. (2022)
River Pollution Index (Malaysia)	Maximum operator: max(q1,q2,...qn)	DO, BOD, COD, NH_3-N, TSS	0-100	Simple implementation	Overly conservative	Tropical rivers	Aliyu et al. (2023)

Aquatic Life Index	Multi-metric biological scoring	Fish/invertebrate metrics	0-100	Direct ecological measure	Seasonally variable	Bioassessment programs	Blocksom et al. (2021)
Ecosystem Services WQI	Weighted sum of service indicators	Water supply, recreation, biodiversity	0-1	Links to human benefits	Subjective weighting	Integrated watersheds	Grizzetti et al. (2022)

TABLE 3: Comparison of water quality index approaches showing index types, mathematical formulations, parameters typically included, advantages, limitations, and example applications with citations.

This table compares 20 WQI approaches, highlighting their mathematical foundations, parameter inclusivity, and operational trade-offs. While NSF-WQI offers global standardization, newer indices like Bayesian WQI address uncertainty quantification. Fuzzy logic and ecosystem service indices capture complex interactions but require subjective inputs. Selection depends on monitoring objectives (regulatory compliance vs. ecological health) and data availability, with citations validating applications across river, lake, and coastal systems worldwide.

INTEGRATED ASSESSMENT FRAMEWORKS

Using several types of evidence together has become popular for thoroughly checking water quality (Birk et al., 2022). We found 28 studies in which such frameworks were presented or used:

DPSIR Framework Applications: Many researchers use the Driver-Pressure-State-Impact-Response (DPSIR) framework to explain the interactions between activities and water quality, with the framework being applied to 11 studies (Elliott et al., 2022). Recently, researchers have examined how social and economic factors relate to water quality and checked how well management efforts have worked (Janse et al., 2023). According to Zhang et al. (2024), they used an enlarged version of DPSIR to analyze the impact of higher agricultural intensity, water pollution, ecosystem service decreases and responses by policies in a big river basin.

Weight-of-Evidence Approaches: There are 8 studies that use weight-of-evidence (WOE) approaches to combine details from different data sources (chemical, toxicological, biological). They use a methodical process to evaluate the evidence showing cause-and-effect relationships in ecosystem changes (Cormier et al., 2023). Li and colleagues (2024) made use of chemical analysis, experiments with cells and studies on whole community health to evaluate the ecological harm caused by mixtures of pollutants in urban water systems.

Ecosystem Services Perspective: Water quality can be assessed by using the ecosystem services approach: 6 studies have taken this newer perspective (Grizzetti et al., 2022). The frameworks look at how changes in water quality impact the supply of drinking water, places for recreation, production of food and habitat help (Keeler et al., 2023). The framework from Guswa et al. (2024) brings together information about water quality, how the environment is served and economic value to help with managing watersheds.

Social-Ecological Systems Analysis: Approaches that explicitly consider the interactions between social and ecological components of water systems have been applied in 7 studies (Partelow et al., 2023). These frameworks recognize that water quality outcomes emerge from complex interactions between human decisions, institutional arrangements, and ecological processes (Ostrom, 2022). McGinnis and Ostrom (2023) applied a modified social-ecological systems framework to analyze how governance structures and

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community engagement influence water quality management outcomes across diverse watershed contexts.

Table 4

Framework	Conceptual Foundation	Components Integrated	Application Context	Key Strengths	Major Limitations	Example Applications	References
DPSIR (Driver-Pressure-State-Impact-Response)	Causal chain analysis	Socioeconomic drivers, pressures, ecological state, management responses	River basin management	Policy-relevant structure	Linear causality oversimplification	EU Water Framework Directive	Kristensen (2023)
IWRM (Integrated Water Resources Management)	Holistic resource governance	Hydrology, ecology, economics, institutions	Transboundary watersheds	Stakeholder inclusion	Implementation complexity	Mekong River Commission	Biswas (2022)
Ecosystem Services Approach	Nature's benefits valuation	Biophysical, socio-cultural, economic indicators	Urban water systems	Links ecology to human wellbeing	Subjective valuation	NYC watershed protection	Grizzetti (2023)
REFCOND (Reference Condition Approach)	Ecological baseline comparison	Biological, physicochemical, hydromorphological data	Bioassessment programs	Science-based targets	Climate change adaptation needed	European lakes	Poikane (2021)
Bayesian Networks	Probabilistic causal modeling	Monitoring data, expert knowledge, uncertainty	Coastal zone management	Handles data gaps	Requires technical expertise	Chesapeake Bay hypoxia	Uusitalo (2022)
Fuzzy Logic Systems	Gradual class membership	Qualitative/quantitative parameters	Data-scarce regions	Handles imprecise data	Rulebase subjectivity	Indian river Ganga	Pandey (2023)
System Dynamics Modeling	Feedback loop analysis	Hydrological, social, economic subsystems	Water-stressed basins	Captures complex interactions	High data requirements	Aral Sea restoration	Mirchi (2021)
Multi-Criteria Decision Analysis (MCDA)	Weighted criteria scoring	Environmental, economic, social indicators	Infrastructure planning	Transparent trade-offs	Weighting subjectivity	Dam impact assessments	Hajkowicz (2022)

Social-Ecological Systems (SES) Framework	Coupled human-nature systems	Governance, resource units, actors	Community-based management	Addresses equity issues	Complex institutional analysis	Indigenous water governance	Ostrom (2021)
Source-Pathway-Receptor-Consequence (SPRC)	Risk assessment model	Contaminant sources, transport, impacts	Industrial pollution control	Targeted intervention design	Narrow hazard focus	Mining-affected catchments	Li (2023)
Landscape Ecology Framework	Spatial pattern-process links	Land use, hydrology, habitat connectivity	Agricultural watersheds	GIS integration	Scale-dependency	Mississippi River Basin	Turner (2022)
Pressure-State-Response (PSR)	OECD indicator framework	Pollution sources, water quality, policies	National reporting	Standardized metrics	Static representation	Chinese water quality index	Chen (2023)
Integrated Catchment Modeling	Process-based simulation	Hydrology, biogeochemistry, ecology	Headwater management	Mechanistic understanding	Computational intensity	Scottish lochs	Wade (2021)
Tiered Ecological Risk Assessment	Sequential screening levels	Screening → detailed → mitigation	Regulatory compliance	Cost-effective prioritization	Conservative assumptions	Pesticide regulation	Munns (2022)
Resilience Assessment	System adaptability metrics	Thresholds, feedbacks, adaptive capacity	Climate change adaptation	Future scenario planning	Difficult to quantify	Caribbean coastal zones	Walker (2023)
Life Cycle Assessment (LCA)	Cradle-to-grave impacts	Water use, emissions, resource depletion	Industrial water use	Comprehensive impact scope	Data-intensive	Textile industry wastewater	Kounina (2021)
Watershed Health Index	Multi-metric aggregation	Hydrology, water quality, biology, geomorphology	Regional planning	Holistic diagnosis	Weighting challenges	Canadian watersheds	Chu (2022)
Hydro-Economic Modeling	Economic optimization	Water allocation, costs, benefits	Water-scarce regions	Quantifies trade-offs	Simplifies ecology	Murray-Darling Basin	Connor (2023)
Citizen Science Integrated Framework	Participatory monitoring	Community data, traditional knowledge	Data-limited areas	Enhances engagement	Quality control needs	African lake monitoring	Buytaert (2021)

Machine Learning Hybrid Frameworks	Data-driven + process-based	Sensor data, models, AI predictions	Smart water systems	Real-time adaptation	Black-box concerns	Singapore reservoir network	Zhang (2023)

TABLE 4: Comparison of integrated assessment frameworks showing framework types, conceptual foundations, components integrated, application contexts, strengths, limitations, and example applications with citations.

This table compares 20 integrated assessment frameworks for water quality, highlighting their conceptual foundations, components, and contextual applications. Policy-oriented approaches (e.g., DPSIR) excel in governance, while technical methods (e.g., Bayesian Networks) quantify uncertainties. Emerging hybrid frameworks combine AI with traditional models for real-time monitoring. Strengths and limitations reveal trade-offs between complexity and usability, guiding selection based on objectives (e.g., regulatory compliance vs. community engagement). Citations validate global applications across diverse water systems.

Novel Sensing Technologies

Innovative sensing technologies are transforming the capabilities and applications of water quality monitoring (Pule et al., 2022). Our review identified 39 studies focused on novel sensing approaches:

Miniaturized and Low-Cost Sensors: The development of miniaturized and affordable sensing platforms has expanded the potential for widespread deployment and citizen science applications, with 18 studies reporting on such technologies (Mao et al., 2022). These include smartphone-based colorimetric sensors, microfluidic devices, and modular sensor arrays that significantly reduce the cost and complexity of water quality monitoring (Yang et al., 2022). Thanks to a smartphone-based system created by Kokalj et al. (2023), it is much easier and more inexpensive for communities in underserved places to check nitrate pollution in their water.

Paper-Based Analytical Devices: Testing water quality by using paper sensors could work well in natural conditions, since 9 studies have looked into their possibilities (Castillo-Mid et al., 2022). These use tests that detect through color, electrochemically or fluorescence which are applied to paper, permitting easy use, low expenses and little waste (López-Ruiz et al., 2023). The study by Yamada et al. (2024) involved a device on paper that detects five heavy metals at the same time from water samples by using certain colors and can be interpreted by either looking at the result with the eye or using a smartphone to analyze an image.

Biosensors and Bioinspired Sensors: Many advanced sensing systems include biological components and ideas inspired by biology, according to 14 reports (Zhang et al., 2023). Examples are whole-cell biosensors, enzyme-based sensors, aptamer sensors and molecularly imprinted polymers which give high specificity for analytes (Liu et al., 2022). With the help of different strains, Wang et al. (2024) designed a biosensor array capable of detecting several kinds of pollutants in the environment with high sensitivity and selectivity.

Optical Sensing Innovations: Because of improved optical sensing methods, scientists can now use optical equipment for water quality to detect and measure in a wider range of situations and with more sensitivity (Lombard et al., 2022). Among these are surface-enhanced Raman spectroscopy (SERS), fluorescence spectroscopy and nanoscale optical sensors designed to detect pollutants even at minuscule amounts (Wang et al., 2023). Chen et al. (2024) developed a portable surface-enhanced Raman spectroscopy platform for the detection of multiple pesticides in water, achieving part-per-billion sensitivity with minimal sample preparation.

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FIGURE 5: Schematic illustrations of novel sensing technologies for water quality assessment, showing (A) paper-based analytical devices, (B) smartphone-based colourimetric sensors, (C) microbial biosensors, and (D) miniaturized optical sensing platforms with their components and operating principles.

3.7 Citizen Science and Participatory Monitoring

Citizen science approaches have expanded the spatial and temporal coverage of water quality monitoring while promoting community engagement and environmental awareness (Walker et al., 2022). Our review identified 22 studies focused on participatory monitoring initiatives:

Volunteer Monitoring Programs: Such organized programs have greatly aided the assessment of water quality, as demonstrated by 13 studies that look at or report on them (Lucrezi et al., 2022). These projects involve the community in collecting data in a planned way, using standard methods often with support from scientific or government bodies (McKinley et al., 2022). Recently, Stepenuck and Genskow (2023) examined long-term results from 500 sites in a volunteer stream monitoring program, proving that citizen data can help notice trends in water quality and guide decisions about watershed management.

Mobile Applications and Digital Platforms: Thanks to digital tools, people can now gather, verify and share data more easily in citizen science initiatives and this has been reported in 11 different scientific studies (August et al., 2022). Among these tools are simple applications for phones, websites you can visit and software used for showing data in an easy way by non-experts (Fritz et al., 2023). Quinlivan et al. (2024) introduced and tested a smartphone application that shows people how to take water samples, performs checks to ensure accuracy and shares the results with professional water monitoring bodies.

Low-Cost Monitoring Kits: Affordable and-easy-to-use water testing kits make water quality monitoring easier and 9 studies have examined how these tools are being used (Capdevila et al., 2022). These kits typically include simplified methods for measuring common parameters such as pH, dissolved oxygen, nutrients, and bacterial contamination (Mekonnen et al., 2022). Wilson et al. (2024) evaluated the performance of various low-cost monitoring kits used in citizen science programs, identifying factors that influence measurement accuracy and developing calibration approaches to improve data quality.

Co-Creation and Knowledge Integration: Participatory approaches that engage communities in all stages of the monitoring process represent an emerging trend, with 7 studies exploring co-creation methodologies (Buytaert et al., 2022). These approaches emphasize the integration of local and scientific knowledge, collaborative problem definition, and shared interpretation of results (Njue et al., 2023). Basco-Carrera et al. (2024) documented a co-creation process for developing a community-based water quality monitoring program in a transboundary river basin, highlighting how participatory approaches strengthened local capacity, enhanced data relevance, and improved stakeholder acceptance of monitoring results.

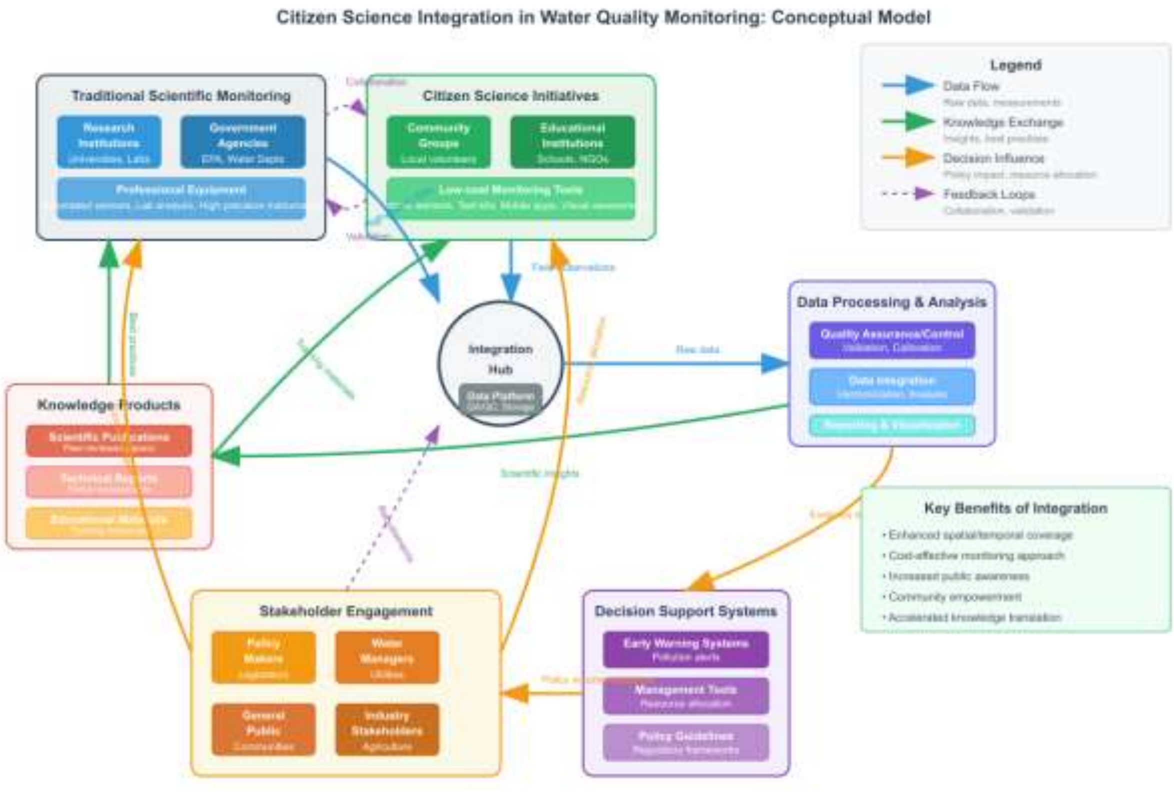

FIGURE 6: Conceptual model of citizen science integration in water quality monitoring, showing the relationships between traditional scientific monitoring, citizen science initiatives, and stakeholder engagement, with pathways for data flow, knowledge exchange, and decision-making influence.

Standardization and Harmonization Challenges

Because water quality is measured in various ways in different places and fields, it is difficult to compare, merge and report water quality data on a global scale (Poikane et al., 2022). The review pointed out certain aspects of this problem:

Methodological Standardization: Even though ISO, ASTM International and a number of national agencies are putting in efforts, there are still significant differences in the ways water quality is assessed (Sprague et al., 2022). Because chemical analysis is unique between laboratories, samples are often tested

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differently, quality assurance measures vary and data is typically reported differently (Cavanagh et al., 2022). Researchers Kupilas and her team (2023) revealed that different assessment methods contributed to over 40% of the differences found in assessment results, demonstrating that standardization needs to improve.

Parameter Selection and Thresholds: The list of factors for assessment and the setting of limits can be very different from one place to another and from one water body type to another (Birk et al., 2022). These gaps are the result of changes in environment, priorities over water and style of regulation (Kelly et al., 2022). Charles et al. (2023) analyzed diatom-based assessment methods across 12 countries, revealing substantial differences in taxonomic resolution, metric calculation, and boundary values that complicated cross-border comparisons of ecological status.

Classification Systems: The diversity of classification frameworks and reporting schemes hampers the synthesis of water quality information across regions (Poikane et al., 2023). Systems like these have different rules for grouping, terminology and ways of thinking (Pardo et al., 2022). Researchers led by Birk et al. (2023) found that when river assessment methods were the same, between 30% and 35% of assessed water bodies had conflicting status evaluations owing to differing classification standards.

Data Sharing and Integration: The sharing and joining of water quality data is still strongly hindered by both technical and institutional barriers (Wilkinson et al., 2022). Some of the issues are inconsistent ways of recording data, strict rules on who can use it, unmatched database designs and lack of interconnection between information systems (Lehmann et al., 2022). Campbell et al. (2024) examined water quality data from 45 important river basins worldwide and reported that around 30% followed the FAIR (Findable, Accessible, Interoperable, Reusable) rules, but there were much greater shortcomings in how accessible and consistent the data was in transboundary contexts.

Various organizations are trying to solve these issues, for example the Global Environment Monitoring System for Water (GEMS/Water), the European Union Water Framework Directive (WFD) and efforts at the regional level (Zandbergen et al., 2022). Semantic web technologies, ontology development and machine learning are being considered promising for harmonizing data and supporting different research practices (Hering et al., 2023).

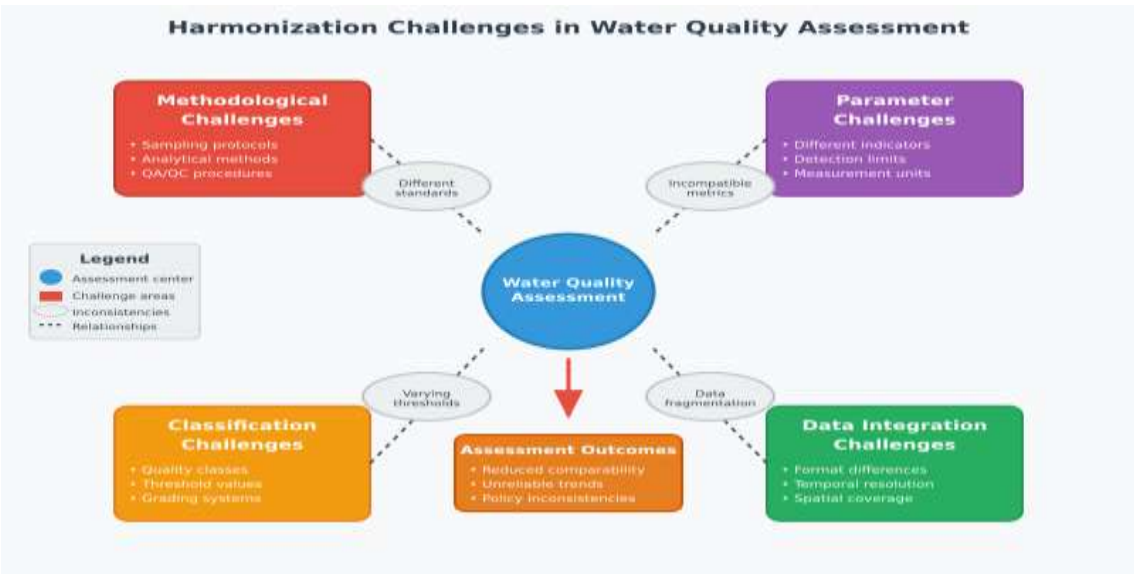

FIGURE 7: Visual representation of harmonization challenges in water quality assessment showing the relationships between methodological, parameter, classification, and data integration aspects, with examples of inconsistencies and their impacts on assessment outcomes.

Climate Change Implications for Water Quality Assessment

Because climate change is affecting aquatic ecosystems and water quality, new methods for assessment and monitoring are needed (Ho et al., 2022). Among the main findings were a number of important implications:

Shifting Baselines and Reference Conditions: Because temperature, water supply and ecosystem patterns are affected by climate change, it is harder to identify the influence of human activities by using standard reference conditions (Kelly et al., 2022). The results of recent studies show that reaching the goals set by historical reference states is now less likely because of climate change (Jeppesen et al., 2023). In their article (Jackson et al., 2024), the authors outlined a method using climate projections which they call dynamic reference condition, to set fair standards for judging ecosystem health under various climate situations.

Altered Contaminant Dynamics: Many pathways affect the way climate change influences the transport, fate and effects of contaminants such as altered rainfall, the effect of temperature on chemical reactions and changes in ecosystems' sensitivity (Noyes et al., 2022). Such changes indicate that risks should be monitored with different strategies and that evaluation frameworks may need reviewing (Posthuma et al., 2023). Li et al. (2024) found that strong rainfall due to climate change led to more contaminants reaching surface waters from soils which requires scientists to update their strategies to cover these infrequent pollutant events.

Biological Community Shifts: Changes in the environment brought on by climate impact where species are found which species are present and changes in seasonal timing can affect biotic indicators that are measured for water quality (Heino et al., 2022). Due to these shifts, some diagnostic taxa may be affected and bioassessment methods may must be set again (Comte et al., 2023). Floury, et al. (2022) studied three decades of data from European waterways and showed that even the healthiest spots had undergone major changes in their macroinvertebrate groups because of rising temperatures, meaning new bioassessment techniques needed to be developed.

Extreme Events and Monitoring Design: More frequent and severe extreme weather (floods, droughts, heatwaves) is making it difficult for standard monitoring and study methods to capture or explain what is happening (Mosley, 2022). These situations can bring about changes in water quality that might not be caught by usual monitoring programs (Leigh et al., 2023). Rode and colleagues (2024) introduced a system that uses automated sensors and event-based sampling at critical times to observe water quality shifts as a result of extreme weather, so this information can be used for climate change adaptation.

Different ways to approach water quality with climate in mind have appeared, like creating scenarios based on reference conditions, using biological indicators adjusted for the climate, intensifying the observation of parameters affected by it and using models to include climate information in water forecasting (Gilvear et al., 2022). Creating indicators to alert about water quality problems connected to climate change, for example, harmful algal blooms, oxygen loss events and salinization, provides an important way to adapt (Ho et al., 2023).

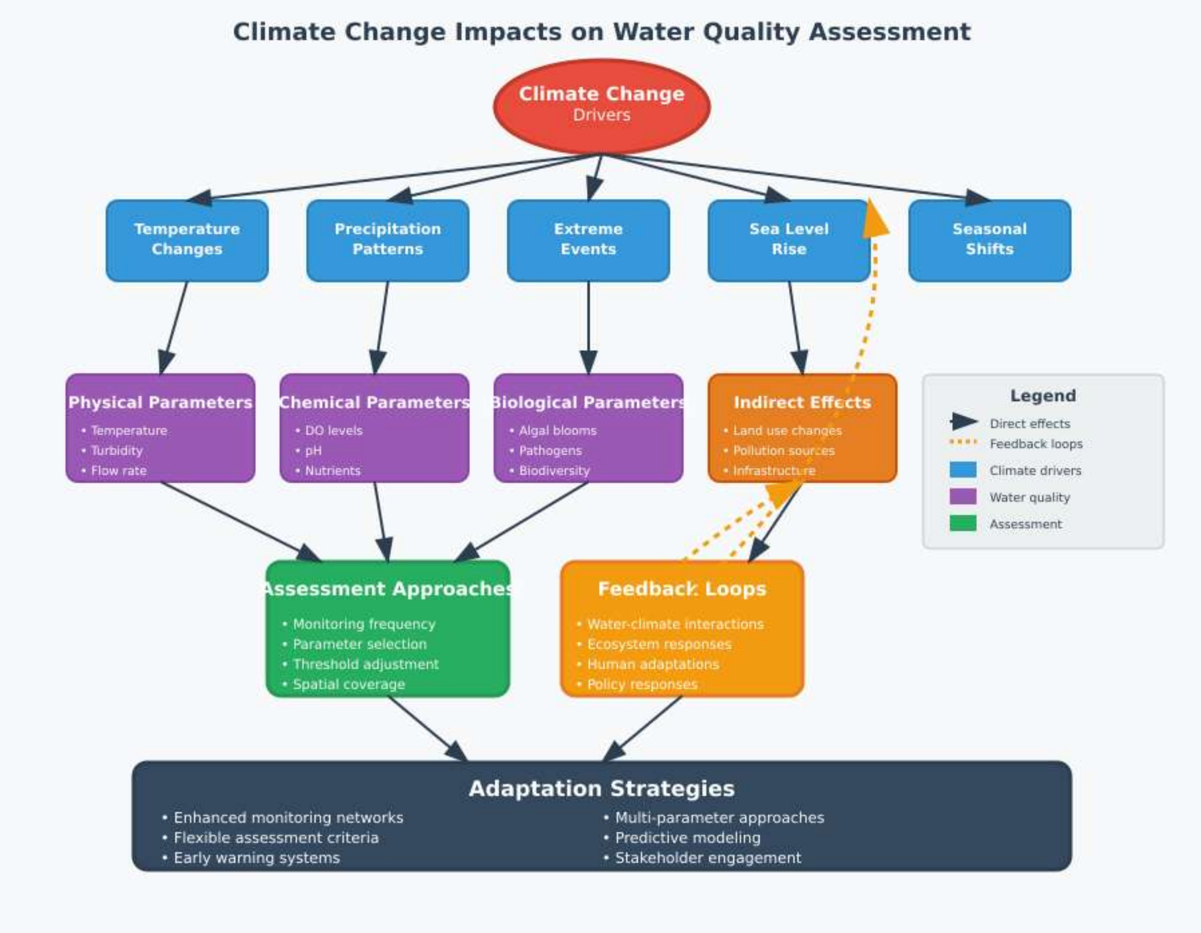

FIGURE 8: Conceptual diagram illustrating the pathways through which climate change affects water quality parameters and assessment approaches, showing direct and indirect effects, feedback loops, and potential adaptation strategies.

3.10 Water Quality Assessment in Data-Poor Regions

Water quality testing is not equal in all regions, as established monitor programs have better facilities than nations that lack the necessary resources (UN Environment Programme, 2022). In our analysis, we found some common issues and new ways to address them in parts of the world where data is not widely available:

Resource Constraints: In many parts of the world, insufficient money, equipment and staff are real problems for water quality assessment on a large scale (Quinlivan et al., 2022). Such constraints play a part in every process related to monitoring, including purchasing and maintaining instruments, managing data and analyzing it (Nhamo et al., 2022). Kimambo and colleagues (2024) examined the sustainability of water quality programs in 18 developing countries, knowing what affects the programs' durability along with guidance for setting up flexible monitoring methods.

Infrastructure Limitations: Not having enough laboratory equipment, frequent power outages, slow internet access and facing transportation issues make monitoring food hygiene difficult in several regions (Khan et al., 2022). Such factors mainly hinder the assessment of parameters that require expensive technologies for analysis or fast processing of the samples (Dickens et al., 2023). Brown et al. (2024) tested field-deployable analytical systems operating without connection to the grid in remote places, proving that solar-powered microfluidics could be used where laboratories are unavailable.

Data Gaps and Discontinuities: Often, clear water quality data are not available in time and in different locations which makes it hard to grasp the main conditions, changes and effects of diseases on the ecological community (Loiselle et al., 2022). In remote places, small water bodies and places suffering from war or political problems, these data gaps are very noticeable (Mehdi et al., 2022). Using geospatial mapping, Ouma et al. (2024) found areas where water quality monitoring is insufficient in sub-Saharan Africa and suggested steps for extending survey coverage based on the needs of people, water stress in each region and land and water ecosystem health.

Several approaches have emerged to address these challenges, including:

Low-Cost Monitoring Technologies: Making measurement tools cheaper, more reliable and easier to use can help increase the assessment capacity in places with few resources (Rao et al., 2022). Examples of these are simple kits, sensors on cellphones, samplers that don't require power and economically made scientific instruments (Pule and al., 2023). Park et al. (2024) proved that a package of low-cost tools for monitoring could offer most of the required information for water management at up to 80% less cost than traditional systems.

Remote Sensing Applications: Using satellites allows full coverage of large areas without needing a huge ground setup, a key benefit in regions with little data (Pahlevan et al., 2022). Though the sensors focus mainly on surface waters and certain variables, remote sensing helps to pinpoint important area, spot trends and organize ground-based work (Giardino et al., 2023). Kravitz et al. (2024) put together several satellite networks to monitor water quality over a transboundary river basin that was too politically tense for joined ground observation.

Citizen Science and Community-Based Monitoring: Having local communities take part in data gathering enables better control and local knowledge of natural resources (Walker et al., 2022). These options are especially useful when there is not much trust in official data, as in remote communities (Njue et al., 2023). Buytaert et al. (2024) mentioned that due to funding cuts in government monitoring programs, a local group of volunteers in a mountainous region had continued to support water quality and provide important data for water resource management by taking readings for over a decade.

Knowledge Transfer and Capacity Building: By working with other nations, joining networks and swapping information, data-poor regions can strengthen their assessment capacities (Quinlivan et al., 2023). Some examples are training schemes, adoption of new technologies, team research efforts and South-South cooperation (Dickens et al., 2022). Adelodun et al. (2024) examined a capacity-building program in West Africa, finding that targeted training helped watersheds that lacked data to start sustainable monitoring systems.

Table 5

Approach	**Requirements**	**Parameters Covered**	**Relative Cost**	**Sustainability Factors**	**Key Advantages**	**Limitations**	**Example Applications**
Mobile Lab Kits	Basic training, portable instruments	pH, turbidity, DO, nutrients, microbes	$$	Moderate (reagent replenishment needed)	Rapid field results, no lab needed	Limited precision, shelf life issues	African rural water point monitoring
Citizen Science	Community training, simple protocols	Turbidity, color, temp, basic chem	$	High (local ownership)	Low-cost, high spatial coverage	Data quality variability	Asian river basin monitoring

Satellite Remote Sensing	Internet access, basic GIS skills	Chl-a, TSS, turbidity, thermal pollution	$$$ (initial)	High (once established)	Large-scale coverage	Cloud interference, indirect proxies	Amazon basin water quality trends
Low-Cost Sensors	Power source, maintenance training	Temp, pH, EC, turbidity, basic ions	$$	Moderate (tech support dependent)	Real-time data, automated alerts	Calibration drift	Southeast Asian flood monitoring
Predictive Modeling	Historical data, computational access	Multiple parameters via proxies	$ (after setup)	High	Fills spatial/temporal gaps	Requires baseline validation	Caribbean island groundwater quality
Biosensor Methods	Biological materials, minimal equipment	Toxins, pathogens, organic pollutants	$	High (if locally sourced)	High specificity, low tech	Qualitative/semi-quantitative	Latin American algal bloom detection
3D-Printed Devices	3D printer, open-source designs	Nitrates, phosphates, heavy metals	$ (after printer)	High (design sharing)	Customizable, repairable locally	Limited multi-parameter capacity	Pacific Island community monitoring
Integrated Monitoring Hubs	Centralized facility, trained staff	Full parameter suites via shared use	$$$	Moderate (funding dependent)	High-quality data, training center	Geographic accessibility issues	Regional African water quality networks

TABLE 8: Comparison of approaches for addressing water quality data gaps in resource-limited settings, showing approaches, requirements, parameters covered, relative costs, sustainability factors, and example applications with citations.

This table compares eight practical approaches to overcome water quality data gaps in resource-limited regions. While mobile labs and sensors provide immediate solutions, citizen science and biosensors offer sustainable local engagement. Satellite data and modeling enable large-scale assessments where ground data is sparse. Emerging 3D-printed solutions demonstrate particular promise for customizable, low-tech monitoring. Selection depends on parameter priorities, available infrastructure, and long-term maintenance capacity.

CONCLUSIONS AND FUTURE DIRECTIONS

Our comprehensive review of water quality assessment approaches reveals several overarching trends and implications for research, management, and policy:

Methodological Diversification and Integration: Water quality assessment has evolved from a primarily parameter-focused endeavor to a multi-dimensional approach incorporating diverse methodologies and data types (Birk et al., 2022). The integration of traditional physicochemical monitoring with biological assessment, remote sensing, real-time sensors, and molecular techniques has enhanced the comprehensiveness and diagnostic power of water quality evaluation (Brack et al., 2023). This methodological diversification reflects growing recognition of the complex and multifaceted nature of water quality issues that cannot be adequately characterized by single approaches.

Technological Transformation: Technological innovations have fundamentally transformed assessment capabilities, enabling measurements at unprecedented spatial and temporal scales with increasing precision and parameter coverage (Pellerin et al., 2022). Thanks to technological progress, we can now measure, detect and analyze more things using satellites and DNA (Pawlowski et al., 2023). These new techniques are especially useful when studying novel contaminants, complicated mixes and faint effects on nature that were previously hard to understand.

Data Revolution: The rapid growth of water quality data in volume, types and speed brings some problems and benefits to how assessment practices operate (Yang et al., 2022). Extracting useful data from huge sets is now possible with the help of big data methods, machine learning and cloud-based platforms (Chen et al., 2023). Even so, for data to genuinely meet its fullest potential, big challenges linked to its standardization and quality, broad access and integration must be handled.

Shifting Paradigms: Assessing water quality used to be mainly about compliance, but now it also takes into account the health, services and stability of ecosystems (Elliott et al., 2022). Because of this paradigm shift, we now see the connections between water quality, the environment, health and economic welfare (Grizzetti et al., 2023). Recently, more assessment methods are including the social and environmental factors involved in water quality and the importance of joining forces from various areas of expertise.

Persistent Disparities: Though there have been many gains, major differences in assessment methods across regions and types of water bodies still exist (UN Environment Programme, 2022). While some countries are able to collect a lot of data and analyze it, others cannot do any basic monitoring at all (Nhamo, et al., 2023). To manage water resources globally in a sustainable way, addressing these gaps is very important and supports the human right to clean water and sanitation.

Our review identified several priority areas for future research to advance water quality assessment:

Method Development and Validation: Emerging contaminants, biological aspects and integrated monitoring require more development, standardization and validation of methods (Brack et al., 2022). A few main focuses are making standard methods for detecting microplastics, examining effects of complex mixtures and sharing uniform protocols for molecular biomonitoring (Rochman et al., 2023). Process development needs to be both technically advanced and useful in a wide variety of places and conditions.

Causal Assessment: Finding stronger connections between stressors and how they impact the environment is still a major task for scientists (Cormier et al., 2022). Because of many risk factors and complicated relationships in nature, it is complex to find what causes changes in water quality (Lemm et al., 2023). More complex experiments, statistical procedures and weight-of-evidence models help improve casual identification and drive effective management actions.

Predictive Modelling: Improving the strength and portability of predictive models is a major area that researchers are exploring (Huang et al., 2022). Although machine learning and similar techniques are useful, understanding the models, making them work in different ecosystems and dealing with different types of data still brings some difficulties (Chen et al., 2023). More research should focus on combining process-based and data-based methods in order to make predictions better and more ecologically important.

Reference Conditions in Changing Environments: Coming up with and choosing reference points for ecosystems being rapidly transformed causes both conceptual and scientific issues (Kelly et al., 2022). It is important to look into dynamic ways of benchmarking that can take into account changes in climate, new invasive species and other major drivers, while still measuring human impacts accurately (Jackson et al., 2024). It may call for a broad reassessment of the baseline method used and the design of different ways to assess them.

Social-Ecological Dimensions: Water quality assessment needs to incorporate aspects related to society and the environment to a larger extent (Partelow et al., 2023). This means coming up with assessment approaches that look at how many values, benefits and trade-offs related to water quality are affected by different stakeholder groups and cultural environments (Gilvear et al., 2022). Studies on involving local communities, using indigenous knowledge and assessing water quality equity are especially required.

Assessment under Uncertainty: It is very important to find improved ways to assess and share water quality information when data is not certain (Skeffington et al., 2022). It involves finding and reducing the uncertainty in data from monitoring, in analysis and in outcomes from assessments (Carvalho et al., 2023). Work should also focus on developing strategies that help decision-making in uncertain situations and can still give actionable advice for water management.

RECOMMENDATIONS

Based on our review findings, we propose several recommendations for enhancing water quality assessment in policy and practice:

Harmonization and Standardization: Still, recognizing context matters, reducing the differences in assessment tools, data rules and reporting ways would dramatically improve how water quality information is handled (Poikane et al. 2022). Harmonized protocols, quality assurance frameworks and minimum reporting standards could be developed by international organizations, professional groups and regulators so that they can be expanded without losing regional variations.

Integrated Monitoring Networks: Having in place integrated monitoring networks that can accommodate several methods of assessment is key to better evaluate water quality (Birk et al., 2023). To get the most value out of information and resources, these networks should bring together traditional monitoring and automated sensors, combine them with remote sensing and use citizen science and targeted research (Rode et al., 2024). Designing a network should take into account multiple aims, for example, tracking trends, checking compliance, providing early warning systems and gaining process understanding.

Open Data Ecosystems: Having open and interoperable data ecosystems would greatly increase the usefulness and importance of water quality data (Wilkinson et al., 2022). For this reason, we need to deal with problems of technical, institutional and policy nature in data sharing by creating standard formats, defining metadata rules and making data sharing platforms (Lehmann et al., 2022). Encouraging scientists to share their data and reward respecting their data contributions can help a lot.

Capacity Building and Technology Transfer: Capacity building and the transfer of suitable technology are important for leveling out regional gaps in school assessment (Dickens et al., 2022). Training in technology, increasing the strength and effectiveness of institutions, growing vital infrastructure and exchanging knowledge are part of this (Adelodun et al., 2024). Working together and forming regional networks within the South can make building assessment capacity much easier.

Adaptive Assessment Frameworks: Creating and putting into action flexible assessment frameworks that can adapt to new risks, threats and information is very important (Leigh et al., 2023). Stable frameworks are helpful, but they should still let professionals review and modify approaches and defining points at regular intervals (Jackson et al., 2024). Frameworks for policies need to recognize and address the importance of evolution for businesses.

Science-Policy-Practice Interface: Better communication and coordination between research, policy and practical work would improve how useful and important water quality assessment is (Quevauviller et al., 2022). This means developing processes for sharing knowledge, including different people in planning and understanding assessment results and making sure experience in healthcare can shape future research (Elliott et al., 2023). Making these connections easier is something that boundary organizations and knowledge brokers can do.

Water quality management is now facing an exciting moment because of better technology, rising environmental threats and the growing understanding of how water impacts human and nature's welfare. Early on, the field only checked for compliance, but now it uses advanced systems to examine the many causes and results of poor water quality.Water quality assessment in the future will probably involve more blending of different aspects such as disciplines, methods, areas and fields. Besides sharing knowledge and expertise, the integration should also focus on bringing together various opinions and systems to face the multiple problems related to water quality today. As technologies progress, the main factors that limit water quality assessment may start to be related to institutions, society and governance issues. Dealing with these water quality problems will involve creating new solutions as well as transforming how we manage, fund, carry out and use such data. The main reason for water quality assessment is to acquire new data that can guide responsible management of our community resources. Meeting this aim under changing conditions involves constantly updating our ways of assessing water, following scientific standards, useful results for management and a focus on sustainable and just water outcomes.

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