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Advances in Water Quality Assessment & Treatment Technologies for Safe & Sustainable Water Supply

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ABSTRACT: Global freshwater systems face compounding pressure from population growth, industrial pollution, climate variability, and emerging contaminants, driving parallel innovation across water quality assessment and water treatment technology. This paper reviews recent advances in both domains, synthesizing the machine-learning-and-Internet-of-Things (IoT) literature on real-time water quality monitoring and prediction with the materials-science literature on membrane-based desalination, multifunctional filtration, and emerging-contaminant removal. Particular attention is given to the specific technical mechanisms, IoT sensor networks, machine-learning-based parameter prediction, electrochemical heavy-metal sensing, and advanced membrane and nanomaterial treatment processes, that the reviewed studies identify as driving measurable improvements in monitoring accuracy and treatment efficiency. Comparative tables map water quality parameters to the sensing and machine-learning methods used to monitor them, cross-reference treatment technologies against the specific contaminant classes each addresses, and set reported performance metrics, detection limits, classification accuracy, and monitoring accuracy gains, against the technological approach that produced them. The review finds that IoT-integrated machine-learning monitoring systems now achieve substantially higher measurement accuracy than traditional manual methods, while membrane, nanomaterial, and hybrid treatment architectures are increasingly capable of addressing previously intractable emerging contaminants such as per- and polyfluoroalkyl substances (PFAS), but that regional infrastructure constraints, particularly in low-resource settings, and the sustainability of treatment by-products remain significant unresolved barriers to universal safe water supply.

I. INTRODUCTION

Water scarcity has emerged as a formidable global challenge, with projections indicating a worsening scenario in the future, driven by the compounding effects of population growth, industrial pollution, and climate change [1]. The scale of this scarcity is structurally severe: roughly 97% of the global water reservoirs consist of seawater, and generally less than 1% of the world's water supply is readily available as freshwater, necessitating desalination and advanced treatment technologies for most freshwater-security strategies [1]. Compounding this scarcity challenge, the World Health Organization reports a persistent rise in water pollution, identifying it as a significant contributor to widespread illnesses and fatalities worldwide, establishing water quality, not merely water quantity, as a central global public-health concern [1].

Addressing these compounding pressures has driven parallel innovation across two related but methodologically distinct domains: water quality assessment, primarily advanced through machine learning and IoT-based sensing, and water treatment, primarily advanced through membrane science, nanomaterials, and hybrid treatment architectures. On the assessment side, machine learning (ML) and Internet of Things (IoT) technologies are rapidly reshaping how water quality is monitored and managed, with sensor networks strategically deployed throughout water bodies, pipelines, treatment plants, and distribution networks measuring a broad spectrum of parameters encompassing temperature, turbidity, pH levels, and the presence of contaminants such as chemicals or heavy metals [2]. On the treatment side, the growing scarcity of freshwater resources, coupled with industrial pollution, necessitates the development of efficient and sustainable water treatment technologies, with membrane-based desalination and heavy-metal removal processes at the forefront of these technologies, providing efficient and reliable solutions to meet the growing demand for clean water [1].

The convergence of these two domains, real-time, data-driven assessment feeding directly into adaptive treatment management, is increasingly recognized as central to future water-management systems. A forward-looking treatment of future trends in water quality management identified advanced monitoring and sensing technologies, including the Internet of Things and satellite-based remote sensing, as central to this transformation, providing real-time and large-scale data for more precise water quality assessment, while the integration of big data analytics and artificial intelligence offers predictive insights and enhanced decision-making capabilities that enable proactive, rather than merely reactive, management strategies [3]. This paper reviews recent advances across both water quality assessment and water treatment technology within a single comparative framework, examining how machine-learning-driven monitoring and materials-science-driven treatment innovation are together reshaping the pursuit of safe and sustainable water supply.

Research Objectives

- To review recent advances in machine-learning and IoT-based water quality assessment, including sensor networks, predictive modeling, and heavy-metal detection.
- To synthesize the membrane-science and nanomaterial literature on advanced water treatment technologies, including desalination and emerging-contaminant removal.
- To examine region-specific and resource-constrained water treatment research, with particular attention to sub-Saharan African contexts.
- To evaluate the sustainability and circular-economy dimensions of contemporary water treatment technology, including treatment by-product management.
- To identify future research priorities for integrated, sustainable water quality assessment and treatment systems.

II. LITERATURE REVIEW

2.1 Machine Learning and IoT for Water Quality Monitoring

A substantial and rapidly growing literature has established machine learning and IoT sensor networks as the dominant paradigm for real-time water quality assessment. A comprehensive review of advances in machine learning and IoT for water quality monitoring documented the breadth of parameters now measurable through deployed sensor networks, including salinity, heavy metals, chlorine, total phosphorus, magnesium, calcium, sodium, potassium, fluoride, and nitrate, noting that these characteristics become detrimental to water and cause a host of health problems when they surpass regulatory standards [2]. The same review found that k-means clustering and related unsupervised machine-learning techniques have demonstrated usefulness across outlier detection, zoning analysis, and prediction modeling specifically, enabling researchers to uncover hidden patterns and structures in water-quality datasets that traditional statistical methods do not readily reveal [2].

Comparative evidence on measurement accuracy directly quantifies IoT-based monitoring's advantage over traditional manual methods. A critical review of water quality analysis using IoT and machine learning models found that an IoT-based monitoring system was 95% accurate in measuring pH, turbidity, total dissolved solids, and temperature, while the traditional manual method achieved only 85% accuracy on the same parameters, a ten-percentage-point accuracy gap directly attributable to continuous, automated sensing relative to periodic manual sampling [4]. A related review of machine learning and IoT applications specifically for water quality assessment found that IoT-based systems measuring temperature, pH, and conductivity, combined with forecasting models including long short-term memory (LSTM) networks and Facebook Prophet, could predict water quality trends effectively, with the Facebook Prophet model specifically demonstrating superior accuracy and resource utilization in supporting water-management decision-making for smart cities [5].

2.2 Machine Learning for Heavy Metal and Contaminant Prediction

Beyond general water quality parameter monitoring, a specific and practically important research strand has applied machine learning to predict heavy-metal contamination from more easily measurable, low-cost physicochemical parameters, addressing the constraint that direct heavy-metal measurement typically requires time-consuming laboratory analysis. A study developing an explainable machine-learning framework for predicting heavy-metal concentrations in shallow aquifer systems found that Random Forest was the most suitable model among those tested, and that quick-measure physicochemical parameters could be used as effective predictors for arsenic, iron, and manganese specifically, directly addressing the practical challenge that monitoring ex-situ water parameters such as heavy metals needs time and laboratory work, which can retard the response to ongoing pollution events [6]. The study's explicit four-step integrated assessment framework, addressing model-selection uncertainty, feature-selection uncertainty, predictive uncertainty, and model interpretability, is methodologically significant because it directly confronts a documented tension in this literature: although black-box or opaque models are often more accurate and reliable, operators and managers have found it difficult to trust and act on predictions from models whose reasoning is not interpretable [6].

Electrochemical sensing combined with deep learning has extended this predictive capability to direct, multiplexed contaminant detection at high accuracy. A study developing an IoT-integrated, deep-learning-assisted electrochemical sensor for multiplexed heavy-metal sensing in water, using gold-nanoparticle-modified carbon thread electrodes and differential pulse voltammetry, achieved detection limits of 0.99 micromolar, 0.62 micromolar, 1.38 micromolar, and 0.72 micromolar for cadmium, lead, copper, and mercury ions respectively, with the associated deep-learning models achieving near-perfect accuracy, precision, recall, and F1 scores, representing robust performance with minimal false positives and negatives [7]. Validated on real water samples from lakes in Hyderabad, India, and designed for eventual integration with a portable electrochemical measurement system, this sensor architecture illustrates the field's trajectory toward field-deployable, low-cost, high-accuracy multi-contaminant detection systems [7].

2.3 Emerging Contaminants and PFAS Assessment

A distinct and increasingly urgent research focus concerns emerging contaminants specifically, particularly per- and polyfluoroalkyl substances (PFAS), whose persistence and health effects have driven substantial recent research attention. A review of the latest frontiers in water quality assessment focused specifically on perfluoroalkyl compounds found that combining advanced machine-learning methodologies with water quality assessment holds significant potential for improving detection and monitoring of these emerging contaminants specifically [8]. The same review identified a notable gap in the current treatment literature, observing that although driven by the urgency to address water pollution, sustainability assessments of treatment processes often receive limited attention, with considerable recent focus instead placed on the regeneration, reuse, and disposal of ion exchange and granular activated carbon materials within a circular-economy framework that promotes reducing, reusing, recycling, and recovering rather than treating exhausted treatment media as waste [8].

2.4 Membrane-Based Desalination and Advanced Filtration Materials

On the treatment side, membrane-based technologies remain the dominant approach for addressing both water scarcity through desalination and contamination through advanced filtration. A comprehensive review of emerging membrane technologies for sustainable water treatment found that membrane-based desalination and heavy-metal removal processes are at the forefront of efforts to meet growing clean-water demand, providing a comprehensive review of recent advancements in desalination technologies with particular focus on emerging materials that have significantly influenced both desalination and heavy-metal removal performance [1]. The review specifically identified forward osmosis (FO) membrane technology as an area requiring further methodological development, noting the need for more comprehensive evaluations that pair innovative draw solutes with specifically designed FO membranes to fully assess their potential and optimize FO performance [1], and distinguished the field's two dominant desalination approaches, thermal and distillation methods and membrane separation technology, with membrane separation having garnered widespread adoption due to its comparatively lower energy requirements [1].

Complementary chapter-length treatments of future trends in water quality management identified nanotechnology as a further transformative force in filtration and detection specifically, noting that nanotechnology is revolutionizing filtration and detection methods, while innovative treatment technologies such as membrane bioreactors (MBRs) and electrochemical processes promise higher efficiency and sustainability relative to conventional treatment architectures [3]. The same source introduced the emerging concept of self-healing water systems, an uncharted frontier in sustainable water management integrating biomimetic materials, artificial intelligence, nanotechnology, and microbial-assisted remediation to create autonomous, adaptive, and regenerative water networks capable of responding to infrastructure degradation without the resource-intensive manual interventions traditional reactive water systems require [3].

2.5 Resource-Constrained and Regional Water Treatment: Sub-Saharan Africa

A significant strand of recent research has specifically addressed water treatment technology development within resource-constrained regional contexts, recognizing that global, infrastructure-intensive solutions frequently do not transfer effectively to lower-resource settings. A review of sustainable water treatment in sub-Saharan Africa, synthesizing findings from multi-country datasets, cross-regional assessments, and peer-reviewed studies spanning West, East, Southern, and Central Africa, identified recurring structural constraints including energy instability, infrastructure deficits, and high-turbidity raw waters as central design considerations that global treatment-technology reviews frequently overlook [9]. The review explicitly distinguished its approach from many global reviews that prioritize high-performance but infrastructure-intensive solutions, instead foregrounding region-specific constraints including variable raw-water quality, high turbidity, natural organic matter (NOM), unreliable energy supply, limited operational capacity, and weak operations-and-maintenance frameworks [9].

This region-specific framework's practical contribution lies in its integration of materials science, membrane engineering, and digital technologies within a sustainability framework specifically tailored to these constraints, synthesizing recent advances in multifunctional filter materials, hybrid treatment architectures, and AI-assisted technologies for complex, multi-contaminant removal under the energy and infrastructure limitations sub-Saharan African water systems characteristically face [9]. This regionally grounded approach is methodologically significant for the broader water-treatment literature because it demonstrates that treatment-technology effectiveness cannot be evaluated independent of the specific infrastructure and resource context in which deployment occurs.

2.6 Wastewater Treatment Innovation and Circular-Economy Resource Recovery

Parallel to drinking-water treatment innovation, substantial recent research has addressed wastewater treatment technologies specifically, increasingly framed within circular-economy and resource-recovery objectives rather than pollutant removal alone. A comprehensive review of recent advances in wastewater treatment technologies, addressing innovations and new insights, found that water pollution has been made worse by growing world population, industrialization, rapid urbanization, and the far-reaching effects of climate change, causing ecological harm particularly from fertilizer runoff into water bodies, and aimed to provide a comprehensive overview of current wastewater treatment technologies and their potential contribution to a more sustainable future [10]. A related review of green technologies for sustainable resource recovery in wastewater treatment emphasized omics-based approaches specifically, finding that omics techniques, examining DNA, RNA, proteins, and compounds on a global scale, offer mechanistic understanding of how microbes degrade contaminants and how to design treatment systems for more efficient and sustainable outcomes, including recovering resources such as biofuels and bioenergy directly from the treatment process [11].

The same green-technologies review proposed new comparative performance measurement approaches for green wastewater treatment facilities, moving away from conventional pollutant-removal indicators toward metrics incorporating Life Cycle Assessment (LCA) for resource loss and global warming impact, environmental measures for a holistic ecological score, and real-time ecological monitoring, reflecting the broader field's shift toward evaluating treatment technologies on multidimensional sustainability criteria rather than treatment efficiency alone [11]. This LCA-based evaluation approach directly parallels the circular-economy framing identified in the PFAS-focused review (Section 2.3), reinforcing that sustainability assessment, rather than contaminant-removal performance in isolation, is an increasingly central evaluative criterion across the water-treatment literature broadly.

2.7 Integrated Machine Learning and IoT Systems: Methods and Future Directions

A recent synthesis specifically addressing the integration of machine learning and IoT technologies for smart water quality monitoring consolidated the field's current parameter-specific detection capabilities and limitations. The review found that heavy metals such as arsenic, lead, and mercury, along with other trace elements, represent toxic contaminants of regulatory concern, although their continuous monitoring remains limited by the sensitivity of current field-deployable sensors, while microbial indicators including Escherichia coli and Enterococci are widely applied to assess drinking-water safety and recreational-water risks, yet direct real-time monitoring of these microbial indicators is challenging, with IoT deployments often relying on proxies such as turbidity or fluorescence rather than direct microbial detection [12]. The same review identified algal pigments, most notably chlorophyll-a and phycocyanin, as effective proxies for harmful algal blooms, increasingly monitored through optical sensors and remote platforms specifically designed for this application [12]. This parameter-by-parameter accounting of current sensing capability and limitation is valuable because it clarifies that the field's substantial documented progress (Sections 2.1 through 2.3) is unevenly distributed across contaminant classes, with heavy metals and standard physicochemical parameters comparatively well served by current sensor technology, while microbial and algal-bloom indicators remain more dependent on indirect proxy measurement.

2.8 Sensor Deployment Architecture and Network Design Considerations

Beyond the parameter-specific detection capabilities reviewed above, a distinct body of research addresses the network-level architectural decisions governing how IoT sensor deployments are physically organized across a water system. A related review documented that water quality monitoring using machine learning and IoT increasingly relies on layered network architectures, distinguishing sensing layers responsible for raw parameter capture from transmission layers handling data communication and application layers performing prediction and alerting, a three-layer architectural distinction that recurs across multiple deployment case studies in the reviewed literature [13]. This layered-architecture framing is directly relevant to the protocol-level findings, MQTT-SN, CoAP, and 5G-enabled solutions, documented in parallel predictive-maintenance research for other engineering domains, suggesting that IoT architectural patterns are converging across water-quality monitoring and other real-time environmental sensing applications.

A separate applied study of IoT-based data-driven real-time monitoring for heavy-metal control in hydroponic agricultural systems documented a specific, non-drinking-water application of the same underlying sensing and control architecture, finding that real-time heavy-metal monitoring could be integrated directly into agricultural control loops to maintain optimal growing conditions, extending the water-quality monitoring literature's relevance beyond municipal drinking-water and wastewater contexts into agricultural and food-production applications specifically [14].

2.9 Research Gap

While the machine-learning-and-IoT assessment literature reviewed in Sections 2.1 through 2.3 has established robust evidence for substantial accuracy gains in real-time water quality monitoring, and the membrane-and-materials treatment literature reviewed in Sections 2.4 and 2.6 has established comparably robust evidence for advanced contaminant-removal and desalination performance, comparatively few studies directly integrate the region-specific infrastructure constraints documented for sub-Saharan Africa (Section 2.5) with the sustainability and circular-economy evaluation frameworks developed primarily in well-resourced research contexts (Sections 2.3 and 2.6), despite the sub-Saharan African review's explicit finding that global, infrastructure-intensive solutions frequently do not transfer effectively to energy-constrained, lower-capacity settings. This review addresses that gap by organizing the reviewed evidence within a comparative framework spanning water quality parameter, assessment/treatment technology, and reported performance or constraint.

III. METHODOLOGY

This study adopts a qualitative, descriptive, and comparative research design synthesizing peer-reviewed and recent review literature on water quality assessment and treatment technology. Reviewed works were compared along four axes: domain focus (assessment/monitoring or treatment technology); technological approach (IoT sensor networks, machine-learning prediction, membrane/nanomaterial treatment, or hybrid systems); contaminant or parameter class addressed (physicochemical parameters, heavy metals, emerging contaminants/PFAS, or microbial indicators); and deployment context (global/well-resourced settings or resource-constrained regional settings such as sub-Saharan Africa).

IV. RESULTS AND DISCUSSION

4.1 Water Quality Parameters Mapped to Assessment Method and Reported Performance

Table 1 maps the principal water quality parameters reviewed onto the assessment methods used to monitor them and the performance each method reports.

Table 1. Water Quality Parameters Mapped to Assessment Method and Reported Performance

Parameter/Contaminant	Assessment Method	Reported Performance	Key Reference
pH, turbidity, TDS, temperature	IoT sensor network	95% accuracy vs. 85% for traditional manual methods	IoT/ML critical review [4]
pH, temperature, conductivity	IoT + LSTM / Facebook Prophet forecasting	Prophet model superior in accuracy and resource use	ML/IoT assessment review [5]
Arsenic, iron, manganese (groundwater)	Random Forest ML on low-cost physiochemical proxies	Effective, explainable prediction from quick-measure parameters	Heavy metal prediction study [6]
Cd2+, Pb2+, Cu2+, Hg2+ (multiplexed)	Electrochemical (DPV) + deep learning, IoT-integrated	Detection limits 0.62-1.38 micromolar; near-perfect classification metrics	IoT/DL electrochemical sensor [7]
PFAS / perfluoroalkyl compounds	ML-enhanced water quality assessment	Significant potential for improved detection (qualitative)	PFAS frontiers review [8]
Microbial indicators (E. coli, Enterococci)	Proxy-based (turbidity, fluorescence) IoT monitoring	Limited direct real-time detection; proxy-dependent	ML/IoT integration review [12]
Harmful algal blooms (chlorophyll-a, phycocyanin)	Optical sensors, remote platforms	Effective pigment-based proxy monitoring	ML/IoT integration review [12]

4.2 Treatment Technologies Mapped to Contaminant Class and Application Context

Table 2 consolidates the treatment technologies reviewed against the specific contaminant class or application each addresses and the deployment context each was developed for.

Table 2. Treatment Technologies Mapped to Contaminant Class and Deployment Context

Technology	Contaminant/Application	Deployment Context	Key Reference
Membrane-based desalination (FO, RO)	Salinity / freshwater scarcity	Global, infrastructure-available settings	Membrane technologies review [1]
Membrane bioreactors, electrochemical processes	General efficiency/sustainability improvement	Global	Future trends chapter [3]

Nanotechnology-based filtration	Filtration and detection enhancement	Global	Future trends chapter [3]
Ion exchange / granular activated carbon (regenerated)	Circular-economy contaminant removal & reuse	Global, sustainability-focused	PFAS frontiers review [8]
Multifunctional filter materials, hybrid architectures, AI-assisted tech	Multi-contaminant removal (turbidity, NOM)	Sub-Saharan Africa (energy/infrastructure-constrained)	SSA sustainable treatment review [9]
Omics-informed biological treatment	Wastewater contaminant degradation, resource recovery	Global, circular-economy focused	Green wastewater technologies review [11]
Self-healing, biomimetic/AI-integrated systems	Autonomous, adaptive infrastructure management	Emerging/uncharted (conceptual)	Future trends chapter [3]

4.3 Sustainability and Infrastructure Constraints Cross-Referenced Against Proposed Approaches

Table 3 shifts from technology to constraint, cross-referencing documented sustainability and infrastructure barriers against the approaches the literature proposes.

Table 3. Sustainability and Infrastructure Constraints and Proposed Approaches

Constraint	Documented In	Proposed Approach	Key Reference
Limited sustainability assessment of treatment processes	PFAS/emerging contaminant research	Circular-economy reuse/regeneration (IX, GAC)	PFAS frontiers review [8]
Energy instability, infrastructure deficits	Sub-Saharan Africa water treatment	Multifunctional, low-energy hybrid materials	SSA sustainable treatment review [9]
High-turbidity, variable raw-water quality	Sub-Saharan Africa water treatment	Region-specific multifunctional filter design	SSA sustainable treatment review [9]
Model interpretability vs. accuracy trade-off	Heavy metal ML prediction studies	Explainable AI frameworks (4-step uncertainty assessment)	Heavy metal prediction study [6]
Limited sensitivity of field-deployable sensors for trace toxins	ML/IoT integration review	Continued sensor R&D; proxy-based interim monitoring	ML/IoT integration review [12]
Treatment by-product/resource loss (LCA-relevant)	Green wastewater technology research	LCA-based holistic performance metrics; resource recovery	Green wastewater technologies review [11]

The consolidated evidence across Tables 1 through 3 indicates that water quality assessment technology has achieved substantial, well-quantified accuracy improvements through IoT-machine-learning integration, while water treatment technology has achieved comparably substantial advances in membrane, nanomaterial, and hybrid architecture performance, but that two cross-cutting constraints recur across both domains: sustainability evaluation remains comparatively underdeveloped relative to raw removal-performance metrics [8], [11], and technological solutions validated in well-resourced global contexts frequently do not directly transfer to energy- and infrastructure-constrained regional settings such as sub-Saharan Africa [9]. The model-interpretability tension documented in heavy-metal prediction research [6] further suggests that even where assessment technology achieves high raw accuracy, operational adoption depends on additional factors, explainability and operator trust, that accuracy metrics alone do not capture.

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V. FUTURE RESEARCH DIRECTIONS

Three priorities emerge from the reviewed literature. First, the region-specific, infrastructure-constrained treatment framework developed for sub-Saharan Africa [9] should be extended and directly compared against the circular-economy and LCA-based sustainability frameworks developed primarily for well-resourced contexts [8], [11], to establish which sustainability metrics and treatment architectures transfer effectively across infrastructure contexts and which require fundamentally different design approaches. Second, given the documented gap between well-monitored parameters (heavy metals, standard physicochemical indicators) and poorly monitored ones (microbial indicators, harmful algal blooms, dependent on indirect proxies) [12], further sensor-development research should prioritize direct, field-deployable detection methods for microbial and algal-bloom indicators specifically, rather than continuing to rely on proxy-based inference. Third, the explainability-accuracy trade-off identified in heavy-metal prediction modeling [6] should be systematically extended across the broader water-quality machine-learning literature, developing standardized interpretability benchmarks that allow operators and regulators to evaluate not only a model's raw predictive accuracy but its suitability for operational deployment and regulatory decision-making. Fourth, the layered sensing-transmission-application network architecture documented across multiple IoT deployment studies [13] should be formally standardized, allowing cross-study comparison of sensor-network reliability independent of the specific machine-learning model layered atop that network.

VI. CONCLUSION

This review has examined recent advances in water quality assessment and treatment technologies for safe and sustainable water supply, synthesizing machine-learning-and-IoT-based monitoring research with membrane-science and materials-based treatment innovation. Across the reviewed literature, IoT-integrated machine-learning monitoring systems have demonstrated substantial and well-quantified accuracy improvements, including a documented ten-percentage-point accuracy gain over traditional manual monitoring methods and near-perfect classification performance for electrochemical heavy-metal detection, while membrane, nanomaterial, and hybrid treatment architectures have extended effective contaminant removal to increasingly challenging targets, including per- and polyfluoroalkyl substances and other emerging contaminants. Two structural challenges nonetheless persist across the field: sustainability evaluation of treatment processes remains comparatively underdeveloped relative to contaminant-removal performance metrics, and technological solutions validated in well-resourced contexts frequently require substantial redesign before they can be deployed effectively in energy- and infrastructure-constrained regional settings. Achieving genuinely safe and sustainable water supply globally will require continued integration of accurate, interpretable assessment technology with treatment architectures explicitly designed around regional infrastructure realities and full-lifecycle sustainability criteria, rather than contaminant-removal efficiency evaluated in isolation.

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