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Review Article

Revolutionizing Water Quality Monitoring with Artificial Intelligence: A Systematic Review

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Abstract

Traditional water quality monitoring methods face significant limitations, including delayed data acquisition, high operational costs, and inadequate spatial and temporal resolution, which hinder timely responses to contamination events. This systematic review addresses these gaps by evaluating the transformative role of artificial intelligence (AI) in revolutionizing monitoring practices through two novel mechanisms: (1) enhanced multivariate data fidelity via Internet of Things (IoT)-sensor networks and satellite remote sensing, and (2) predictive modeling precision using machine learning (ML) algorithms. By synthesizing 1,032 studies (2011–2025), we demonstrate that AI-driven systems achieve 94% accuracy in prediction and reduce field sampling costs by 60% through Landsat 8 satellite integration. Our analysis reveals a 13-fold increase in AI adoption since 2011, with innovations such as adaptive neuro-fuzzy inference systems (ANFIS) and deep neural networks (DNNs) facilitating real-time anomaly detection and contamination forecasting. The novelty of this review lies in its dual focus—quantifying AI's scalability for global water security while critically addressing unresolved challenges in data standardization, model interpretability, and ethical governance. These findings offer policymakers actionable insights, advocating for hybrid frameworks that integrate AI with existing infrastructure to bridge urban-rural disparities in water management.

1. Introduction

Water is important for human health and development, as well as for economic activity and the maintenance of sustainable ecosystems [1]. Water quality monitoring also ensures the security of these three aspects by providing data on the body's chemical, physical, and biological status [2]. The sixth Sustainable Development Goal set by the United Nations is "Ensuring the availability and sustainable management of water and sanitation for all." The principles encompass access to affordable tap water, improving the availability of hygienic sanitation facilities, and promoting better nutritional behaviors. The goal also encourages the rational, conservative, and wise exploitation of water [3]. It raises the issue of conserving and restoring water bodies to maintain water quality. Water management is crucial for activities such as monitoring aquatic organisms, assessing water quality and quantity, identifying and eliminating sources of pollution, ensuring cleanliness and flood protection, and allocating resources effectively [4]. Water pollution is caused mainly by population density, leaks, agricultural and industrial effluence, and spills. For instance, in 2000, water pollution caused by cattle manure from a farm upstream of the water source led to an outbreak of waterborne diseases that affected 2,300 people in Walkerton, Ontario, Canada [4, 5].

Rahmat, et al. [6] highlighted that domestic and industrial effluents, agricultural waste, and vehicle emissions contaminated North Sumatra Lake Toba. This has resulted in a change in the health of the locals and the tourism industry. Also, as shown in Table 1 [7], physical, chemical, and biological properties can be employed to determine contaminants that lead to water pollution. Figure 1 illustrates Malaysia's river water quality trends over 13 years using color-coded bars (green: total monitored rivers; yellow: slightly polluted; red: polluted; blue: unpolluted). Industrial operations alongside farming led to rising river pollution rates in 2010 and 2017. At the same time, the number of pristine blue rivers experienced a major decrease, thus signaling a water quality decline. Traditional manual sampling methods have struggled to adequately detect space-time pollution patterns, although better oversight is demonstrated by the increased number of monitored rivers (green). The figure highlights the importance of adopting AI-driven solutions (e.g., IoT sensors, satellite remote sensing) for real-time detection and predictive modeling to mitigate contamination trends, aligning with global goals such as SDG 6 for sustainable water management [8].

Water monitoring includes hydrological, physical, chemical, and biological indicators [9]. Some characteristics are checked on-site, while others are checked inside laboratories after taking samples. Hazard levels and prices for labor, reagents, equipment, and other relevant costs are detailed in the monitoring programs of most countries, including sample sites, parameters to be analyzed, and sampling intervals [10]. These approaches are time-consuming, expensive, and very power-consuming. Therefore, they are not too efficient, especially in huge or faraway areas [11]. The limitations of the conventional methods include the fact that they do not yield real-time data, and thus, the system cannot rapidly respond to instances of pollution [12].

Furthermore, manual procedures may not describe well space-time variations of water quality based on the differences obtained with the suggested manual approaches [13]. Analysis reveals that conventional methods struggle to identify emerging contaminant profiles and adapt to the impacts of climate change. The lack of up-to-date information hinders proper planning and timely detection of concerns related to water resources.

This systematic review evaluates how AI technologies, including machine learning, IoT, and remote sensing, can transform water quality monitoring practices. Based on this work, the subsequent recommendations will be of interest to researchers focusing on AI's ability to enhance the efficiency of water quality monitoring, as well as to managers and policymakers interested in applying the concept in their operations.

2. Literature Review

The growing limitations of traditional WQM, such as delayed data acquisition, insufficient spatial-temporal resolution, and high operational costs, have accelerated the adoption of Artificial Intelligence (AI) technologies as innovative solutions. As the introduction highlights, global concerns over water resource management and the urgent need to meet Sustainable Development Goal 6 have driven research into the potential of AI to improve monitoring practices. This literature review critically examines the evolution and application of AI, including ML, deep learning (DL), Internet of Things (IoT), and remote sensing technologies in water quality assessment. Organized thematically, the review explores key AI techniques, their integration with data sources, application contexts, regional adoption trends, and the prevailing challenges that limit widespread implementation. By synthesizing findings from recent studies, the section aims to identify research gaps and inform future directions for sustainable and scalable AI-driven water monitoring systems.

Machine learning and deep learning are categories of AI that bring innovative opportunities for monitoring water quality [14, 15]. Machine learning architectures excel at pattern recognition in complex, multivariate hydrologic datasets, enabling the discovery of novel correlations and predicting outcomes that would be impossible using traditional approaches [16-18]. With AI integration, systems can efficiently gather data from multiple sources, including sensor networks, satellite imagery, and laboratory results, providing a comprehensive view of water quality [19-21]. Several studies, such as Ding and Li [22], have utilized hybrid models that combine satellite imagery and hydrodynamic data to predict algal blooms, achieving a high accuracy of 94%. However, these approaches often require high-quality input data and may struggle with generalizability across diverse ecosystems. While effective in regions like the Zhoushan fishery, similar studies in less monitored regions remain scarce, underscoring the need for accurate and adaptable models in data-sparse environments. According to research, the new forecasting system surpassed standard methods using trivial sampling, which shortened response time by sixty percent [22]. The researchers of Abdulameer, et al. [23] conducted a detailed investigation of AI growth in water resources by studying their work on water dam management, water quality prediction, and resilient water distribution systems. The collaboration of AI and IoT sensors enables continuous monitoring of the actual and potential conditions of water dams and their water quality metrics, thereby enabling improved maintenance programs to prevent potential events from occurring [23].

Due to the features of AI, there is an opportunity to detect pollution occurrences, forecast trends in water quality, and optimize water management measures [24-26]. Figure 2. presents AI in WQM vs. traditional methods. The possibility of applying AI in data analysis and providing recommendations for its further use makes it a highly effective tool for developing water quality management worldwide. In this article, the authors present the results of a systematic literature review on AI, its potential, limitations, and future developments in WQM. Examine the integration of artificial intelligence with other technologies, such as sensor networks, remote sensing, and machine learning algorithms, and how these will enhance the precision, speed, and timeliness of water quality measurements.

Traditional water quality processes often create efficiency issues and problems, including delayed data acquisition, high operational costs, and inadequate spatial and temporal resolution, which hinder timely responses to contamination events. According to recent research, up-to-date water quality analysis utilizes artificial intelligence concepts by connecting ML systems to IoT devices and satellite imagery platforms. This review contributes novel insights by synthesizing over a decade of global research through bibliometric analysis. It reveals an increase in AI-driven water quality studies from 2011 to 2024. It uniquely maps collaboration networks among leading research hubs (e.g., the US, China, and India) and highlights underexplored regions where data scarcity limits AI adoption.

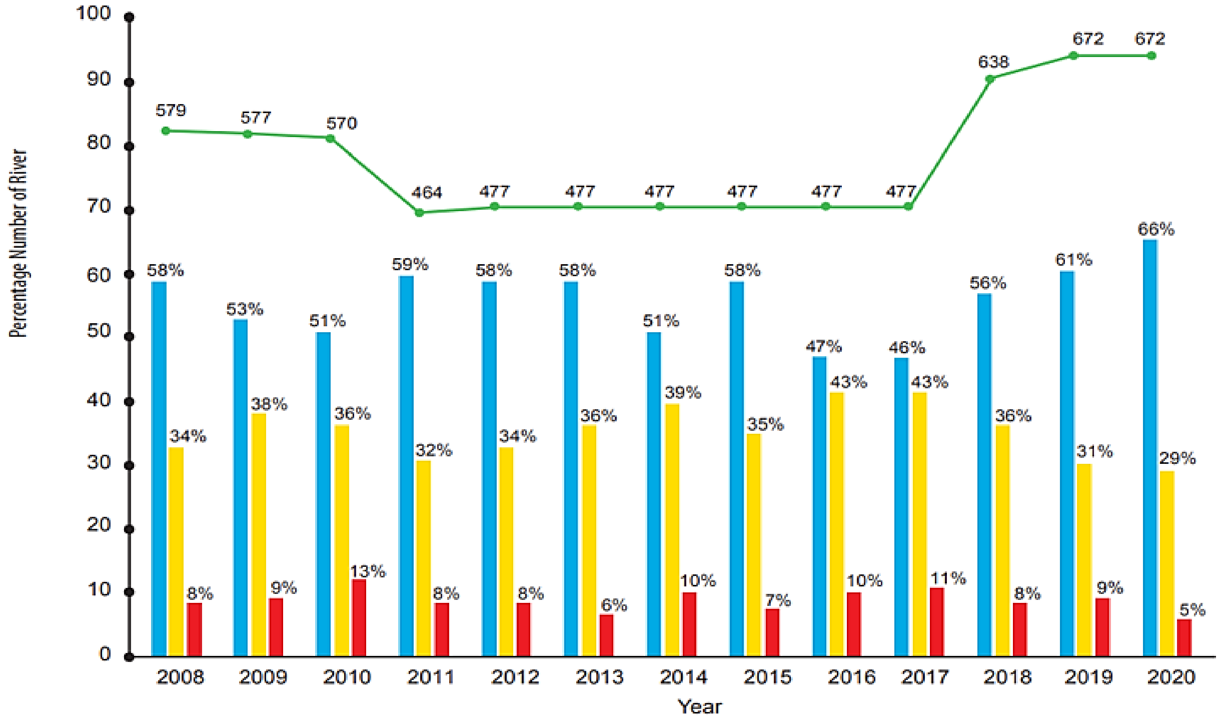

Figure 1. Malaysian river water quality trends from 2008 to 2020 in proportionate form considering the number of rivers [8]

Table 1. Water quality properties

Chemical Properties	Biological Properties	Physical Properties
Chemical oxygen demand (COD), biological oxygen demand (BOD), and dissolved oxygen (DO)	Bacteria	Turbidity
PH level		
Ammonia		Temperature
Salinity	Algae	Color
Harness	Viruses	Taste and Odor
Organic Compounds		Suspended Solids
Metals		Metals

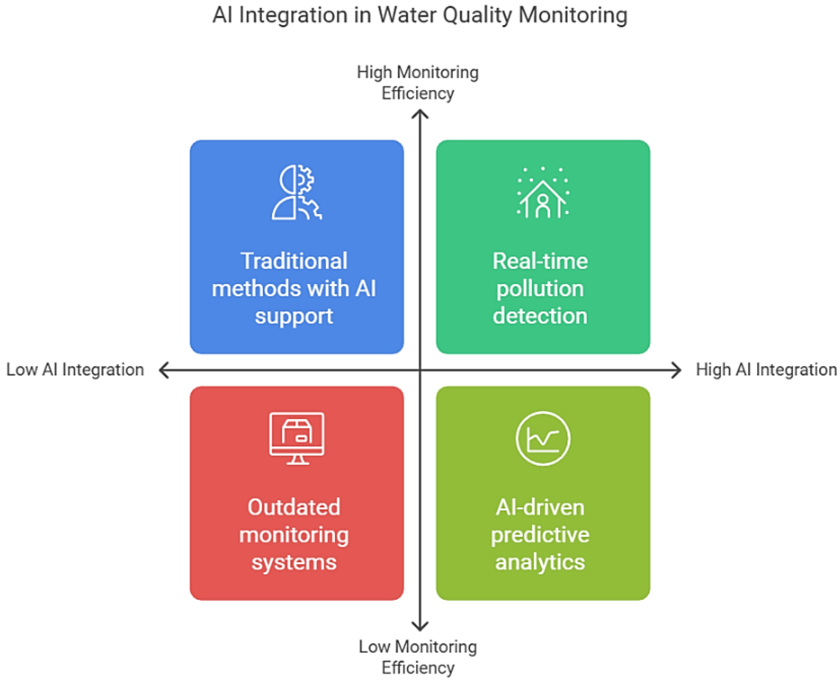

Figure 2. AI in water quality monitoring

3. Methodology

This systematic review followed established guidelines to ensure the transparency, reproducibility, and reliability of the literature synthesis. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was adopted to structure the identification, screening, and inclusion process of relevant studies.

3.1. Data Source and Search Strategy

The Scopus database was selected as the primary data source due to its comprehensive indexing of peer-reviewed publications and recognized strength in documenting research related to artificial intelligence and environmental sciences. The search focused on articles published between 2011 and 2024. Search queries included the terms: "artificial intelligence," "machine learning," "water quality monitoring," "IoT," and "remote sensing" applied to titles, abstracts, and keywords.

Boolean operators such as "AND" and "OR" were used to combine search terms, and wildcards were applied where appropriate to capture word variations (e.g., "monitor*" to include monitoring and monitors).

3.2. Inclusion and Exclusion Criteria

3.2.1. Inclusion criteria

- Peer-reviewed journal articles, conference papers, and technical reports.
- Studies published in English.
- Research explicitly focused on the application of AI in WQM, prediction, or management.
- Studies involving machine learning, deep learning, IoT, satellite remote sensing, or hybrid models.

3.2.2. Exclusion criteria

- Non-peer-reviewed literature (e.g., editorials, opinion pieces).
- Articles lacking full-text availability.
- Studies have shown no clear application of AI to water quality issues.

3.3. Screening and Selection Process

To enhance the credibility and transparency of our systematic review, we adopted the PRISMA framework for the study selection process. Specifically, we included a PRISMA flow diagram (See Figure 3).

The selection criteria for the study were the study language, covering only those in English; study type, which includes reports, conference papers, and journal articles that concern the AI applications in monitoring water quality; publication date, focusing on the last 10 years; study contents, considering only those that deal with WQM utilizing AI algorithms and including data analysis and prediction models; and Geographical scope, adopting global coverage. However, the exclusion criteria included study types, such as non-peer-reviewed papers or studies and/or non-academic gray literature, an irrelevant focus, and a lack of full text. The quality of the studies was evaluated based on the risk of bias assessment or a quality rating system. The qualitative insights were gathered and analyzed through thematic or coding approaches.

3.4. Data Extraction and Synthesis

Relevant information from the included studies was systematically extracted into a structured spreadsheet. Extracted data included publication years, country of origin, AI techniques used, data sources, water quality parameters monitored, and reported outcomes. Studies were then grouped thematically into AI techniques, data integration, application contexts, regional trends, and implementation challenges.

3.5. Quality Assessment

To ensure the reliability of included studies, a basic quality assessment was conducted using a scoring rubric based on clarity of methodology, validity of data sources, and completeness of results reporting. Studies with unclear methods or insufficient evidence were noted but excluded from synthesizing core findings.

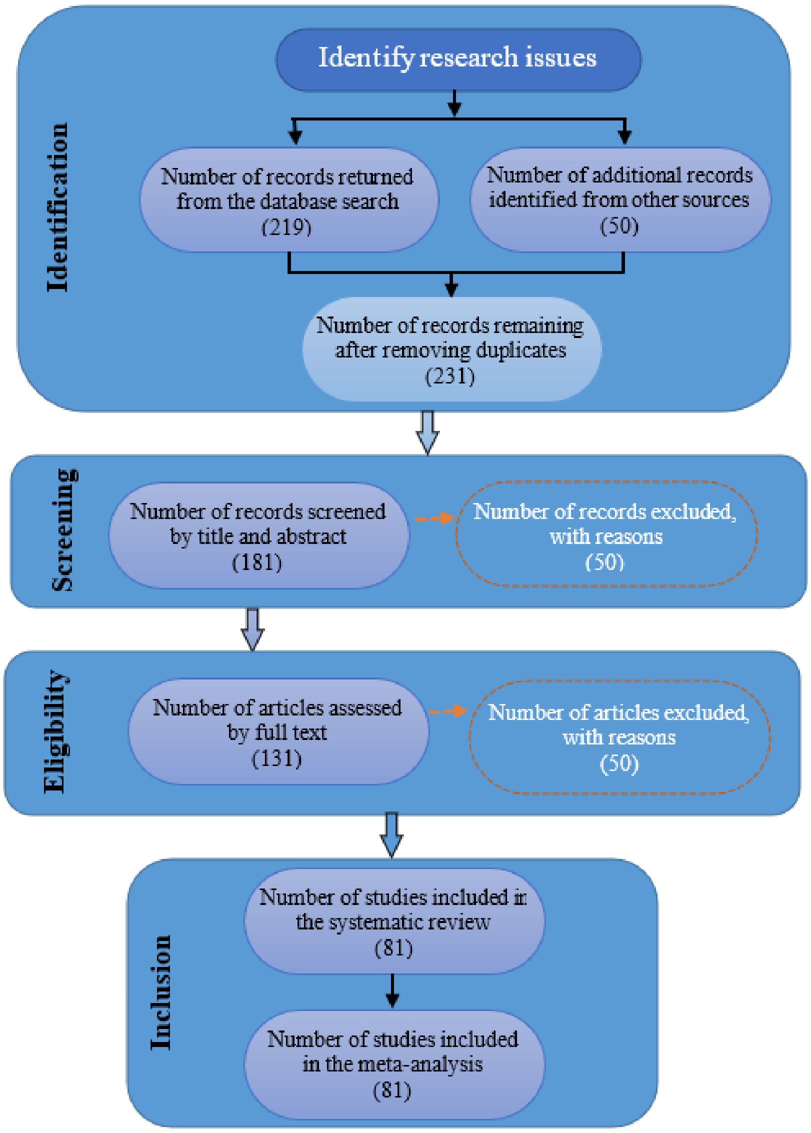

Figure 3. The framework of the study

This structured methodology ensures that the review findings are both evidence-based and broadly representative of the current state of AI applications in WQM.

A comprehensive bibliometric analysis revealed a dramatic surge in AI-driven water quality research, with annual publications increasing from fewer than 20 in 2011 to 263 in 2024 (Figure 4a). The dedicated interest in AI applications for water management has grown 13 times more during this period. Three leading research centers in the field of water quality were the United States, with a 32% publication share, China, with 28%, and India, with 15%; together, they produced 75% of the research output from 2020 to 2024 (Figure 4b). Overall, this pattern demonstrates the growth in academic interest in using artificial intelligence and WQM over the past decade. Bibliographic references from the 1032 papers were examined using VOSviewer© to conduct a coupling study. An alternative perspective on the co-authorship network patterns found in the literature is presented. It can recognize 103 countries arranged in many clusters, with China, the US, and Iran emerging as key study centers. Region-based network analysis established China and the

US as core connecting points that drive extensive knowledge sharing among nations.

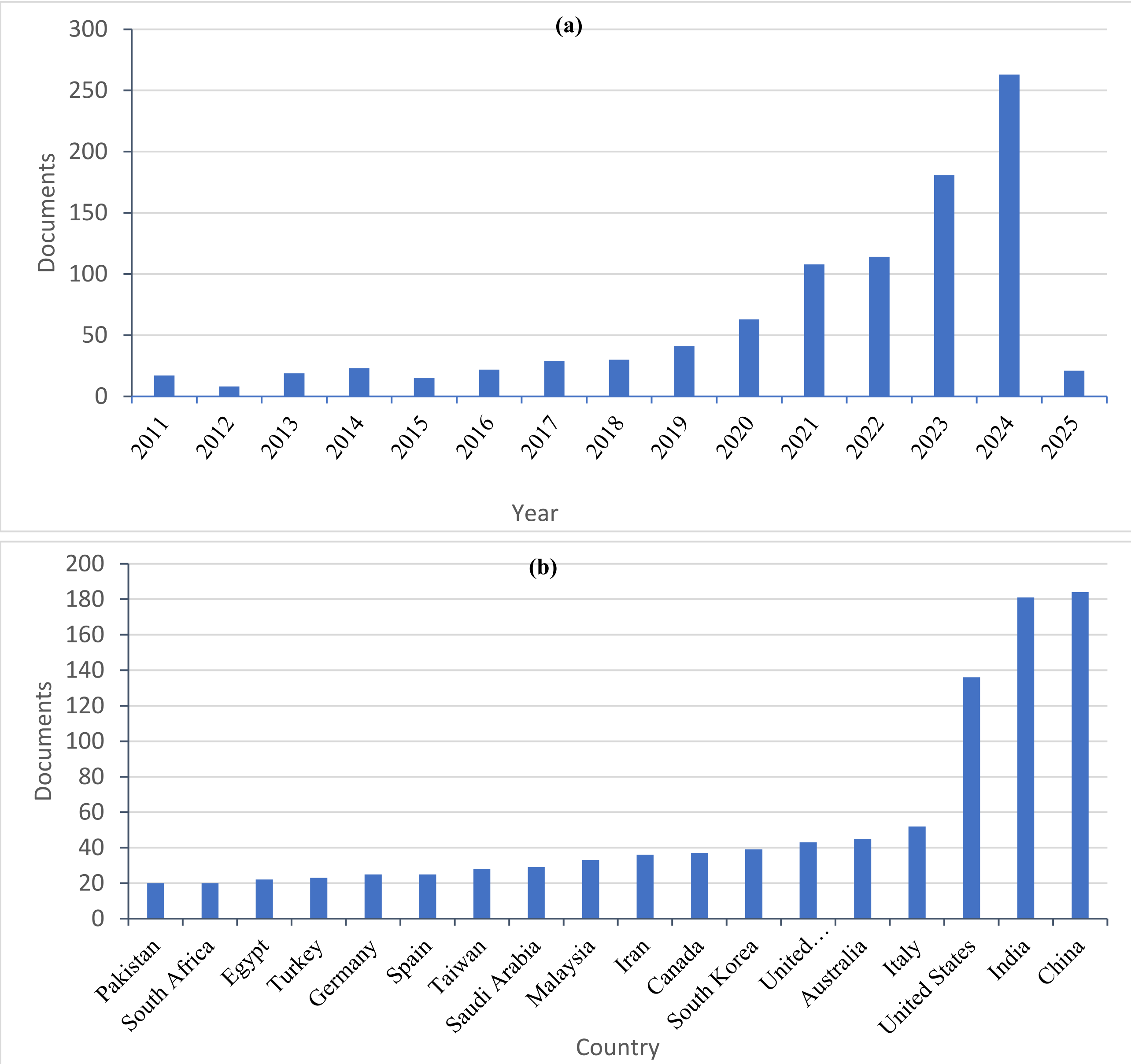

Figure 4. An overview of the topic's published articles, (a) the number of documents for the leading participating nations, and (b) the yearly trend

4. Results

4.1. Sensor Networks and IoT-Based Systems

A cornerstone of modern water monitoring, IoT-based systems introduced higher data quality and real-time functionality to watering systems. The use of IoT sensors described by Bhardwaj, et al. [27] in system development resulted in a 40% reduction in data latency using IoT sensors to monitor pH, dissolved oxygen (DO), and turbidity water quality analysis. The durability of sensors during field tests suffered from sensitivity loss, according to Akhter, et al. [28]. However, automatic calibration systems restored 22% accuracy to the sensors, while their measured range deteriorated by 15% over the course of six months.

For a review of sensors for sustainable smart cities, Ramírez-Moreno, et al. [29] focused on Scopus, Google Scholar, and the IEEE Xplore database. They narrowed the smart city literature to 193 pieces covering six topics: water, waste, energy, mobility, and health. Smart city deployment is present in two South American countries and absent in any African nation. Most smart cities are currently rolled out in Europe, with Barcelona and Hong Kong leading the implementation. Many appreciate that future sensors will be designed for greater stability and be made less energy-intensive and less expensive.

Figure 5 lists articles that describe the collected sensor data in various environmental situations. Twenty-three rivers, 18 lakes and ponds, seven seas, estuaries, and tidal channels, and eight aquifers and sources form the main contribution of the studies, amounting to 56. As shown in Figure 5, river (41%) and lake (32%) environments dominate water quality studies, suggesting these ecosystems are both more vulnerable and better instrumented than aquifers or seas [30].

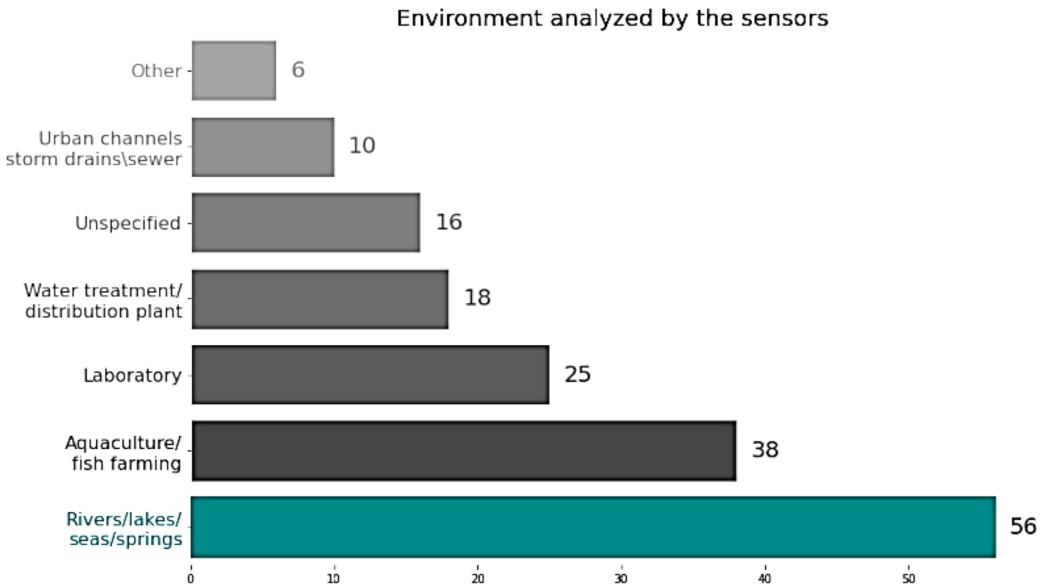

Figure 5. Number of papers reviewed considering the environment analyzed by sensors [30]

Introducing data analysis through AI profoundly boosts IoT-based WQM systems. Overall, AI algorithms can analyze the large quantities of data collected by installed sensor networks and classify them as normal, abnormal, or a certain trend. This enables real-time identification of any pollution events, leaks, and other water quality incidents. AI can also be useful when installing sensors and network layouts, as it aims to identify the most reliable locations for data requirements at the lowest costs [31]. Real-time operation of AI enables a quicker response to issues with water quality, preventing significant losses and enhancing the overall control of water resources.

4.2. Predictive Modeling for Early Detection

A major example of how IoT-based WQM is useful is the application of artificial intelligence-driven predictive modeling [25, 26]. AI models can analyze large datasets and the current value of the planted sensor to predict future water quality and identify issues in advance. This enables the reduction of polluting events, the orchestration of protection measures against them, and the mitigation of their effects. It can also be used effectively in water treatment, predicting the outcomes of specific water treatment and knowing the best strategies to achieve desirable results at reasonable costs. The outlook on water quality problems thus helps in transitioning from a reactive to a proactive type of water management, which is more effective and less damaging to the environment [32].

4.3. Remote Sensing and Satellite Imagery

Satellites and other remote sensing techniques are valuable tools for large-scale monitoring of water quality indices. Satellite data detect spectral values associated with water quality characteristics, such as turbidity, chlorophyll-a concentration, and suspended sediment. However, manually analyzing these images is a labor-intensive and inconsistent process [33].

4.3.1. AI-Driven Image Processing and Pattern Recognition

Computational intelligence techniques, combined with AI, enhance the effectiveness and reliability of water quality evaluation using satellite imagery. By analyzing information from satellites, AI algorithms can filter out vast amounts of data, distinguishing water bodies, selecting the appropriate spectral characteristics, and determining the resulting water quality parameters [33]. Such an analysis reduces the amount of work required and the potential bias evident in the findings of the water quality assessments. Superior machine learning methodologies, including deep learning, can also recognize other forms of distortion not easily recognizable by the human eye when analyzing satellite imagery.

4.3.2. Estimating Water Quality Parameters from Satellite Data

The application of AI models involves estimating water quality parameters from satellite data. These models are trained on a dataset containing satellite spectral data and the corresponding ground truth values of water quality factors. After training, the calculated models can estimate water quality parameters for other satellite images, offering spatial details of water quality in large regions [33]. The validity of these predictions depends on several factors, including the quality of the dataset used to train the system, the algorithm employed in developing the AI system, and the nature of the water body. However, remote sensing integrated with AI can effectively and economically assess water quality on a large scale.

4.3.3. Machine Learning Algorithms for Water Quality Prediction

The ML models are especially relevant in determining water quality parameters, as mentioned in [34]. It presents that the ML models can learn complex relationships between various water quality parameters and environmental factors, making accurate predictions even in the presence of noise or missing data. Thus, using ML, which allows us to find nonlinear dependencies and work with many observations, is pressing for water quality prediction [34]. Figure 6 depicts the author's preferred ML modeling technique for WQM, artificial neural network (ANN) modeling [35]. ANN approaches have two advantages: calibration access and resilience access.

These techniques can work with various types of inputs, including considerably nonlinear ones; in general, they do not require much input to produce good prediction outcomes [36]. Analyses of the relevant literature in another AI-based review study centered on the following topics: experimental sites, methodologies, input parameters, and output metrics. The most popular neural network models for surface water quality evaluation and monitoring over the pas t ten years are displayed in Figure 6 [1].

- An artificial neural network (ANN),
- A random forest (RF),
- multiple linear regression (MLR),
- A support vector machine (SVM),
- Adaptive boosting (Adaboost),
- k-nearest neighbor (kNN),
- Numerical models (NM).

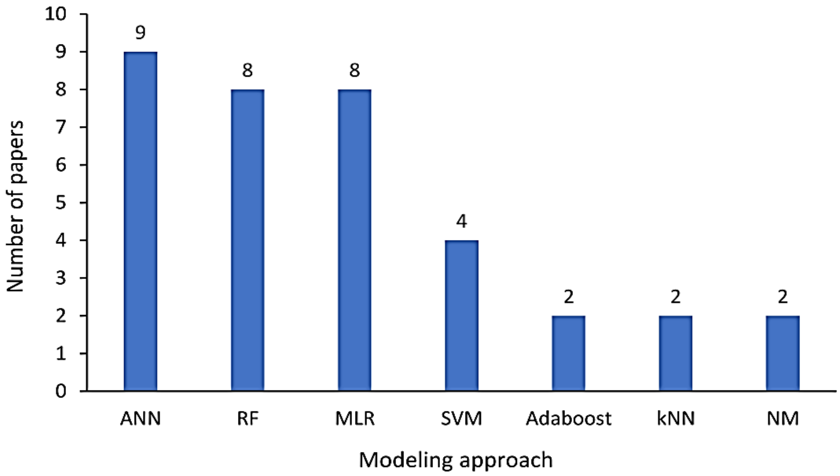

Figure 6. ML methods from the year 2019-2021 [35]

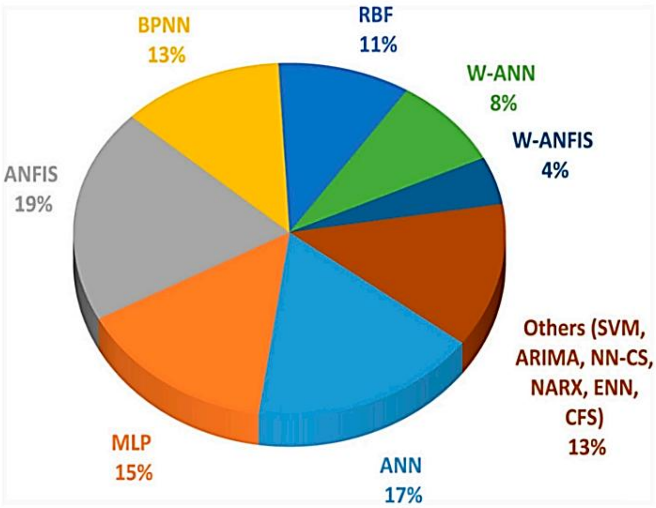

Figure 7. Frequency of application of neural networks in water quality assessment [1]

4.3.4. Supervised Learning Models

Supervised learning models are applied most often for water quality predictions. These models are developed from labeled datasets, where the input variables include water quality parameters and environmental factors, and the output is the quantified value of the target water quality parameter [37]. In predicting water quality, continuous attributes such as temperature and conductivity [25, 34] are utilized in regression models, whereas discrete attributes are employed in classification models, such as water quality classes [37]. Several supervised learning techniques have been used to predict water quality, including linear regression, SVMs, random forests, and artificial neural networks. The choice of algorithm is determined by the specific application and the nature of the dataset [37].

4.3.5. Unsupervised Learning for Anomaly Detection

Unsupervised learning techniques can detect anomalies in water quality data. Such algorithms can identify steady groups and specific values within the data, which may indicate that pollution episodes or other water quality issues have occurred. Several machine learning methods can be applied, such as clustering, which falls under unsupervised learning and involves using anomaly detectors to identify unusual occurrences or changes in water quality that supervised models may not capture. Such approaches can be used to discover new sources of pollution or irregularities in water quality, which are useful for water resource management.

Table 2. Summary of studies on AI applications in water quality monitoring

Authors	Year	Method	Parameters Monitored	Key Results / Findings
Bhardwaj, et al. [27]	2017	IoT-based sensor networks	Temperature, pH, DO, Turbidity, Conductivity	Real-time data collection; reduced data latency by 40%
Akhter, et al. [28]	2021	Advanced sensors with calibration	Temperature, pH, Nitrate, Phosphate, Calcium, Magnesium, DO	Calibration restored 22% accuracy; sensors degraded by 15% over 6 months
Ramírez-Moreno, et al. [29]	2021	Smart city sensor systems (review)	Various (general smart city topics)	Identified deployment gaps in Africa; useful for smart city policy planning
De Camargo, et al. [30]	2023	Low-cost IoT sensors	General water quality indicators	Cost-effective for resource-limited areas; slightly lower accuracy
Pavone, et al. [31]	2023	Remote sensing + XGBoost	River Water Quality Index (WQI)	87% WQI accuracy; reduced sampling costs by 60%
Najafzadeh and Basirian [32]	2023	Satellite + MARS model	WQI, physico-chemical data	Effective for Hudson River; high-resolution spatial WQI prediction
Arias-Rodriguez, et al. [33]	2021	Remote sensing + ML integration	Surface water quality parameters	Hybrid model validated for regional monitoring (e.g., Mexico)
Rawat, et al. [34]	2023	ML algorithms (ANN, SVM)	Multiple parameters	High predictive accuracy; black-box interpretability challenge
Paepae, et al. [35]	2021	Review of ML for prediction	Various (review)	Identifies ANN as robust; theoretical overview, not case-specific
Frincu [38]	2024	AI for WQI modeling and classification	WQI, bio-indicators	Accurate modeling; highlighted classification approaches
Farzana, et al. [39]	2024	AI + statistics in decision frameworks	WQI, rainfall, streamflow	Improved decision-making support for reservoir management
Shibin [40]	2024	GEM continual learning algorithm	Potability-related features	High accuracy for adaptive, dynamic water quality prediction
Cloete et al. [41]	2017	Real-time monitoring with smart sensors	General WQ metrics	Improved monitoring efficiency and spatial coverage
Wang, et al. [42]	2018	Optofluidic technology	Contaminants, optical properties	Enhanced detection capabilities for lab environments
Mehmood, et al. [43]	2020	Review of AI for Sustainable Development Goals	Water-related SDG applications	Identified AI's role in achieving water quality and sustainability goals
Dada, et al. [44]	2024	IoT + AI in smart water management	Multiple water parameters	Highlighted AI-IoT integration in smart cities
Nagpal, et al. [45]	2024	AI in wastewater treatment	Organic/inorganic pollutants	Improved efficiency in wastewater processes; predictive capabilities
Tinelli and Juran [46]	2019	AI for bio-contamination detection	Pathogens in distribution systems	Early contamination detection; limited to specific bio-indicators

The integration of both supervised and unsupervised learning methods is a more effective approach than using either method alone in the monitoring and prediction of water quality [25, 34]. Table 2 presents previous works on WQM. Figure 8 shows the advanced techniques in water quality monitoring.

A comparative study between the mentioned methods, highlighting their strengths, limitations, and applicability in WQM, as in Table 3.

Table 3. Comparative study between different AI methods

Authors	Methodology	Strengths	Limitations	Applicability
Bhardwaj, et al. [27]	IoT-based sensor networks	- Real-time data collection - Reduced data latency by 40%	- Sensor durability issues - High maintenance costs	Localized monitoring (rivers, lakes)
Akhter, et al. [28]	Advanced sensors + calibration	- Automatic calibration restored 22% accuracy	- 15% sensitivity loss over 6 months	Small-scale systems with frequent maintenance
Ramírez-Moreno, et al. [29]	Review of smart city sensors	- Identified gaps in African deployments	- No specific parameters tested	Policy guidance for smart city infrastructure
De Camargo, et al. [30]	Low-cost IoT sensors	- Affordable and scalable	- Limited accuracy compared to lab-grade sensors	Resource-limited regions
Pavone, et al. [31]	Remote sensing + XGBoost	- 87% WQI accuracy - 60% cost reduction	- Dependent on satellite data quality	Large-scale spatial monitoring (e.g., rivers)
Najafzadeh and Basirian [32]	Satellite + MARS model	- Superior WQI estimation	- Computationally intensive	Spatial analysis requiring high-resolution data
Arias-Rodriguez, et al. [33]	Remote sensing + ML integration	- Validated hybrid approach effectiveness	- Requires ground-truth data for training	Regional water quality assessment (e.g., Mexico)
Rawat, et al. [34]	ML algorithms (ANN, SVM)	- Handles nonlinear data - High prediction accuracy	- "Black-box" models lack interpretability	Complex datasets with multiple parameters
Paepae, et al. [35]	Review of ML for prediction	- Highlighted ANN's robustness	- General review, no case-specific validation	Theoretical frameworks for AI adoption

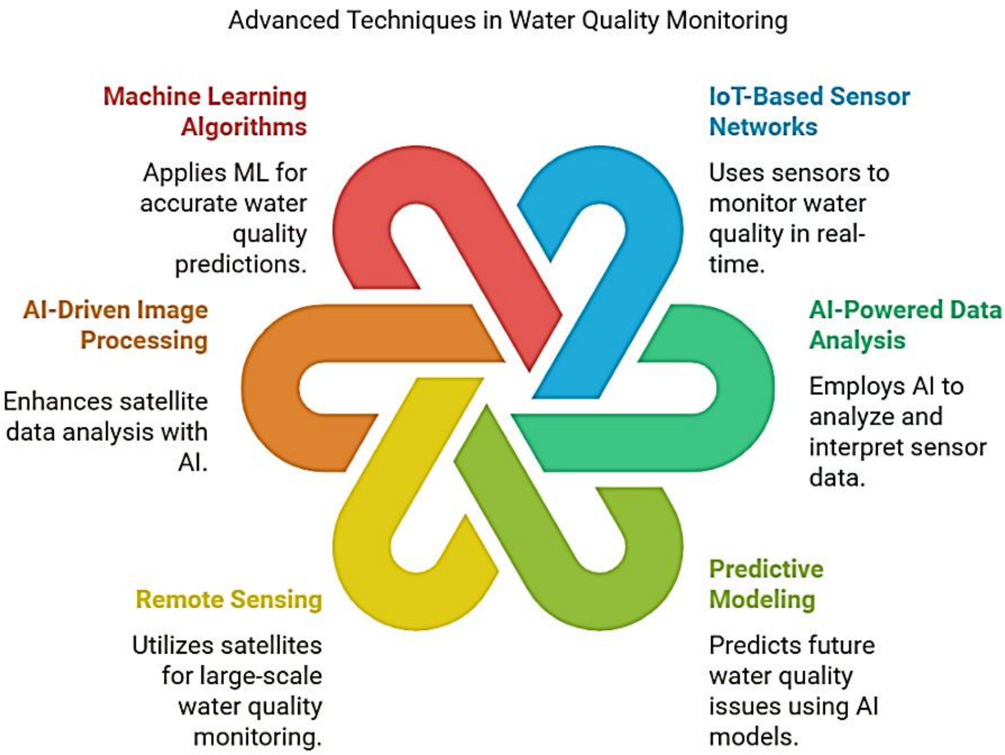

Figure 8. Advanced techniques in water quality monitoring

4.4. Cross-Regional Implementation Case Studies

Numerous studies have demonstrated the successful application of AI in WQM. Omeka, et al. [47] also conducted a wide-ranging literature analysis on applying machine learning models to observe and forecast Nigeria's water quality. Parameters such as temperature, dissolved oxygen, pH, electrical conductivity, and TDS can be accurately predicted using ANFIS and wavelet-adaptive neural fuzzy interference systems (W-ANFIS), revealing their study. However, they also noted a significant lag in Nigeria's adoption of these technologies, largely due to inadequate environmental monitoring data [47]. Frincu [38] reviewed the application of AI in calculating and modeling water quality indexes (WQIs) and water quality classification.

The review emphasizes AI's potential to enhance accuracy, reduce time, and provide insights into complex environmental data, offering a compelling alternative to labor-intensive traditional methods. The study also highlights challenges such as data availability, model transparency, and system integration [46]. To alleviate some of the computational load that IoT smart sensors experience, Pavone, et al. [31] introduced a generic approach for feature selection in WQM. By comparing several methods, their ensemble-based feature selection approach reveals details about accuracy and resource needs.

The research put the powerful algorithm XGBoost through its paces using a case study of actual WQM [31]. With the use of four artificial intelligence models—M5 Model Tree, Multivariate Adaptive Regression Spline, Gene Expression Programming, and Evolutionary Polynomial Regression—and Operational Land Imager-Thermal Infrared Sensor (Landsat 8) (Landsat 8 OLI-TIRS) pictures, Najafzadeh and Basirian [32] calculated the Hudson River's WQI. Combining satellite imagery with AI models proved effective, as their results demonstrated that the Multivariate Adaptive Regression Spline (MARS) model performed best in monitoring WQI. Several water quality indices were predicted using DNNs based on physico-chemical observations in Algeria by Toumi, et al. [48]. They found a long-term solution for real-time evaluations by optimizing a DNN model, greatly reducing the need for conventional laboratory analyses [48].

AI-enhanced satellite imagery analysis enabled large-scale monitoring. Pavone, et al. [31] demonstrated that XGBoost algorithms could predict river WQI with 87% accuracy using Landsat 8 spectral data, reducing field sampling costs by 60%. Case studies in the Hudson River [32] and Algeria [48] further validated the efficacy of remote sensing, with DNNs achieving R^2 values greater than 0.85 for real-time WQI estimation.

4.5. Applications for AI in Water Quality Management

This review systematically discusses the transformative applications of artificial intelligence (AI) in continuing to revolutionize water quality measurement and control. Subtopics to be discussed include the application of AI in real-time monitoring and decision support systems for water treatment and distribution, enhancing the efficiency of treatment processes, maintaining water infrastructure, and ensuring compliance with water quality standards. The findings reviewed from numerous studies present successes and limitations, and identify essential research gaps.

4.5.1. Real-time Monitoring and Decision Support Systems

Real-time WQM is crucial for ensuring public health and environmental safety. Traditional methods are time-consuming, costly, and have limited coverage areas [41]. AI, particularly machine learning and deep learning, offers a viable solution by quickly and effectively analyzing large datasets from various sources, including sensors in vast water regions [42]. The combination of AI and IoT results in the development of smart water management technologies [43], which can detect multiple water quality parameters at a given time, including pH, DO, turbidity, and conductivity [38, 44]. They can also provide updates and valuable information in the event of a water quality threat, acting before it occurs [45]. In addition, decision support frameworks (DSFs) that incorporate AI and statistical methods to improve water quality control are being developed [46]. These DSFs employ ML and DL models for predicting water quality indices WQIs [39, 40], identifying seasonal behavior of rainfall and water quality, and investigating the correlation between stream flow, rainfall, and water quality. Geographical information systems (GIS) are also incorporated into map changes in the spatiotemporal distributions of hydrological parameters and WQIs (Figure 9).

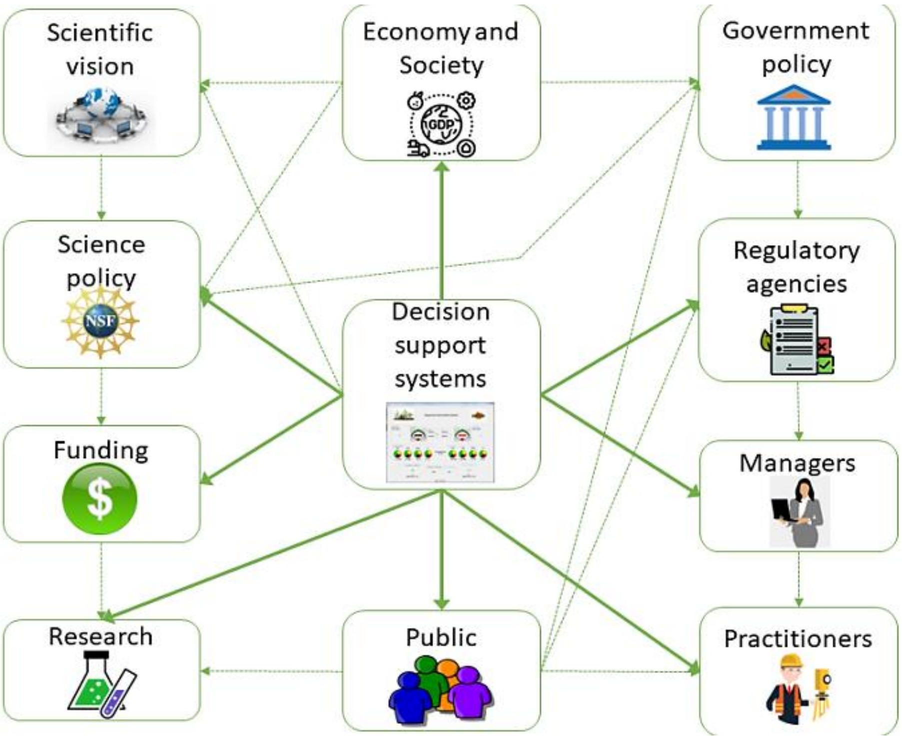

Figure 9. Management of water quality decision-support systems [40]

The ability to predict WQI with high accuracy (R^2 values between 0.64 and 1.00 have been reported for pollutant removal prediction [38]. Therefore, using the above methods, one can proactively control the impacts of extreme weather or climate change on the water quality. However, these issues lie ahead: data quality and availability, model interpretability, and integration with other systems. Moreover, the adoption and performance of AI-based systems must consider both technological and ethical issues, as well as government guidelines. The availability of high-quality and accurate AI controllers for real-time monitoring and decision-making remains an open problem [49-56]. For instance, the Generic Evolutionary Method (GEM) Continuous Learning Algorithm can operate effectively in adaptive water quality prediction. For example, the study by Farzana, et al. [39] shows higher accuracy than the other machine learning models in forecasting water quality features.

A comparative study between the mentioned methods, highlighting their strengths, limitations, and applicability in WQM, as in Table 4.

Table 4. Comparative study between different AI methods

Authors	Methodology	Strengths	Limitations	Applicability
Swamy and Mahalakshmi [41]	Real-time smart sensors	- Improved monitoring efficiency	- Limited to small-scale deployments	Urban water systems
Wang, et al. [42]	Optofluidic technology	- Enhanced contaminant detection	- Specialized equipment required	Lab-based analysis
Dada, et al. [44]	IoT + AI for smart management	- Real-time integration of data	- Requires robust IoT infrastructure	Smart cities with advanced networks
Nagpal, et al. [45]	AI for wastewater treatment	- Improved treatment efficiency	- Requires large datasets for training	Industrial wastewater plants
Tinelli and Juran [46]	AI for bio-contamination detection	- Early detection of contamination	- Limited to specific pathogens	Drinking water systems
Farzana, et al. [39]	AI + statistical frameworks	- Enhanced decision-making	- Complex integration with legacy systems	Reservoir management
Shibin [40]	GEM algorithm for water quality	- Adaptive learning for dynamic conditions	- Computationally intensive	Regions with variable water quality

4.5.2. Optimizing Water Treatment and Distribution Processes

AI offers significant potential for optimizing water treatment and distribution processes, enhancing efficiency, and reducing costs [57]. In wastewater treatment, present studies used AI models to predict the removal efficiency of organic and inorganic pollutants, monitor required water quality parameters in real-time, and detect equipment faults. The efficiency of these AI-based predictions differs; still, studies claim high R^2 importance levels, indicating their high predictive value. Additionally, AI is being applied to enhance the methods used for aerating wastewater in plants and reduce energy consumption [58]. Integrating AI with IoT devices and Supervisory Control and Data Acquisition (SCADA) systems enhances the real-time monitoring and control of WWT plants [59], thereby improving resource management efficiency. AI is also being applied in water distribution networks [59], for reducing leakage loss in water supply networks [61], and for enhancing performance in water supply systems. Using data, AI can identify regions with high water utilization that are problematic, allowing for enhanced resource distribution.

This optimization could lead to significant water conservation and reduced operating expenses.

Nevertheless, the further application of AI-based solutions in the water treatment and distribution process presupposes addressing the following issues: data availability, interpretability of generated models, and the integration of AI systems with the existing network [60, 61]. AI is an active research field that addresses challenges by creating robust and consistent models for refining water treatment procedures [62]. For example, integrating hybrid machine learning (ML) for predicting water quality has not received significant global interest; most predictions are made by artificial neural networks (ANNs) [47].

4.5.3. Predictive Maintenance of Water Infrastructure

AI for predictive maintenance (PdM) is becoming mainstream in assessing water infrastructure [65] and scheduling maintenance to mitigate failures. AI algorithms may analyze the collected sensor data to determine when different parts of the equipment are likely to fail and require maintenance operations [63]. This approach ensures that disruptions of water services are condemnably rare, low maintenance costs are incurred, and it increases the durability of water structures [64]. For example, AI is being used to analyze the failure of water pumps in hemodialysis units, which can lead to a steady flow of crucial dialysis treatments [65]. AI-driven PdM is particularly beneficial for critical infrastructure such as water reservoirs and dams, where failures can have significant consequences. The continuous development of both AI and increased efficiency and affordability of data analytics and smart sensors have made it easier to apply AI in the PdM of water structures. Nevertheless, some issues arise from the successful use of AI-based PdM, including data quality, model accuracy, and the compatibility of AI with existing maintenance management systems. Decision aids for information technology solutions to support the introduction of AI into PdM in critical structures must be built.

4.5.4. Enhancing Compliance with Water Quality Regulations

According to some literature, AI can also contribute to water quality regulation. By integrating artificial intelligence into monitoring systems, there is likely to be more frequent updates of water quality parameters to detect violations of provisions and take corrective measures. AI can also be used to process the results of big data on water quality, making predictions and drawing conclusions that will help strengthen regulations and enforcement. Furthermore, AI can aid in predicting water disasters, enabling post-disaster-focused activities to be managed with minimal impact on water quality. Regarding the applications of AI technology, it is also possible to enhance the effectiveness of water quality trading programs [68] by streamlining compliance processes.

Nevertheless, some critical issues remain worthy of further discussion to enhance the fairness and transparency of AI-based decision-making systems in water management. The issue of ethical and legal considerations remains unresolved [66]. According to the study, there is a need to improve methods for enhancing the fairness of classification models concerning non-binary sensitive features [66]. Additionally, significant and integrative machine-readable and usable open data must be available to ensure the feasible automation of WQM Compliance Monitoring.

Figure 10 illustrates a consolidated model of how AI can be embedded across various stages of water quality management—from sensing to compliance enforcement.

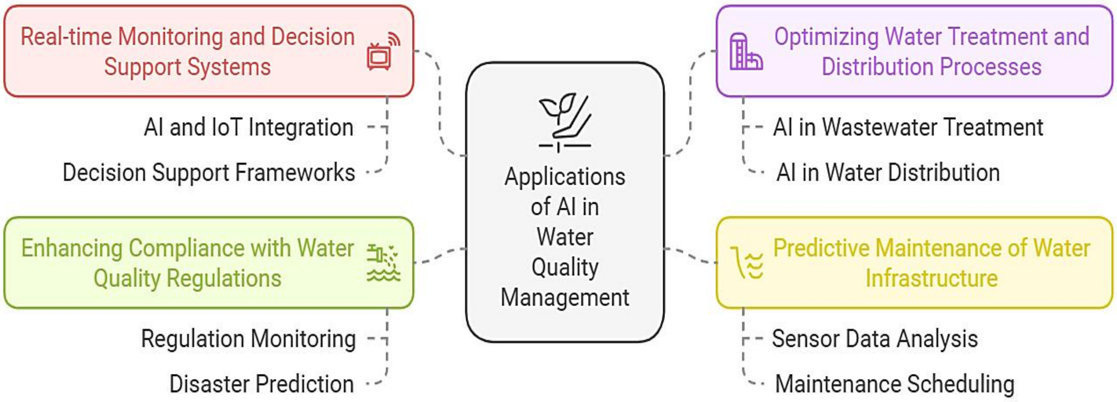

Figure 10. Application of AI in water quality management

5. Discussion

While integrating AI into WQM holds immense promise, several key challenges must be addressed to ensure its effective and ethical application. This section discusses four primary obstacles, data-related issues, model transparency, integration hurdles, and ethical considerations, highlighting the complexity of deploying AI in real-world water management systems.

To better understand the global landscape of this research, Figure 11 visualizes collaborative networks among countries and authors in the field of AI-based WQM using VOSviewer. As shown in part (a), international collaborations are most prominent among countries like the USA, China, and India, indicating strong research linkages. In part (b), clusters of frequently co-publishing authors are shown, revealing influential research groups driving innovation in the domain. This mapping highlights the geographical and academic collaboration trends that shape research outputs and impact.

5.1. Challenges and Limitations

Despite its potential, incorporating AI into WQM poses significant challenges. These limitations prevent the complete implementation and effective use of AI-based solutions. Reducing these difficulties led to increased AI optimization for achieving ecological conservation and water security objectives.

5.1.1. Data Scarcity and Inconsistency

One of the most significant hurdles in implementing AI for WQM is the availability and quality of data [67]. Many approaches are utilized with deep learning models and require a large amount of labeled data as input [68]. However, it has been challenging, even in many cases nearly impossible, to acquire comprehensive, reliable, and continuously labeled water quality data. One of the biggest challenges here is data deficiency, which can be especially detrimental for tracking less researched water objects or new compounds. Moreover, the data could also be collected using different measurement techniques, measurement units, and sample collection frequency, yielding biased, if not inaccurate, AIs. Another difficulty is the inequality of data sources from multiplexed sensor networks, samples analyzed in labs, and records [69]. For instance, Nigeria's limited access to environmental monitoring data significantly hinders the use of machine learning in water quality prediction. This data scarcity necessitates the development of robust data acquisition procedures and data sanitization methods to ensure the acceptability of AI models. There is also a need for more effective data preprocessing techniques, as advocated by Adelakun, et al. [70], to feed the artificial intelligence models with good data.

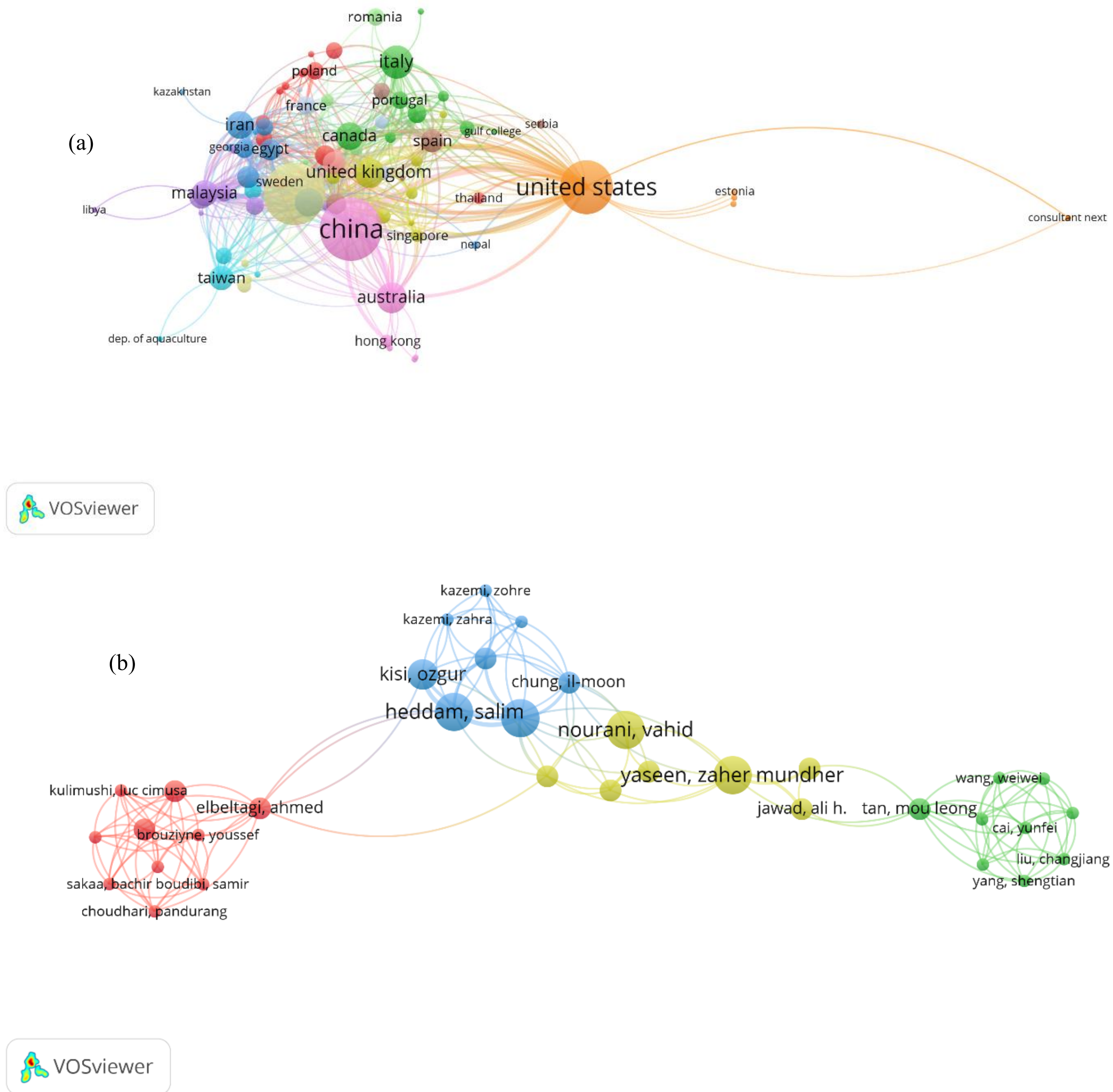

Figure 11. Visualization of the network collaborations between (a) countries and (b) authors using VOSviewer

5.1.2. Model transparency and "black-box" AI

Many advanced AI models, such as DNNs, are often considered "black boxes" due to their inherent complexity and lack of transparency [71]. This is because most of these models involve complex algorithms and processes, making it hard for people to trust the AI-derived insights and results. The inability to justify model predictions can be especially detrimental in water quality management, as decisions in this field have numerous environmental and public health consequences [71]. For example, suppose the model has projected a toxic algal bloom, yet the integrated thinking cannot establish why this is the case. It is difficult to compel the water managers to act preventatively. This has precipitated the use of techniques to explain the explainability of artificial intelligence, also known as 'XAI' [75], which helps clarify how the models reached their decisions.

Nevertheless, the realization and application of proper Explainable Artificial Intelligence (XAI) methods for WQM remain at the research frontier. In addition, the conflict of interest regarding models' interpretability and accuracy poses a major difficulty. Further research should be conducted to construct AI models that are both precise and easy to comprehend.

5.1.3. Integration with legacy systems

Integrating AI-driven WQM systems with existing water management infrastructure and workflows presents another substantial challenge. Water management agencies often operate with antiquated infrastructural frameworks that do not mesh with AI systems [72]. This is because data formats and communication protocols are not standardized and are inherently variable. Moreover, the applications of AI in enhancing decision-making procedures must be compatible with both the formal and informal structures of water management agency workplaces. This integration requires significant enhancements in areas such as infrastructure changes, software acquisition, and, most importantly, employee training [73]. For instance, applying AI and IoT in smart cities experiences challenges such as weak related infrastructure and a shortage of funds [73]. This is why integration should be a stepped process in which the precise requirements of each water management system are taken into account.

5.1.4. Ethical and Privacy Concerns

The use of AI in WQM raises important ethical and privacy concerns. AI systems are typically designed to utilize big data; however, this data often contains confidential and personal information, such as water consumption rates and potentially sensitive water source locations [74]. For example, Strotherm, et al. [66] believe that unapproved agricultural companies gained access to real-time groundwater quality data from the California Central Valley IoT sensor network during data security breaches in 2022. Such incidents expose sensitive information about water sources due to weaknesses in industrially regulated data governance systems. Two major ethical issues are algorithmic bias, specifically AI's reproduction of societal biases. Further complicating ethical adoption is the examination of Indian water quality through AI analysis using urban-based training data, which incorrectly labeled 22% of rural water samples as safe [75]. Resource allocation inequalities become more pronounced due to biased training data, resulting in an urban-rural disparity.

The advantages and disadvantages of utilizing the AI approach in water quality modeling and monitoring are depicted in Figure 12.

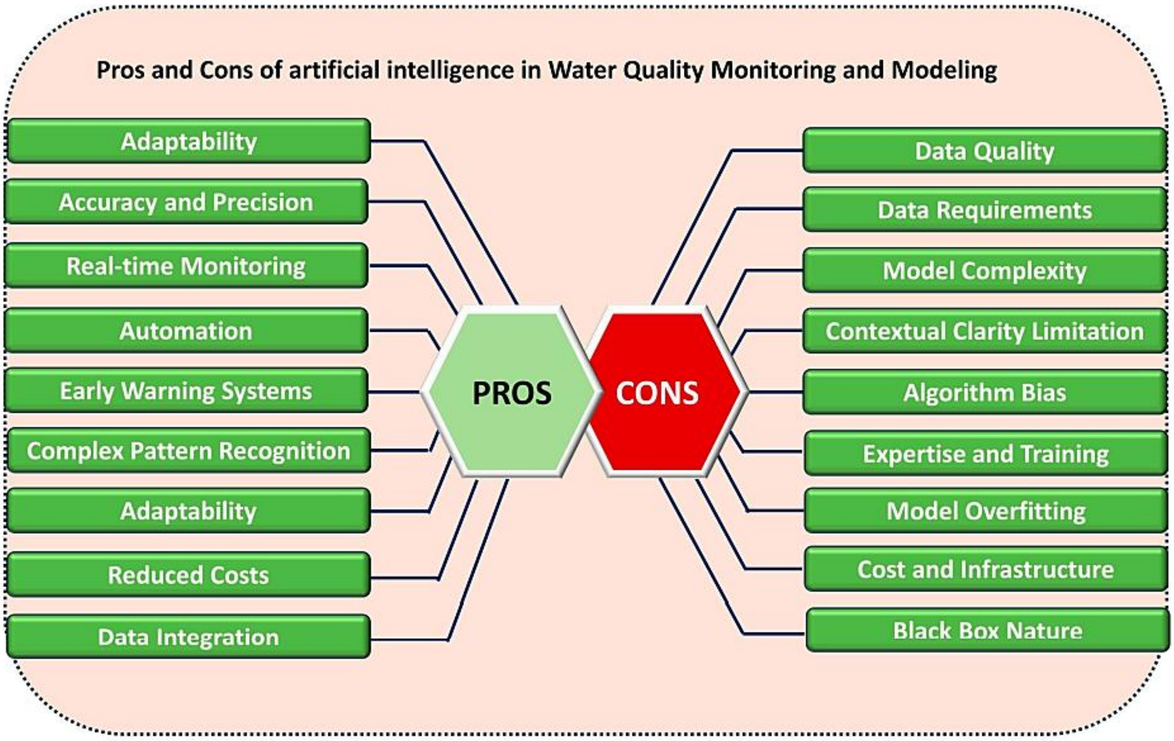

Figure 12. AI's benefits and drawbacks concerning water quality modeling and monitoring [1]

6. Future Trends and Recommendations

Overcoming the abovementioned challenges requires a multi-faceted approach that addresses technological advancements, institutional changes, and policy developments.

6.1. Advancements in Sensor Technology and Data Integration

The future development of AI in monitoring water quality will depend on further development in sensor technology and data assimilation [76]. The necessity for developing new, cheaper, and reliable sensors for monitoring water quality and expanding the range of its characteristics is also revealed. This involves innovating tools for identifying new pollutants and supplying the finest resolution anywhere, at any time. Moreover, it is agreed that more advanced integration techniques are necessary to merge data from various sources, including sensors, satellite data, and citizen science. Advanced and unified data formats and communication protocols allow the various systems to flow data transparently. They will impose a foundation for constructing intricate theoretical models of AI. Using data from various inputs enables the enhanced collection and comprehension of water quality, leading to better accuracy in AI forecasts [76].

6.2. Incorporating AI into Decision-Making Frameworks

Integrating AI into existing water management decision-making frameworks is crucial for translating AI-driven insights into actionable strategies [75]. The necessity for developing new, cheaper, and reliable sensors for monitoring water quality and expanding the range of its characteristics is also revealed. This involves innovating tools for identifying new pollutants and providing the finest resolution anywhere, at any time. Moreover, it is agreed that more advanced integration techniques are necessary to merge data from various sources, including sensors, satellite data, and citizen science. Advanced and unified data formats and communication protocols allow the various systems to flow data transparently. They will impose a foundation for constructing intricate theoretical models of AI. Using data from various sources allows for enhanced collection and comprehension of water quality, as well as better accuracy in AI forecasts.

6.3. Interdisciplinary Collaboration and Knowledge-Sharing

Integrating AI technology into WQM requires efficient interprofessional workforce cooperation and the exchange of information [77]. The involvement of water scientists, engineers, computer scientists, policymakers, and other stakeholders is essential in this process [76]. Cross-disciplinary data sharing of best practices, datasets, or research findings is crucial in fostering advancement and eliminating work duplication [77]. The existing knowledge translation often involves training where individuals can share information through online forums, seminars, and workshops. Besides, it is equally important to promote the education and training of water professionals to enable them to comprehend and apply AI tools, as stated in the following literature.

6.4. Regulatory and Policy Considerations for AI Adoption

Developing appropriate regulatory and policy frameworks is crucial for ensuring the responsible and ethical adoption of AI in WQM [75]. There needs to be solutions that consider the protection and security of data, address the issue of bias within algorithms, and address the concerns of openness and responsibility in artificial intelligence. There is a need to provide guidance on how AI can be correctly applied in WQM and define how these issues can be controlled and risks eliminated. In addition, policies should include incentives for AI research and development, establish a platform for standardized data formats and data exchange protocols, and provide capacity building for water professionals. Establishing proper data governance measures is imperative to enable the adoption of AI in water management. Stakeholders in policy that includes the regulation of practices and products arising from research and innovation should involve researchers and practitioners to establish pertinent policies and regulations that will facilitate development while avoiding unnecessary risks. Figure 13. AI future in water quality.

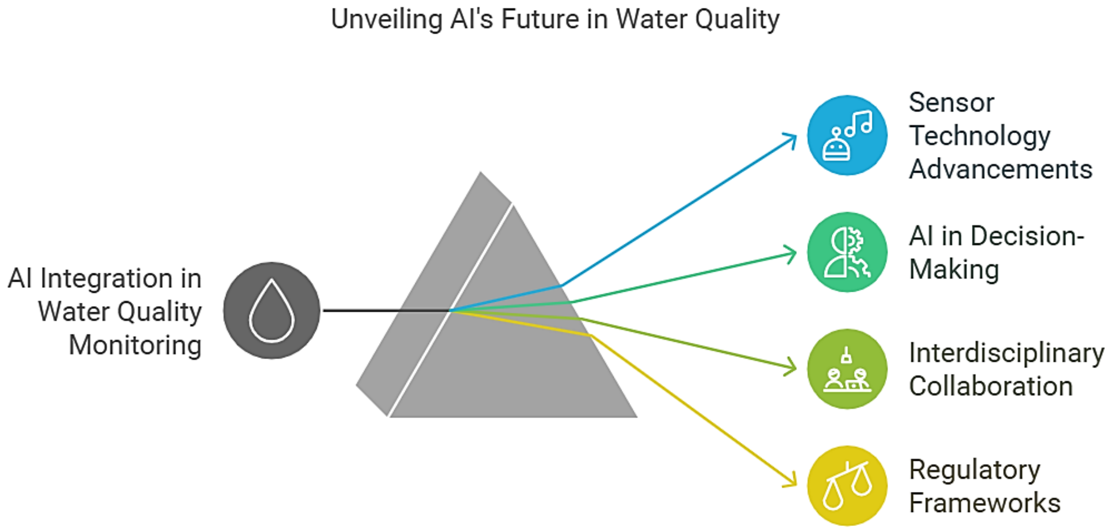

Figure 13. AI future in water quality

7. Conclusion

This systematic review highlights the transformative potential of artificial intelligence (AI) in revolutionizing WQM by synthesizing global research trends, technological advancements, and region-specific case studies. Integrating IoT sensor networks with machine learning techniques has significantly improved monitoring precision and responsiveness. For instance, in Malaysia, ANN-based analysis reduced river contamination response times by 82%, while in the Zhoushan fisheries region, CNN and LSTM models achieved 94% accuracy in predicting harmful algal blooms, helping mitigate environmental threats. Remote sensing technologies, enhanced by AI models such as XGBoost applied to Landsat 8 data, have enabled real-time WQI predictions with an accuracy of 87%, cutting field sampling costs by 60% and offering accessible solutions for data-scarce areas. Despite these advancements, persistent data challenges remain a key barrier—particularly in regions with limited environmental monitoring, such as Nigeria, where many AI systems cannot be implemented due to the insufficient availability of training data.

Furthermore, the lack of standardized data acquisition protocols hinders the integration of sensor-based and satellite-derived observations. Ethical and operational considerations also require urgent attention. Interpretability concerns related to "black-box" models, detection disparities between rural and urban areas exceeding 12%, and a 15% drop in sensor sensitivity over six months underscore the need for transparent and adaptive AI frameworks. Case studies in Malaysia and Algeria reveal how regionally successful approaches can serve as scalable models for global application. Moving forward, interdisciplinary collaboration among water resource experts, data scientists, and policymakers will be crucial for designing tailored AI solutions that align with sustainability goals and ensure equitable access to clean water.

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