ADSUJSR 14 (1) (2026) 07 - 17
Adamawa State University Journal of Scientific Research (ADSUJSR)
ISSN: 2705-1900 (Online); ISSN: 2251-0702 (Print)
https://www.adsujsr.adsu.edu.ng

A SYSTEMATIC REVIEW OF WATER QUALITY MONITORING: TECHNOLOGIES, TRENDS, CHALLENGES, AND FUTURE DIRECTIONS

Pambi G. V.*, Danladi A., Waida D. M.
Department of Physics, Adamawa State University, Mubi, Nigeria
**Corresponding author email: ask4glandu@gmail.com*

Received in April 2026
Accepted May 2026

Abstract
Water quality monitoring is essential for sustainable environmental management and public health protection. Conventional monitoring approaches are limited by sparse spatial coverage and delayed laboratory analysis. This study presents a PRISMA-based systematic review of emerging water quality monitoring technologies, focusing on the integration of Internet of Things (IoT) sensor networks, remote sensing platforms, machine learning algorithms, and biosensor technologies. A total of 103 scientific studies published between 2020 and 2025 were analyzed. The results indicate that IoT systems enable real-time data acquisition, remote sensing provides large-scale spatial monitoring, machine learning enhances predictive modelling, and biosensors offer high sensitivity for contaminant detection. However, challenges related to data integration, sensor reliability, scalability, and infrastructure remain significant barriers. A conceptual framework for integrated monitoring systems is proposed, along with a future research roadmap. The findings provide insights into the development of intelligent and sustainable water quality monitoring systems.

Keywords: Water quality monitoring; Internet of Things (IoT); machine learning; remote sensing; biosensors; real-time analytics; environmental management; TinyML

Introduction

Water is one of the most important natural resources that are essential for human survival, agriculture, industrial processes, and environmental sustainability. The quality and safety of water resources has become a major global concern. However, escalating population growth, climate change, and anthropogenic activities have significantly increased the vulnerability of both surface and groundwater resources to contamination systems (Saleh & Stanley, 2023a; Abalasei, 2025; Priya, 2024).

Conventional water quality monitoring methods, that are based on laboratory analysis of collected samples, remain fundamental due to their high analytical precision and regulatory acceptance. However, they

are often limited by their delays in reporting times, scalability, high operational cost, and labor-intensive procedures, which have motivated the innovation of more automated, real-time, and integrated monitoring systems (Essamlali et al., 2024; Deng et al., 2024).

There are new technologies such as, Internet of Things (IoT), wireless sensor networks, ML/AI, and UAV-based remote sensing, that have facilitated the evolution from discrete sampling to continuous, predictive monitoring (Wu et al., 2025; Yan et al., 2024). At scales never before realized, satellite platforms (Sentinel-2 and Landsat-8) and ML can identify chlorophyll-a, turbidity, and colored dissolved organic matter (Wasehun, Fenta, & Belachew, 2025). Low-cost sensors and TinyML open up possibilities to developing countries with infrastructure constraints (Ooko et al., 2025; Amador-Castro et al., 2024). Biological indicators (e.g., algae and macroinvertebrates) are used to complement technological approaches, providing ecosystem-level of understanding (Bamania, 2023).

The weakness of the contextual model, and the new technologies in sensing, data analytics, and communication networks have resulted in the emergence of innovative methods of monitoring that can deliver real-time and continuous water quality monitoring. Internet of Things (IoT), wireless sensor networks, Artificial Intelligence/ Machine Learning (AI/ML) models, and unmanned aerial vehicle (UAV)-based remote sensing are emerging technologies that considerably modify the progression of water quality monitoring and aim at continuous, predictive, as well as spatially extensive methods (Essamlali et al., 2024; Deng et al., 2024).

These technologies enable automated data collection, large-scale environmental observation, and predictive analytics that support proactive water management strategies.

Effective water quality monitoring helps to keep the regulations and allows managing the situation with adaptability as a result of early contamination detection. While biological indicators like algae and macroinvertebrates, remain vital for assessing long-term ecological integrity, their true potential is realized when paired with modern technology (Bamania, 2023). Integrating biological profiling (such as DNA sequencing) with remote sensing creates a sensitive, ecosystem-level view of water health (Bamania, 2023). These real-time frameworks provide the continuous, low-cost feedback necessary for robust early-warning systems and reliable drinking water management (Saleh & Stanley, 2023a).

Regardless of these developments, there are a number of challenges that are associated with the use of modern monitoring technologies. The problems surrounding sensor reliability, data quality, connectivity limitation, energy consumption and infrastructure constraints are also a major problem especially in developing countries.

The objectives of this review, therefore, is to examine the limitations of traditional water quality monitoring techniques, analyze emerging technological approaches, identify current trends and research gaps, and highlight future directions for improving the efficiency and sustainability of water quality monitoring systems.

Methodology of the Review

Systematic review process was employed in this study. This is the most robust review method, usually with the involvement of more than one author, which systematically assess and appraise literature with pre-existing inclusion criteria (Randles and Finnegan, 2023).

Literature Search Strategy

The review is based on Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure openness and repeatability of the literature review process (Page et al., 2021). The relevant publications were searched in the following scientific databases; Google Scholar, Web of Science, Scopus, IEEE Xplore, ScienceDirect, SpringerLink, and MDPI. The search focused on studies published between 2020 and 2025 to ensure that the review captured the most recent technological developments in the field.

The search for literature used in this review, strategically provide a wide range of coverage of interdisciplinary research in environmental science, engineering, computer science, and water resource management. The search queries include the combinations of the following keywords: “water quality monitoring,” “IoT water monitoring,” “machine learning water quality prediction,” “remote sensing water quality,” “biosensors water monitoring,” “TinyML environmental monitoring,” “real-time water quality systems.”

Inclusion Criteria

Publications included in the review are those that satisfied the following criteria: peer-reviewed journal articles, conference proceedings, studies published in English, empirical studies, validated simulation studies, or applied case studies.

Exclusion criteria

Studies were excluded if they lacked sufficient methodological clarity, focused on unrelated environmental monitoring topics, or were published before 2020 unless considered as foundational studies.

Data extraction and analysis

The relevant information from each selected publication was systematically extracted. The major parameters that were anayzed consist of monitoring techniques, water quality indicators measured, spatial and temporal resolution, advantages and limitations of the technologies, and their use in other environmental and economic settings. A comparative analysis was then carried out to determine the emerging technological trends and research gaps.

PRISMA Screening Process

The PRISMA screening involve the databases and keywords identification; the relevant articles screening and selection; the relevant articles eligibility; and the selection articles inclusion (Elkhwesky, Manzani & Elbayoumi, 2022).

The initial search across ScienceDirect, Scopus, and Google Scholar yielded 103 publications. After applying the duplicate and date criteria, the dataset was reduced to 78 studies. Title and abstract filtering further narrowed the lists to 53 publications. Following full-text screening, 38 studies remained, which met all inclusion criteria and were used for the final systematic review as presented in the flowchart diagram of Figure 1.

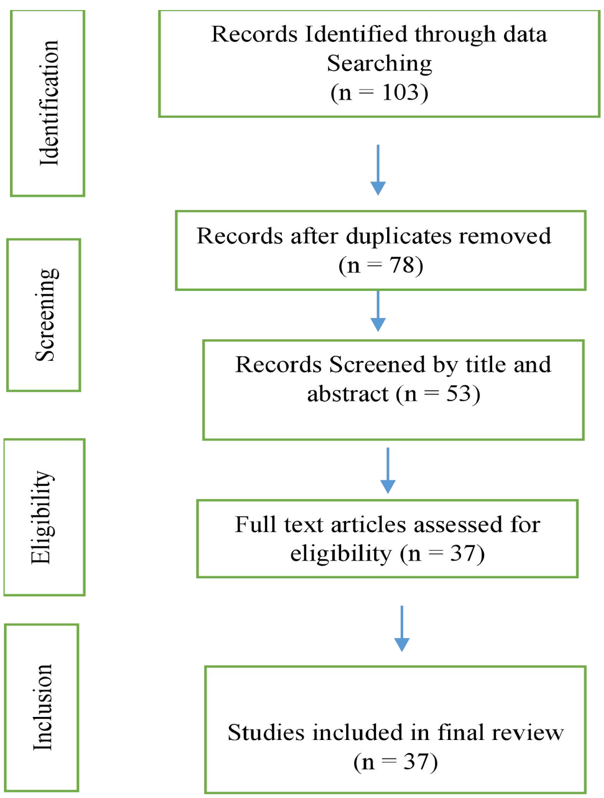

Figure 1: The PRISMA flowchart diagram.

RESULTS AND DISCUSSION

Traditional water quality monitoring approaches

Traditional water quality monitoring techniques primarily involve laboratory-based chemical and physical analysis, biological monitoring, and manual field measurements as presented in Table 1. These methods remain fundamental in water monitoring because of their high analytical accuracy and standardized procedures

Table 1. Comparison of Traditional Water Quality Monitoring Methods

Method	Parameters Measured	Key Advantages	Major Limitations	Typical Applications	Reference
Laboratory chemical analysis	pH, DO, BOD, COD, nitrates, heavy metals	High accuracy; standardized protocols	Expensive; delayed results; limited spatial coverage	Regulatory compliance and detailed chemical assessment	Saleh & Stanley (2023b)
Biological indicators	Algae, phytoplankton, macroinvertebrates	Reflects long- term ecological health	Requires taxonomic expertise; slow analysis	Ecosystem health monitoring	Bamania (2023)
Manual field measurements	pH, conductivity, turbidity, temperature	Portable; low cost; immediate readings	Limited temporal coverage; operator variability	Rapid field surveys and community monitoring	Deshvena & Kulkarni (2024)

Biological indicators

Biological monitoring is a technique of using living organisms to measure the environmental conditions. Some of the most effective organisms that can be used to measure water quality include aquatic organisms like algae, phytoplankton and the macroinvertebrates, which are very sensitive to the change in nutrient levels, dissolved oxygen and pollutant levels. (Bamania, 2023).

Though the biological indicators are very informative on ecological insight, they demand special taxonomic knowledge and laboratories to identify the sample. Furthermore, the real-time availability of the results may vary with natural seasonal cycles making their interpretation quite difficult (Bamania, 2023).

Manual field measurements

Manual in situ field measurements provide direct and immediate information on selected water quality parameters, often serving as a bridge between laboratory-based and automated systems.

Portable field instruments enable researchers to determine the parameters of pH, dissolved oxygen and conductivity at the sampling location. These handheld devices offer real time outputs and are widely used in environmental monitoring programs.

The other method that is widely used is the Secchi disk which is used to measure the transparency of water as an indirect measure of turbidity. Although it is easy and cheap, this approach offers only rough values and is affected by the weather conditions like sunlight and interpretation by the data analyst.

Field studies using manual measurements are still useful however, the data collection process is still the periodical one, thus, requiring human presence, implying that pollution events occurring between measurement may be missed. Besides this, there is a possibility of operator variation in results, environmental factors, and issues with the calibration of devices.

Technological advances in water quality monitoring

The water quality monitoring systems have been made much more efficient and scalable through technological innovation. The emerging solutions are IoT sensor networks, machine learning, remote sensing systems, biosensors, and edge computing systems as presented in Table 2.

Table 2. Comparison of Emerging Water Quality Monitoring Technologies

Technology	Typical Parameters	Strengths	Limitations	Example Study
IoT sensor networks	pH, turbidity, DO, TDS	Real-time, scalable, lower O&M	Fouling, power, connectivity	Forhad et al. (2024)
Machine learning	Predictive models	High accuracy, anomaly detection	Training data, transferability	Lokman et al. (2025); Yan et al. (2024)
Remote sensing/UAV	Chl-a, turbidity, CDOM	Large spatial coverage; trend analysis	Weather limits; needs ground truth	Deng et al. (2024); Wu et al. (2025); Wasehun et al. (2025)
Biosensors	Metals, pesticides	Portable, low-cost, specific	Calibration, lifespan	Aira et al. (2024)
Edge/TinyML	Multiple	Local inference, low power	Limited compute/storage	Ooko et al. (2025)

IoT Sensor Networks

IoT-monitoring systems are made up of a series of connected sensors collecting the data on water quality and relaying the data using the wireless network of communication. These systems allow constant tracking of parameters such as pH, turbidity, dissolved oxygen, conductivity, and temperature (Flores-Iwasaki et al., 2025; Forhad, Rahman, & Kabir, 2024; Kalyanam, 2023a). With the incorporation of cloud computing platforms, data may be stored, visualised and analysed in real time. Abnormal conditions can also produce automated alerts in case the conditions are identified. Despite the important benefits of IoT systems, it is necessary to overcome the problems associated with the fouling of sensors, power supply, and network connectivity to guarantee long-term reliability (Forhad, Rahman & Chowdhury, 2024).

Machine learning and AI

Machine learning algorithms are now used to monitor water quality by performing tasks that include prediction, classification and anomaly detection. These methods are able to process the big data that is received by sensors or satellite images to provide the patterns and predict the future environmental conditions. Random forests and neural networks are supervised approaches to learning that have been applied to classify the state of water quality, whereas unsupervised approaches assist in identifying anomalies in sensor readings

(Yan et al., 2024; Bagheri, Yu, & Fu, 2023; Lokman, Ismail, & Aziz, 2025; Odetoyinbo & Oyelakin, 2024).

Remote sensing and geographic information systems

Water quality parameters like; chlorophyll-a, turbidity, and colored dissolved organic matter (CDOM), can be detected at unprecedented scales using remote sensing platforms, such as Landsat imageries, Sentinel-1, and Sentinel-4 (Deng et al., 2024; Wu et al., 2025; Wasehun, Fenta, & Belachew, 2025). Geographic Information Systems (GIS) also facilitate the spatial analysis and mapping of water quality patterns in a large geographical area.

Biosensors

Biosensors are analytical systems that constitute biologically recognized elements coupled with electronic signal transducers. These sensors can identify certain contaminants such as heavy metals, pesticides, and nutrient with high sensitivity (Aira, Olivares, & Delicado, 2024; Zhang, Liu & Wang, 2023).

Edge Computing and TinyML

Edge computing technologies are the technologies that process sensor data directly on the local devices instead of having to use cloud servers. TinyML allows machine learning algorithms to be executed on low-power microcontrollers, which minimizes energy use and network bandwidth (Ooko, Mwangi, & Kamau, 2025).

Current Trends in the Monitoring of Water Quality

Recent studies show that there is a trend of using integrated monitoring systems, which use a combination of technologies to enhance the accuracy and coverage of the data. Hybrid systems of monitoring that combines IoT sensors, remote sensing data, and machine learning algorithms are being developed more often with practical applications.

New developments have changed the nature of water quality monitoring through low cost sensing, ML and data fusion across several platforms. The integration of low-cost sensors and networked with ML has a significant positive impact on the overall scalability and accuracy of the underground water, surface water, and aquaculture (Bagheri, Yu & Fu, 2023; Yan et al., 2024; Flores-Iwasaki et al., 2025).

Real-time monitoring system is also gaining popularity and this has made it possible to quickly identify the incidence of pollution and to be alerted of environmental hazards. The skills of retrieval and lead times of harmful algal bloom and pollution warnings are being enhanced with multi- sensor fusion based on Sentinel-2, PlanetScope, UAV hyperspectral, and in situ measurements (Wasehun, Fenta, & Belachew, 2025; Wu *et al.*, 2025). These improvements have significantly led to the TinyML allowing analysis to be performed efficiently with low power extending the areas with robust monitoring performance to resource-limited or developing areas (Ooko et al., 2025; Amador-Castro et al., 2024).

Another trend is the initiation of citizen science. Low-cost sensors and smartphone applications are used in community-based monitoring programs to gather data on the environmental condition and thus enhance the involvement of the community in the management of water resources. TinyML and sensors with low costs bring features to the developing countries, where the infrastructure is too lean to deploy the more traditional methods (Ooko et al., 2025; Amador-Castro et al., 2024). This method is especially useful in remote areas of monitoring where there might be insufficient connectivity.

Challenges and Limitations of Water Quality Monitoring Technologies

Even though considerable progress has been made water quality monitoring technologies, various technical, operational, and socio-economic issues remain. These weaknesses impact the credibility, the extensive capacity, and the practical application of contemporary monitoring.

Trade-off between accuracy and scalability

Conventional laboratory techniques of water monitoring are more accurate but have a limited spatial-temporal resolution (Saleh & Stanley, 2023b). On the other hand, IoT and remote sensing have a large coverage, but can have a low accuracy, which necessitates periodic verification with laboratory data (Brborić, Petrović, & Stanković, 2023; Essamlali et al., 2024). The combination of these two methods into hybrid structures is needed to maximize accuracy and scalability (Deng et al., 2024; Yan et al., 2024).

Sensor reliability and biofouling

The biofouling, sensor drift and environmental variability are some of the challenges to sensor performance in aquatic environments. The accumulation of biological materials on sensor surfaces degrades measurement accuracy and causes a higher rate of maintenance over time (Wu et al., 2025; Sahoo et al., 2025).

The long-term stability and cost-effectiveness of the mentioned solutions are unclear despite antifouling coating solutions, self-cleaning sensors, and automated calibration methods that have been proposed (Delgado et al., 2021; Sahoo et al., 2025; Rodriguez et al., 2024). Such issues prevent the viability of continuous monitoring systems.

Data Quality and Standardization (DSS)

The integration of IoT, remote sensing, and biosensor platforms generate large volumes of heterogeneous data. However, data interoperability and integration are hindered by the lack of standardized data formats, calibration protocols, and quality assurance frameworks (Deng et al., 2024; Ahmed et al., 2023; Essamlali et al., 2024).

Machine learning models require high-quality training data; inconsistent data quality produces unreliable predictions (Lokman et al., 2025; Bagheri et al., 2023). Standardized protocols and open repositories are essential (Amador-Castro et al., 2024; Wasehun et al., 2025).

Limitations of the Machine Learning Models

Machine learning models have demonstrated a high potential in predicting water quality and detecting anomalies, but they have a several of limitations that limit their practical applications. Most of them are black box models and cannot be interpreted and reduce confidence in decision-making (Yan et al., 2024; Pang et al., 2025; Chen et al., 2020; Zhang et al., 2022).

Moreover, the models that are trained using datasets related to regions tend to have low generalizability when used in other environmental situations (Lokman et al., 2025; Bagheri et al., 2023). Federated learning and physics-informed ML are future solutions (Pang, Wu, & Li, 2025).

Technological Inequality: Developed vs. Developing Regions

The deployment of advanced monitoring technologies is not even all over the world. Developed countries enjoy high-quality infrastructure and financial means, whereas developing countries are limited by the cost, technical, and maintenance capacity (Ahmed et al., 2023; Essamlali et al., 2024; Ooko et al., 2025; Amador-Castro et al., 2024; Adebayo et al., 2025).

Low-cost sensors, open-source hardware, and community-based monitoring can be useful in helping to ensure environmental monitoring accessibility and sustainability in resource-limited settings. (Flores-Iwasaki et al., 2025; Aira, Olivares & Delicado, 2024).

Policy Integration and Decision-Making

Although there are advancements on how data is obtained, there is still poor translation of monitoring data into effective environmental policies. The integration of monitoring systems with regulatory frameworks and decision-support systems is often not well organized, which reduces the impact of monitoring systems on water resource management (Reddy et al., 2020; Deng et al., 2024; Essamlali et al., 2024). In future studies, priority should be given to the governance systems that allow incorporating them in decision-making (Miller et al., 2024; Kumar & Chawdhoury, 2024).

Table 3. Key Challenges and Research Opportunities

Challenge	**Limitations**	**Research Opportunities**	**Key References**
Accuracy-scalability	Lab precision vs. spatial-temporal coverage	Hybrid frameworks integrating validation with automation	Saleh & Stanley (2023b); Deng et al. (2024)
Sensor reliability	Biofouling, drift, maintenance costs	Antifouling coatings, self-cleaning, auto-calibration	Wu et al. (2025); Delgado et al. (2021)
Data standardization	Heterogeneous formats, no QA/QC	Open repositories, common schemas, protocols	Essamlali et al. (2024); Wasehun et al. (2025)
ML limitations	Black box, poor transferability, data scarcity	Physics-informed ML, federated learning	Pang et al. (2025)
Technological inequality	Resource constraints in developing regions	Low-cost sensors, open hardware, citizen science	Ooko et al. (2025); Amador-Castro et al. (2024)
Policy integration	Weak data-to-governance translation	Regulatory alignment, trigger-based protocols	Miller et al. (2024); Chawdhoury, 2024

Future research roadmap

Future water quality monitoring systems will increasingly evolve toward integrated, intelligent, and autonomous frameworks. The development of hybrid monitoring systems that combine IoT sensors, remote sensing, biosensors, and machine learning to achieve high accuracy and large-scale coverage is a key priority (Kalyanam, 2023b; Deng et al., 2024; Zhang & Zhang, 2024).

The development of edge computing and TinyML will enable real-time on-device data processing, reduce latency, and optimize the efficiency of the system, especially in remote environments (Ahmed et al., 2023). Simultaneously, new methods like physics-informed and explainable AI are likely to increase the accuracy and interpretability of models.

The self-calibration and antifouling technology will continue to enhance the sensor reliability when deployed over an extended period (Sahoo et al., 2025). Furthermore, the creation of standardized data frameworks and open-access platforms will be

important in ensuring interoperability and supporting large-scale analytics (Deng et al., 2024).
The low-cost and scalable solutions should also be targeted in the future in order to foster adoption in the developing areas (Flores-Iwasaki et al., 2025). Lastly, the closer interconnection between monitoring systems and policy and decision-support structures will have to be introduced in order to convert the data into the effective water management strategies (Reddy et al., 2020).

Conclusion

This study provided a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-based systematic review of water quality monitoring technologies, including IoT, remote sensing, machine learning, and biosensors. Though, the traditional methods are highly accurate, they are lack coverage, but on the other hand modern technologies provides an opportunity to monitor in real-time and at large scale, but they have issues related to reliability, data integration, and scalability.
The findings show that integrated and hybrid monitoring systems are the most efficient way of addressing the current limitations of the field. However, challenges such as sensor performance, data standardization, and unequal technological access must be addressed.
On the whole, the shift to smart and unified monitoring technologies facilitated by advanced analytics and integration of policies is the key to sustainable management of water resources.

REFERENCES

Abalasei, M. E., Toma, D., Dorus, M., & Teodosiu, C. (2025). The impact of climate change on water quality: A Critical Analysis. *Water*, *17*(21), 3108. https://doi.org/10.3390/w17213108

Adebayo, I. T., Ajibola, S., Ahmad, A., Cartujo, P., Muritala, I., Elegbede, I. O., & Martos, V. (2025). Understanding the application of digital technologies in aquaculture supply chains through a systematic literature review. *Aquaculture International*, *33*(6), 397.

Ahmed A. A, Sayed S, Abdoulhalik A, Moutari S, Oyedele L (2024). Applications of machine learning to water resources management: a review of present status and future opportunities. J Clean Prod 441:140715. https://doi.org/10.1016/j.jclepro.2024.140715

Aira, J., Olivares, T., & Delicado, F. M. (2024). SpectroGLY: A low-cost IoT-based ecosystem for the detection of glyphosate residues in waters. *arXiv*. https://arxiv.org/abs/2401.16009

Amador-Castro, F., López-Cano, J., & Sánchez-Zarate, V. (2024). Internet of things and citizen science as alternative water quality monitoring strategies: A systematic review. *Journal of Environmental Management, 358*, 120626.

Bagheri, M., Yu, Z., & Fu, Q. (2023). Applications of artificial intelligence technologies in water and wastewater treatment: A review. *Process Safety and Environmental Protection, 176*, 909–930. https://doi.org/10.1016/j.pseud.2024.04.010.

Bamania, P. (2023). The role of algae in assessing water quality with advanced biotechnological methods. *Journal of Environmental Science and Technology, 18*(3), 145–160.

Brborić, D., Petrović, I., & Stanković, D. (2023). Advanced technologies in freshwater pollution detection: Sensor networks, remote sensing, and real-time monitoring stations. *Environmental Monitoring and Assessment, 195*(11), 1–15. https://doi.org/10.1007/s10661-023-11540-y

Delgado, A., Martins, S., & Azenha, M. (2021). Antifouling strategies for sensors used in water monitoring. *Sensors, 21*(2), 389.

Deng, Y., Zhang, Y., Pan, D., Yang, S. X., & Gharabaghi, B. (2024). Review of recent advances in remote sensing and machine learning methods for lake water quality management. *Remote Sensing, 16*(22), 4196. https://doi.org/10.3390/rs16224196

Deshvena, R., & Kulkarni, P. (2024). Remote sensing and GIS in water quality monitoring: A comprehensive review. *International Journal of Environmental Science, 18*(1), 6–10.

Elkhwesky Z, El Manzani Y, Elbayoumi S. I. (2022). Driving hospitality and tourism to foster sustainable innovation: A systematic review of COVID-19-related studies and practical implications in the digital era. Tour Hosp Res. 14:14673584221126792. doi: 10.1177/14673584221126792.

Essamlali, I., *et al.* (2024). Advances in machine learning and IoT for water quality monitoring: A comprehensive survey. Sensors, 24(8), 3055. https://doi.org/10.3390/s24083055.

Flores-Iwasaki, M., Guadalupe, G. A., Pachas-Caycho, M., Chapa-Gonza, S., Mori-Zabarburú, R. C., & Guerrero-Abad, J. C. (2025). Internet of Things (IoT) Sensors for Water Quality Monitoring in Aquaculture Systems: A Systematic Review and Bibliometric Analysis. *AgriEngineering*, *7*(3), 78. https://doi.org/10.3390/agriengineering7030078

Forhad, H. M., Rahman, M. S., & Chowdhury, M. (2024). IoT-based real-time water quality monitoring system in treatment plants. *Heliyon, 10*(x), eXXXXX.

Forhad, M., Rahman, S., & Kabir, H. (2024). IoT-enabled real-time water quality monitoring system for treatment plants in Bangladesh. *Sensors and Applications, 12*(4), 221–233.

Kalyanam, R. (2023a). IoT-based water management: Real-time analytics for sustainable resource utilization. *International Journal of Environmental Monitoring, 12*(3), 134–150.

Kalyanam, R. (2023b). The integration of AI, IoT, and big data in water resource management. *Industrial Water Systems Review, 22*(3), 6–8.

Kumar, P., Choudhury, D. (2024). Innovative technologies for effective water resources management. In: Izah, S.C., Ogwu, M.C., Loukas, A., Hamidifar, H. (eds) Water Crises and Sustainable Management in the Global South. Springer, Singapore. https://doi.org/10.1007/978-981-97-4966-9_18

Lokman, A., Ismail, W. Z. W., & Aziz, N. A. A. (2025). A review of water quality forecasting and classification using machine learning models and statistical analysis. *Water, 17*(15), 2243. https://doi.org/10.3390/w17152243

Miller, T., Durlik, I., Kostecka, E., Kozlovska, P., Łobodzińska, A., Sokołowska, S., & Nowy, A. (2025). Integrating Artificial Intelligence Agents with the Internet of Things for Enhanced Environmental Monitoring: Applications in Water Quality and Climate Data. *Electronics*, *14*(4), 696. https://doi.org/10.3390/electronics14040696.

Odetoyinbo, T., & Oyelakin, A. (2024). Artificial intelligence in sustainable water management: Opportunities and challenges. *Journal of Sustainable Water Resources, 15*(2), 78–90.

Ooko, S. O., Mwangi, D., & Kamau, J. (2025). Application of machine learning for real-time water quality monitoring using IoT and TinyML in developing contexts. *Journal of Environmental Data Science, 4*(2), 115–128. https://doi.org/10.1016/j.jeds.2025.02.004.

Page M. J, McKenzie J. E, Bossuyt P. M, Boutron I, Hoffmann T. C, Mulrow C. D,…et.al., (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 29; 372:n71.doi: 10.1136/bmj.n71.

Pang, J., Wu, Z., & Li, J. (2025). Deep learning-based remote sensing retrieval of inland water quality parameters. *Advances in Space Research, 78*(6), 1123–1139. https://doi.org/10.1016/j.asr.2025.03.012.

Priya G, Veena K. S, Prajanya S. G, Vachana M. B, Keerthana B, Prakash K. S,...et. al.(2024). Tracking microplastic pathways: real-time IoT monitoring for water quality and public health, MethodsX, Volume 15, 103674, https://doi.org/10.1016/j.mex.2025.103674.

Randles R, Finnegan A. 2023. Guidelines for writing a systematic review. Nurse Educ Today. 125:105803. doi: 10.1016/j.nedt.

Reddy, S., Allan, S., Coghlan, S., & Cooper, P. (2020). A governance model for the application of AI in health care. Journal of the American Medical Informatics Association, 27, 491-497. https://doi.org/10.1093/jamia/ocz192.

Rodríguez Rama, J. A., Presa Madrigal, L., Costafreda Mustelier, J. L., García Laso, A., Maroto Lorenzo, J., & Martín Sánchez, D. A. (2024). Monitoring and Ensuring Worker Health in Controlled Environments Using Economical Particle Sensors. *Sensors*, *24*(16), 5267. https://doi.org/10.3390/s24165267.

Sahoo, B. N., *et al.* (2025). Antibiofouling coatings for marine sensors: Recent advances and practical considerations ACS Sensors, 10(x), 1234–1251.

Saleh, H., & Stanley, G. (2023a). Real-time water quality monitoring: Benefits, challenges, and implementation strategies. *Journal of Water Resource Management, 30*(2), 26–30.

Saleh, M., & Stanley, B. (2023b). Real-time data analytics in water quality monitoring: Enhancing precision and efficiency. *Journal of Environmental Science & Technology, 57*(2), 102–118.

Wasehun, E. T., Fenta, M., & Belachew, M. (2025). Comparative analysis of Sentinel-2 and PlanetScope for chlorophyll-a retrieval in lakes. *Ecological Informatics, 78*, 102500. https://doi.org/10.1016/j.eci.2025.102500.

Wu, Z., Pang, J., Li, J., Chen, X., & Zhou, Y. (2025). A review of remote sensing-based water quality monitoring in turbid coastal waters. *Marine and Coastal Remote Sensing, 12*(1), 77–95. https://doi.org/10.1007/s44295-025-00075-2

Yan, Y., He, X., Bai, Y., Liu, J., Shanmugame, P., Zhao, Y., Zhang, X., Wang, Z., Zhang, Y., & Gong, F. (2024). Monitoring Dissolved Organic Carbon Concentration and Flux in the Qiantang Riverine system using Sentinel-2 satellite images. *Remote Sensing*, *16*(22), 4254. https://doi.org/10.3390/rs16224254

Zhang, H., Liu, X., & Wang, Y. (2023). Advanced sensor materials for long-term underwater deployment: Addressing biofouling and corrosion challenges. Sensors, 23(2), 734-749. https://doi.org/10.3390/s23125759