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Digital Water Quality Monitoring for Pre-Harvest Safety: A Critical Review of IoT, AI and Rapid Sensors in Irrigation Management

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Abstract: *Irrigation water is a recognized pathway for pre-harvest contamination of fresh produce, yet conventional laboratory testing limits monitoring frequency and timeliness of management decisions. This critical review examines how digital technologies such as Internet of Things (IoT)-enabled sensors, rapid biosensors and molecular methods, and artificial intelligence (AI) and machine learning may support irrigation water monitoring and pre-harvest food safety. Literature was purposively selected from Scopus, Web of Science, ScienceDirect, SpringerLink and IEEE Xplore, with an initial scoping from January 2018 to October 2026; the final 29 peer-reviewed studies that met critical relevance criteria clustered between 2020 and 2026, including two 2026 early-online articles, reflecting the recent emergence of this field. The review was complemented by guidance from the Food and Agriculture Organization (FAO), Codex Alimentarius Commission (2023), World Health Organization (WHO) and United States Food and Drug Administration (FDA 2024 Final Rule on Pre-Harvest Agricultural Water). The synthesis shows that IoT systems can increase monitoring frequency for physicochemical parameters and support baseline characterization and anomaly detection, while rapid biosensors and molecular assays offer more direct detection of microbial hazards with reduced time-to-result compared with conventional culture. AI approaches can assist pattern recognition, risk prediction and interpretation of multi-parameter data. However, physicochemical measurements cannot independently confirm microbiological safety, and sensor accuracy, calibration drift, matrix interference, field validation and model transferability remain critical limitations. Integrated digital monitoring may support risk-based water management when combined with validated microbial testing and clear response procedures, but evidence that it directly reduces produce contamination under routine farming conditions remains limited. Recommendations are provided for strengthening field validation and implementation, particularly in resource-limited locations.*
Keywords: Artificial intelligence, irrigation water, Internet of Things, pre-harvest food safety, rapid biosensors, water-quality monitoring, edge-cloud architecture, decision support.

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INTRODUCTION

The safety of fresh fruits and vegetables remains an important concern in agricultural production because these foods are often eaten raw or with little processing (Macieira et al., 2021). Contamination before harvest may therefore reach consumers if appropriate preventive measures are not taken. Irrigation water is one route through which microbial hazards can reach crops, particularly when water sources are affected by human or animal waste, agricultural runoff or other forms of contamination (Banach & van der Fels-Klerx, 2020). The level of risk depends on several factors, including the source and quality of the water, surrounding activities, irrigation methods and the extent to which the edible parts of crops come into contact with the water. Maintaining irrigation-water quality is therefore an important part of both agricultural management and pre-harvest food safety. One difficulty is that water quality does not remain constant. Rainfall, runoff, wastewater discharge, livestock activities and changes in water storage or distribution can affect contamination levels between routine sampling occasions (Sebela & Nemutandani, 2025). A water source considered acceptable during one assessment may present a different risk days or even hours later. Laboratory testing remains essential because it can provide detailed information about microbial and chemical hazards. However, collecting and transporting samples and waiting for laboratory results may delay decisions. Where testing is infrequent, contamination events can occur between sampling points without being detected immediately. This creates a need for monitoring approaches that provide more timely information while maintaining the accuracy and reliability required for irrigation management.

Digital monitoring should not be seen as a replacement for laboratory testing. Its main value lies in complementing established methods by increasing the frequency of observations, identifying changes in water conditions and indicating when further investigation may be needed. The usefulness of a monitoring system depends on what it measures, how its results are validated and whether those results can guide appropriate action. Frequent readings alone offer limited protection if they cannot reliably indicate a relevant hazard. Equally, an alert has little practical value when farmers or water managers lack clear guidance on how to respond. Internet of Things (IoT) technologies provide one way to improve the frequency and accessibility of irrigation-water monitoring. These systems connect sensing devices to communication networks and data-processing platforms, allowing measurements to be transmitted and viewed remotely (Das et al., 2025). Depending on the equipment used, they can monitor parameters such as temperature, pH, electrical conductivity, turbidity and dissolved oxygen. Changes in these measurements may help describe water conditions, identify unusual patterns and indicate when additional sampling or inspection is necessary. Remote access can also reduce the need for personnel to visit every monitoring point for routine measurements. Research on IoT-based irrigation management, including Peng and Zhang (2025), illustrates the potential of connected technologies to support water monitoring and agricultural decision-making. However, connectivity does not automatically make a sensor reliable. Low-cost sensors can make frequent monitoring more accessible, but their readings may be affected by calibration errors, sensor drift, fouling, temperature changes and differences in water composition. Performance may also deteriorate during prolonged use in the field. De Camargo et al. (2023) examined low-cost water-quality sensors for IoT applications, highlighting the importance of evaluating their

performance rather than assuming that affordability and connectivity are sufficient. This matters when measurements inform food-safety decisions. Inaccurate readings could lead to unnecessary restrictions on irrigation or, more seriously, a failure to recognise a developing problem.

Another limitation is that common physicochemical measurements do not directly confirm whether disease-causing microorganisms are present. Turbidity and other water-quality indicators can provide useful information about changing conditions, but they cannot independently establish the presence or absence of a particular pathogen. Pre-harvest safety involves more than maintaining water within selected physical and chemical ranges; it also requires preventing or reducing microbial contamination of produce. An IoT system based only on general water-quality sensors may support risk surveillance, but it cannot provide sufficient evidence of microbiological safety on its own. Combining routine sensor measurements with appropriate microbial testing is therefore important. Rapid biosensors and molecular diagnostic methods offer possible ways to address this limitation. Biosensors use biological recognition elements, such as antibodies, nucleic-acid probes or aptamers, to recognise target substances or organisms and produce a measurable response. Molecular methods, including polymerase chain reaction (PCR) and loop-mediated isothermal amplification (LAMP), can also be used to detect microbial targets. Reviews by Song et al. (2023) and Kotsiri et al. (2022) discuss developments in biosensing for bacterial and viral detection in water, food and environmental samples. Khodaparast et al. (2024) also examine rapid and point-of-care approaches to detecting waterborne pathogens. These technologies are relevant to irrigation management because they can provide more direct evidence of biological hazards than general physicochemical measurements.

Even so, a rapid test is not necessarily suitable for routine farm use. Its performance depends on the target organism, detection limit, sample preparation, water composition, testing conditions and equipment requirements. A method that performs well under controlled laboratory conditions may need further testing before it can be used reliably across different water sources or by different operators. Substances in environmental samples may interfere with detection, while sample preparation can add time and complexity. The organism being tested for also matters. Detecting an indicator organism such as Escherichia coli in an appropriate water-quality assessment is not the same as specifically detecting a pathogen such as E. coli O157:H7. These tests answer different questions, so their results must be interpreted according to the target organism and purpose of the assessment. Combining rapid microbial detection with connected monitoring could provide a more useful picture of irrigation-water conditions. General water-quality sensors can supply frequent measurements, while biosensors or molecular methods can investigate particular microbial hazards. When the results are brought together through a digital platform, they may help water managers identify unusual conditions, arrange confirmatory tests and respond more quickly to possible contamination. For example, an unexpected change in turbidity could trigger additional microbial sampling without being treated as proof of pathogen presence. Similarly, a positive microbial test may require action even when routine sensor readings appear normal. The two approaches are complementary, but neither provides a complete assessment of risk under every condition. Artificial intelligence (AI) and machine learning (ML) may further improve digital monitoring by identifying patterns in water-quality data, predicting selected parameters and supporting contamination-risk assessment. These methods can analyse relationships among measured variables and identify patterns

that may be difficult to recognise from individual readings. Mokhtar et al. (2022), for example, examined statistical and machine-learning approaches for predicting irrigation-water-quality criteria. Research by Omeka (2024) and Omeka et al. (2024) also illustrates the use of data-driven modelling and spatial assessment to evaluate irrigation-water quality in Nigerian settings. Such approaches may help assess water suitability and interpret complex datasets. However, predicting a physicochemical parameter or water-quality index does not establish that microbial contamination is absent. A model can only support conclusions that are justified by its target variables, input data and validation. The reliability of AI also depends on the quality and representativeness of the data used to develop and test a model. A model trained on one water source, season or set of measured parameters may perform differently in another agricultural environment. Missing observations, sensor errors, limited training data and changing environmental conditions can affect its predictions. Reported accuracy, on its own, may therefore provide an incomplete picture of practical usefulness. In food-safety applications, false-negative and false-positive results, uncertainty, interpretability and the consequences of decisions based on model outputs also need attention. El Bilali and Taleb (2024) and Mustapha et al., (2025) discuss opportunities and limitations associated with data-driven approaches to irrigation-water-quality management, including issues relating to data availability, model reliability and practical implementation.

The way digital systems process and communicate information is another important consideration. Cloud platforms can store large volumes of data and support more demanding analyses, while edge computing allows selected information to be processed close to the sensor. This may help generate local alerts when internet connectivity is poor. A combined edge–cloud arrangement can support immediate responses alongside longer-term analysis of monitoring records. Nevertheless, these components do not guarantee dependable decisions. Communication interruptions, power shortages, software incompatibility, data loss and maintenance requirements can all affect performance. An alert is only useful when its meaning is understood and there is a clear procedure for responding to it. Digital monitoring should therefore be assessed not only by its ability to collect and transmit data, but also by whether the information reaches the right person in time and leads to an appropriate response. These issues are also relevant to wider efforts to improve food safety and water management. International guidance and regulatory initiatives increasingly recognise the need to assess and manage risks associated with agricultural water. The United States Food and Drug Administration's 2024 agricultural-water rule under the Produce Safety Rule provides one example of this approach. Its requirements apply within the United States and should not be presented as Nigerian law. However, the broader need to assess water-related hazards and manage them appropriately is relevant to agricultural production in different settings. The Sustainable Development Goals provide a wider context, particularly SDG 2 on food security, SDG 3 on health, SDG 6 on water and sanitation, SDG 9 on infrastructure and innovation, and SDG 12 on responsible production and consumption.

Despite developments in sensing, rapid diagnostics and predictive modelling, it remains important to establish how well these technologies can work together to support pre-harvest food safety under practical agricultural conditions. Studies have examined connected irrigation systems, low-cost sensors, biosensors, molecular detection and AI-based water-quality prediction, but these approaches do not necessarily measure the same outcomes or have the same level of practical readiness. Evidence that a sensor accurately

measures a water-quality parameter does not demonstrate that a biosensor can reliably detect a particular pathogen. Likewise, a model that predicts water suitability is not equivalent to a validated monitoring system that identifies microbial hazards and supports timely management decisions. Meaningful comparison therefore requires attention to what each technology is designed to do, the conditions under which it has been tested and its relevance to actual food-safety decisions.

Three related gaps deserve particular attention. First, the relationship between general physicochemical monitoring and direct microbial-hazard detection needs clearer treatment to prevent the capabilities of individual technologies from being overstated. Second, the reliability of digital sensors and AI systems under changing field conditions requires further consideration, including calibration, sample preparation, uncertainty, connectivity and maintenance. Third, technical performance needs to be linked more directly to the management decisions and food-safety outcomes that monitoring is intended to support. These concerns are especially relevant where laboratory services, reliable internet access, technical expertise and maintenance resources are limited. Nigerian studies of irrigation-water quality provide useful local evidence, but assessments of physicochemical suitability alone cannot resolve questions about microbial hazards or the safety of fresh produce before harvest. A critical review is therefore needed to examine the contribution of IoT-enabled monitoring, rapid biosensors and AI-based decision support to irrigation-water safety, while distinguishing demonstrated capabilities from applications that still require field validation. Combining technologies may improve monitoring, but this benefit should not be assumed without supporting evidence. The review examines what each approach can measure or predict, the limitations affecting its reliability and the conditions needed for practical use. It also considers how monitoring results can inform risk-based water management, including appropriate microbial testing, clear response procedures and evidence that digital information leads to useful decisions. This provides a basis for assessing both the potential of digital monitoring and the work still needed before these systems can be relied upon for routine pre-harvest safety management.

The specific objectives of this review are:

1. To critically examine IoT-enabled water-quality monitoring systems and rapid biosensors for monitoring irrigation-water conditions and detecting microbial hazards relevant to pre-harvest food safety.
2. To evaluate the applications, performance and limitations of artificial intelligence and machine learning, including edge–cloud architectures, for predicting water-quality risks and supporting irrigation-management decisions.
3. To identify methodological, technological and implementation gaps in digital water-monitoring systems and propose practical recommendations for strengthening pre-harvest safety and sustainable agricultural water management.

REVIEW METHODOLOGY

Review Design

This study employed a critical narrative review to examine digital water quality monitoring for pre-harvest agro-food safety. A critical review was adopted over a systematic review because the field spans agricultural science, environmental engineering, food safety and digital technology, with heterogeneous

study designs, technologies and validation approaches that are not directly comparable through quantitative synthesis. The review focused on three interrelated domains: IoT-enabled water quality monitoring, rapid biosensors and molecular detection, and AI/ML-based decision support for irrigation management.

Data Sources and Search Strategy

Literature was purposively identified from Scopus, Web of Science, ScienceDirect, SpringerLink, Wiley Online Library, Taylor & Francis Online and IEEE Xplore. Institutional and regulatory guidance from FAO, Codex Alimentarius Commission (2023), WHO and US FDA [FSMA Final Rule on Pre-Harvest Agricultural Water, 2024] was consulted. Thematic searches combined terms including: 'Internet of Things', 'irrigation water quality', 'artificial intelligence', 'machine learning', 'rapid biosensors', 'Escherichia coli', 'agricultural water safety', 'edge-cloud computing', and 'pre-harvest food safety'. The initial scoping considered literature from January 2018 to October 2026. Following critical screening for relevance to pre-harvest safety and digital irrigation management, the final corpus that directly informed the synthesis clustered between 2020 and 2026, comprising 29 peer-reviewed articles including two 2026 early-online publications available at the time of search. This temporal clustering reflects the recent emergence of low-cost IoT sensors, AI-enabled biosensing and integrated edge-cloud monitoring for agricultural water applications.

Selection Criteria

Inclusion was based on conceptual relevance rather than exhaustive retrieval. Studies were included if they: (a) addressed IoT-based water quality sensing, (b) reported rapid or molecular detection of microbial hazards relevant to irrigation water, (c) applied AI/ML to water quality prediction or irrigation decision support, or (d) provided methodological or regulatory context for pre-harvest water safety. Studies from non-agricultural water domains were considered where methods were transferable to irrigation water.

Data Extraction and Critical Appraisal

For each selected study, data were extracted on: study design, technology and sensing platform, target water quality parameters or microbial targets, analytical methods, validation procedures [laboratory vs field, comparison with reference methods], main findings and reported limitations. Critical appraisal focused on: (a) whether studies measured general physicochemical conditions or direct microbial hazard detection; (b) calibration, accuracy, drift, fouling and matrix interference; (c) sample preparation and detection limits for biosensors; (d) data quality, model training, validation and transferability for AI/ML; and (e) practical readiness for routine farm use.

Synthesis

Findings were synthesized narratively and thematically around the three objectives. Table 1 below summarizes the final corpus of 29 studies that directly informed this critical review. The contribution to Sustainable Development Goals 2, 3, 6, 9 and 12 was considered.

Table 1. Summary of Selected Studies on Digital Water Quality Monitoring for Pre-Harvest Safety

S/N	Author(s) & Year	Technology Focus	Methods / Approach	Main Findings	Critical Assessment / Limitations	Relevance to Pre-Harvest Safety
1	Badr & Noor, 2026	Automated cloud-edge cyber-physical IoT	System design - Sci Rep 16, 31294	Edge-cloud optimizes water-energy-yield	Early-online 2026, field validation needed	Edge-cloud architecture - newest evidence
2	Banach & van der Fels-Klerx, 2020	Microbiological reduction strategies of irrigation water	Review - J Food Protection	Identified mitigation options for fresh produce	General strategies, not digital-specific	Foundational - defines need for treatment
3	Bouziane et al., 2026	Intelligent & explainable IoT-Edge-Cloud architecture	Architecture - IJ-AI	Explainable AI for real-time monitoring	Early-online 2026	Explainable AI + IoT integration - newest
4	Codex Alimentarius Commission, 2023	Safe use & re-use of water in food production	Guidelines - adopted 2023	Risk-based water safety framework	Policy not technology	Policy benchmark for risk-based reuse
5	Das et al., 2025	IoT real-time measuring for irrigation canals	System implementation - J ASETM	Real-time canal monitoring feasible	Limited microbial focus	IoT infrastructure for canals
6	de Camargo et al., 2023	Low-cost water quality sensors for IoT	Systematic review - Sensors 23(9),4424	Few studies compare with reference; limited calibration	Reliability, durability uncertain	Critical appraisal of low-cost sensors - KEY paper
7	El Bilali & Taleb, 2024	State-of-the-art irrigation water quality - data-driven methods	Review - Physics & Chemistry	Opportunities & limitations of	Data availability, reliability issues	AI limitations and future directions

			of the Earth 136	data-driven methods		
8	Glória et al., 2020	Water management for sustainable irrigation using IoT	WSN system - Sensors 20(5),1402	IoT improves irrigation efficiency	Efficiency ≠ safety; no pathogen detection	IoT as monitoring baseline
9	Khodaparast et al., 2024	Advances in point-of-care & molecular techniques for waterborne pathogens	Review - npj Clean Water 7,74	Sample prep & nucleic acid extraction critical	Field applicability, extraction complexity	Rapid molecular detection challenges
10	Kotsiri et al., 2022	Applications of biosensors for bacteria & virus detection	Systematic review - J Env Sci 111	Biosensors promising for rapid detection	Matrix interference, field validation limited	Biosensor potential for irrigation water
11	Macieira et al., 2021	Food safety in local farming of fruits & vegetables	Review - IJERPH 18(18),9733	Pre-harvest contamination pathways	Not technology-focused	Problem statement for fresh produce
12	Mokhtar et al., 2022	Prediction of irrigation water quality indices based on ML	ML & regression - Applied Water Sci 12(4)	ML predicts quality indices accurately	Physicochemical only, not pathogens	AI for quality prediction - not safety confirmation
13	Mokhtar et al., 2023	Prediction of irrigation water requirements - ML	ML models - Water Res Mgmt 37(3)	ML predicts water requirements for green beans	Does not address microbial safety	Water management - complementary
14	Mustapha et al., 2025a	Hybrid ML approach for imbalanced irrigation water quality classification	Hybrid ML - Desalination & Water Treatment 321	Hybrid approach improves classification	Imbalanced data challenge, not pathogen-specific	AI performance improvement for classification
15	Mustapha et al., 2025b	Towards efficient AI techniques for assessment of	Systematic review - ESPR 32(47)	Reviews efficient AI techniques	Focus on physicochemical assessment	Comprehensive AI review - recent

		irrigation water quality				
16	Nnachi et al., 2022	Biosensors for rapid detection of bacterial pathogens	Review - Environ Int 166,107357	Advances in biosensor sensitivity/specificity	Sample prep, environmental interference	Rapid bacterial detection principle - KEY
17	Nsoh et al., 2024	IoT-based automated solutions utilizing ML for smart irrigation	Review - Sensors 24(23),7480	IoT+ML support real-time irrigation	Interoperability, standardisation, cybersecurity	IoT+ML integration for smart irrigation
18	Omeka et al., 2024	Efficacy of GIS-based AHP & ML for irrigation water quality prediction	GIS-AHP + ML - Lower Benue Trough Nigeria	ML predicts suitability, spatial assessment effective	Physicochemical suitability only	Local Nigeria evidence - GIS+ML
19	Omeka M.E., 2024	Evaluation & prediction of irrigation water quality - SE Nigeria	Heuristic GIS + ML - ESPR 31(41)	Integrated approach evaluates & predicts quality	Not microbial, limited to SE Nigeria	Local Nigeria evidence - evaluation
20	Oon et al., 2023	Waterborne pathogens detection technologies	Review - Front Microbiol 14	Advances, challenges, future perspectives	Lab to field translation gap	Pathogen detection context
21	Peng & Zhang, 2025	Integrating AI and IoT for smart agriculture - ML for precision irrigation	Preprint DOI:10.21203/rs.3.rs-5899777/v1	AI+IoT supports precision irrigation	Preprint - requires peer validation	AI+IoT integration - precision irrigation
22	Qian et al., 2023	ML for improved detection of pathogenic E. coli in hydroponic	Impedimetric aptasensor + ML - ACS	ML reduced RMSE by 20% vs conventional	Single pathogen, hydroponic only	Direct pathogen detection with ML - KEY

		water using aptasensors	Omega 8(37)			
23	Sebela & Nemutandani, 2025	Water contamination in livestock production	Review - Am J Animal Vet Sci 20(4)	Impacts, causes, mitigation strategies	Livestock focus, not crop irrigation	Water contamination principles - transferable
24	Slongo et al., 2024	Evaluation of low-cost sensors for water quality monitor	Experimental - 19 sensors vs reference probe	Errors - 0.33% to 33.77%, pH/temp best	Controlled conditions only, fouling not assessed	Sensor accuracy evidence - KEY for critical appraisal
25	Song et al., 2023	Biosensors for waterborne virus detection	Review - J Pharm Analysis 13(11)	Challenges & strategies for virus detection	Virus vs bacteria differences	Viral hazard detection
26	Umutoni & Samadi, 2024	Application of ML approaches in supporting irrigation decision making	Review - Agric Water Mgmt 294,108710	ML supports irrigation decisions	Practical implementation gap	ML decision support - irrigation
27	US FDA, 2024	FSMA Final Rule on Pre-Harvest Agricultural Water	Regulatory rule - accessed 17/10/2026	Risk-based agricultural water assessment required	US-specific but broader principle relevant	Regulatory benchmark - risk-based management
28	Wei et al., 2024	Irrigation with AI: Problems, Premises, Promises	Review - Human-Centric Int Sys 4(2)	Potential and pitfalls of AI in irrigation	Overstatement risk highlighted	Balanced view of AI in irrigation
29	Yi et al., 2023	AI-enabled biosensing for rapid pathogen detection	Deep learning imaging - Water Res 242,120258	Prediction <5.5h, 80-100% accuracy in tested samples	Lab conditions, limited water sources	AI+biosensing integration - KEY example

Source: Author's Compilation, (2026).

Conceptual Framework for Digital Water Quality Monitoring and Pre-Harvest Safety

To guide this critical review, a conceptual framework was developed to link digital monitoring technologies with pre-harvest food safety decisions [Figure 1 below]. The framework distinguishes three

complementary technological domains that emerged from the final corpus of studies clustered between 2020 and 2026.

First, IoT-enabled sensors provide frequent measurements of general water quality parameters including pH, electrical conductivity (EC), turbidity, temperature and dissolved oxygen. These sensors support baseline characterization and anomaly detection but cannot independently confirm microbiological safety. Second, rapid biosensors and molecular methods including aptasensors, loop-mediated isothermal amplification (LAMP) and polymerase chain reaction (PCR) provide more direct detection of microbial hazards such as Escherichia coli. Their value depends on detection limits, sample preparation, matrix interference and field validation. Third, artificial intelligence and machine learning support pattern recognition, risk prediction and interpretation of multi-parameter data.

These three domains converge in an edge-cloud architecture. Edge computing enables local processing and alert generation where internet connectivity is limited, while cloud platforms support data storage and longer-term analysis. The processed information feeds into a decision support system comprising dashboards, alerts and risk assessment tools. The decision support outputs inform pre-harvest actions, including additional targeted sampling, irrigation management and mitigation measures. The final outcomes are improved food safety and sustainable agriculture, contributing to SDGs 2, 3, 6, 9 and 12. This framework was used to structure the critical appraisal in Section 3.

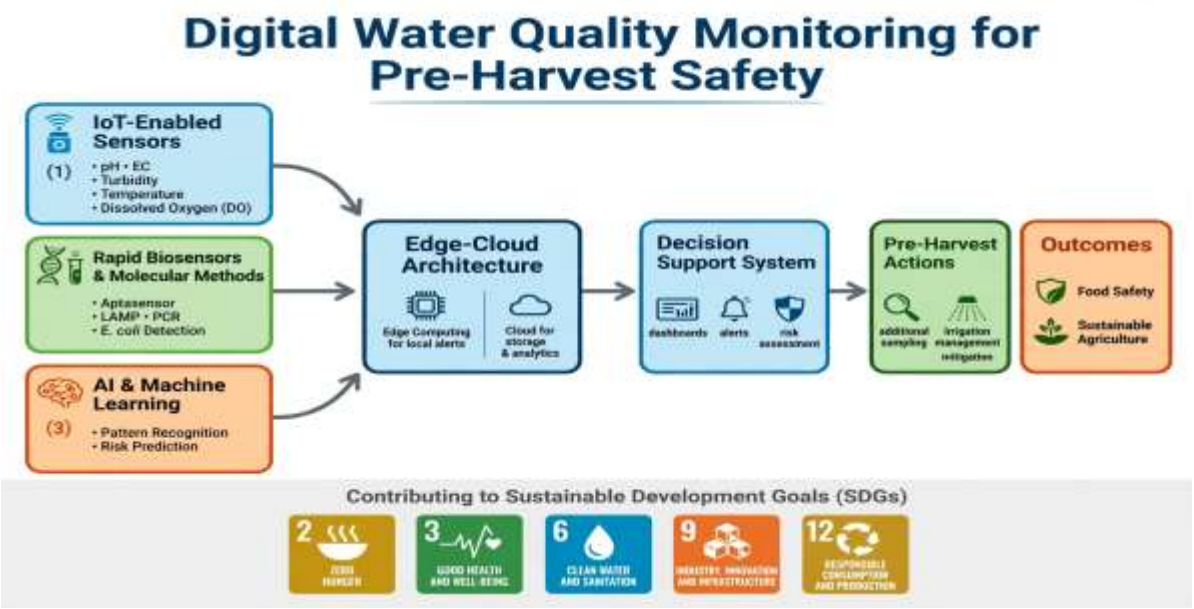


Figure 1. Conceptual framework for digital water quality monitoring for pre-harvest safety, integrating IoT-enabled sensors, rapid biosensors and molecular methods, and AI and machine learning through an edge-cloud architecture to support decision support and pre-harvest actions. Source: Author' Compilation, (2026).

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RESULTS AND DISCUSSION

Research Objective (RO)1: IoT-Enabled Water-Quality Monitoring and Rapid Biosensors

IoT Sensors and Real-Time Monitoring of Irrigation-Water Quality

The Internet of Things (IoT) makes it possible to monitor irrigation-water quality more frequently by connecting sensors to communication networks and digital platforms. Parameters such as pH, electrical conductivity (EC), temperature, turbidity and dissolved oxygen can be measured and viewed remotely. This helps farm managers notice changes that may need further investigation. However, frequent readings do not always mean that the measurements are accurate or useful for food-safety decisions. Much depends on sensor reliability and whether the parameters being measured are relevant to the problem (Glória et al., 2020; de Camargo et al., 2023; Nsoh et al., 2024). Low-cost sensors offer a more affordable way to monitor water, especially where multiparameter equipment and repeated laboratory tests are expensive. However, affordability does not necessarily mean that a device will perform well. In their systematic review of low-cost IoT water-quality sensors, de Camargo et al. (2023) found that relatively few studies compared these devices with reference instruments. Evidence on calibration, durability and performance under actual operating conditions was also limited. This makes it difficult to judge whether some sensors can provide reliable measurements over time.

Slongo et al. (2024) tested 19 low-cost sensors against a multiparameter reference probe and reported relative errors ranging from −0.33% to 33.77%, although most were 5% or less. The pH and temperature sensors performed best. These results show that sensor performance can vary considerably, so individual devices need to be assessed rather than assumed to be equally reliable. However, the tests were conducted under controlled conditions using real water samples. Their findings do not necessarily show how well the sensors would perform during prolonged use in irrigation channels, reservoirs or other agricultural settings. The potential value of IoT also depends on how the system is used. Glória et al. (2020) examined connected technologies for irrigation-water management, while Nsoh et al. (2024) reviewed the use of IoT and machine learning in automated irrigation management. Their work shows how connected systems can support agricultural monitoring and decision-making. Yet, better irrigation management is not the same as improved food safety. A system may help farmers manage water more efficiently without detecting microbial hazards or reducing contamination of fresh produce. Problems with interoperability, standardisation and cybersecurity may also affect its practical use. One important limitation is that common physicochemical measurements cannot confirm whether pathogens such as Escherichia coli O157:H7 or Salmonella are present. Changes in turbidity, pH or EC may signal unusual water conditions, but readings within the expected range do not guarantee that the water is free from microbial contamination. General water-quality monitoring and pathogen-specific detection must therefore be treated as related but different functions.

Sensor performance can also change after installation. Fouling, sediment build-up, measurement drift, temperature changes, power interruptions and communication failures may affect the quality or continuity

of recorded data. De Camargo et al. (2023) called for more long-term comparisons and field studies, while Slongo et al. (2024) highlighted the need for clearer operating and maintenance guidance. Calibration, repairs and replacement parts also add to the cost. For farms with limited technical support, these requirements may make it difficult to maintain a monitoring system over time. IoT sensors are therefore most useful for establishing baseline water conditions, identifying unusual changes and guiding further investigation. Their readings should be checked against suitable reference instruments, with calibration and performance assessed over time using representative agricultural water samples. Where microbial contamination is a concern, sensor measurements need to be complemented by validated rapid detection methods or appropriate laboratory testing. This approach makes it possible to benefit from frequent monitoring without treating general water-quality readings as proof of microbiological safety.

Rapid Biosensors for Detecting Microbial Hazards in Agricultural Water

Rapid biosensors and molecular methods can help reduce the waiting time associated with conventional microbiological testing. Biosensors use biological materials, such as antibodies, aptamers or nucleic-acid probes, to recognise specific organisms or their markers and produce a measurable signal. Molecular methods, including polymerase chain reaction (PCR) and loop-mediated isothermal amplification (LAMP), detect specific genetic material. However, getting a result quickly is not enough. The method must also detect the intended hazard reliably in agricultural water samples (Nnachi et al., 2022; Khodaparast et al., 2024). Agricultural water may contain suspended particles, other microorganisms and substances that interfere with detection. Khodaparast et al. (2024) highlighted sample preparation and nucleic-acid extraction as important steps in rapid molecular testing for waterborne pathogens. Nnachi et al. (2022) also discussed challenges in developing reliable bacterial biosensors. These issues matter because a test that performs well under controlled laboratory conditions may not work as effectively with water collected directly from farms. Sensitivity, specificity and the ability to handle different sample types all need to be considered. The organism being tested for also matters. Escherichia coli can be used as an indicator of faecal contamination, but detecting it does not necessarily mean that a particular disease-causing strain is present. A test for E. coli O157:H7, for instance, targets a specific pathogen, whereas a general E. coli test provides broader information about possible faecal contamination. A negative result for one organism also does not rule out the presence of others. Test results must therefore be interpreted in relation to the target organism and the intended use of the water.

Computational methods are beginning to improve how biosensor results are interpreted. Yi et al. (2023) developed an AI-enabled biosensing approach that used deep learning to analyse microscopic patterns produced by interactions between bacteriophages and target bacteria. They reported prediction times below 5.5 hours, with accuracy ranging from 80% to 100% in the water samples tested. This suggests that image analysis can support pathogen detection, even when samples contain other environmental material. However, these results relate to the organisms and experimental conditions examined. Performance in other water sources or agricultural settings still needs to be established. Qian et al. (2023) used a different approach, combining an impedimetric electrochemical aptasensor with statistical machine learning to estimate concentrations of pathogenic E. coli O157:H7 in surface water used for hydroponic lettuce production. Their selected model reduced test-set root mean square error (RMSE) by at least 20% compared with the conventional analytical method used in the study. This is particularly relevant to

agricultural water because the method focused on estimating the concentration of a specific pathogen rather than predicting general water-quality conditions. Still, the reported improvement does not establish that the same level of performance would be achieved across different farms, water sources or field conditions.

These studies show two ways AI can support rapid detection. Yi et al. (2023) used deep learning to interpret biological patterns, while Qian et al. (2023) applied machine learning to improve estimates from electrochemical measurements. In both cases, the quality of the result still depends on the underlying detection method. Reviews by Nnachi et al. (2022) and Kotsiri et al. (2022) also point to the need to assess biosensors across different targets and sample types. A false negative may allow contaminated water to go unnoticed, while a false positive can lead to unnecessary testing, treatment or restrictions on irrigation. For agricultural use, evaluation should go beyond speed and reported accuracy. Detection limits, sensitivity, specificity, repeatability, sample preparation and the time needed to obtain an actionable result are all important. Results should also be compared with appropriate reference microbiological or molecular methods. Field testing across different water sources and environmental conditions would provide a clearer picture of how these methods perform outside the laboratory. Rapid biosensors could make irrigation-water monitoring more responsive, but their results still need to be considered alongside other testing methods when assessing water safety.

Integration, Performance and Field Readiness of Digital Sensing Systems

Digital water-quality monitoring depends on how well sensors, communication networks, data-processing tools and decision-support systems work together. IoT systems can collect measurements regularly, send them remotely and display changes through dashboards or alerts. This reduces the need to rely entirely on manual observations (Glória et al., 2020; Nsoh et al., 2024). However, connecting these components does not automatically make monitoring accurate or improve food safety. The system must provide reliable data and help users make decisions based on what the measurements can actually show. One major limitation is that conventional water-quality sensors cannot directly confirm the presence of microbial hazards. Measurements of pH, electrical conductivity (EC), turbidity, temperature and dissolved oxygen can reveal changes in water conditions, but they cannot independently establish whether a particular pathogen is present. De Camargo et al. (2023), in their systematic review of low-cost IoT water-quality sensors, found limited comparisons with reference instruments and continuing uncertainties about calibration, accuracy and durability. Collecting readings more frequently does not necessarily make them reliable enough for food-safety decisions. The findings of Slongo et al. (2024) also show why individual sensors need to be assessed carefully. In their comparison of 19 low-cost sensors with a multiparameter reference probe, relative errors ranged from −0.33% to 33.77%, although most were 5% or less. The pH and temperature sensors performed particularly well under the test conditions. This suggests that low-cost devices may be useful for certain monitoring tasks, but their performance varies by sensor and parameter. Results from controlled tests also leave questions about long-term use in irrigation settings, where sediment, temperature changes and biofouling may affect measurements.

Problems can also arise when the different parts of a monitoring system are combined. Inaccurate readings may enter the system, network failures can interrupt data transmission, and software may mishandle

missing or unusual values. Nsoh et al. (2024) discussed interoperability, standardisation and cybersecurity challenges in IoT-based irrigation management. These concerns show that reliability involves more than the sensor itself. Data must also be transmitted, stored and processed correctly before they can support a useful decision. Maintaining performance after installation is another concern. Sensors may age, become fouled or develop calibration drift. Power interruptions and poor network access can also disrupt monitoring. De Camargo et al. (2023) highlighted the need for stronger evidence on long-term reliability, while Slongo et al. (2024) discussed the importance of operational and maintenance requirements. Regular calibration, repairs and replacement parts can be difficult to manage on farms with limited technical support. A device that performs well during initial testing may therefore prove less suitable for routine use once these costs and demands are considered.

A staged validation process would help establish whether a system is ready for practical use. Sensors should first be compared with suitable reference instruments using representative agricultural water samples. Where microbial detection is included, the method should also be checked against appropriate reference microbiological or molecular tests. The complete system then needs to be tested for data loss, transmission delays, power interruptions, alert accuracy and ease of use. AI-based predictions require independent testing as well, to determine whether they remain reliable beyond the data used to develop the model. El Bilali and Taleb (2024) also emphasised data reliability and uncertainty analysis in data-driven irrigation-water-quality management. The way alerts are interpreted matters just as much. For example, a rise in turbidity may justify inspecting the water source or carrying out further microbial testing, but it does not prove that a particular pathogen is present. A positive result from a pathogen-specific test raises a different concern and should be interpreted according to the test's established performance and the relevant water-safety procedures. Pilot studies should record measurement errors, false alarms, missed detections, maintenance needs and the actions taken after alerts. This would help show whether the system is useful beyond simply generating data. Digital sensing systems are most useful when reliable measurements, suitable microbial tests, dependable data handling and clear management procedures are combined. Their readiness should be judged by how well they perform under actual farming conditions and whether the information they provide supports appropriate action. Until this is established, digital monitoring should support risk-based irrigation-water management rather than replace necessary microbial testing or other confirmation procedures.

RO.2: Artificial Intelligence and Digital Decision Support for Irrigation-Water Safety

Machine Learning for Water-Quality Prediction and Contamination-Risk Assessment

Machine learning (ML) can help assess water quality by identifying patterns in data, predicting water-quality parameters and flagging unusual conditions. Methods such as random forests, support vector machines and artificial neural networks have been used for water-quality prediction and irrigation management. However, their usefulness depends on what they are designed to predict and the quality of the data available. Predicting salinity or a water-quality index is not the same as detecting microbial hazards, even when both tasks rely on sensor readings (El Bilali & Taleb, 2024; Wei et al., 2024). Mokhtar et al. (2022) showed that more complex algorithms do not always give better results. In their study of irrigation-water-quality indices in Egypt, they compared support vector machines, extreme gradient

boosting and random forests with several regression methods. Stepwise regression performed best according to their reported evaluation measures. This challenges the idea that advanced ML models will always outperform conventional statistical methods. The choice of model should depend on the problem being studied, the available data and how its performance is tested.

Studies from Nigeria also show the potential of ML in water-quality assessment. Omeka et al. (2024a) compared multilayer perceptron neural networks with multilinear regression to predict irrigation-water-quality parameters in the Lower Benue Trough. The neural network performed better across the reported evaluation measures. In another study, Omeka et al. (2024b) combined geographic information system (GIS) techniques, the analytical hierarchy process (AHP) and ML to assess irrigation-water suitability in an agricultural-mine district in Nigeria. These approaches can help identify suitable areas for irrigation. However, because they focus on physicochemical parameters, their findings do not establish whether the water is microbiologically safe. This distinction matters for pre-harvest food safety. Electrical conductivity, salinity and general water-quality indices cannot independently confirm whether irrigation water contains Salmonella or pathogenic Escherichia coli. El Bilali and Taleb (2024) stressed the importance of reliable input and output variables, sensitivity analysis and uncertainty assessment in ML applications. Mustapha et al. (2025) also identified challenges involving model generalisability and inconsistencies in water-quality indices. Even a model with good reported performance may be unreliable if the input data are unsuitable or the validation is weak.

ML can be more directly useful for microbial risk assessment when it works with signals from a biological detection method. Yi et al. (2023), for example, combined biosensing with deep learning to identify and quantify target bacteria from microscopic patterns produced through bacteriophage interactions. They reported prediction times below 5.5 hours and accuracy ranging from 80% to 100% in the water samples evaluated, including samples with environmental interference. This provides more direct evidence of pathogen detection than a model based only on physicochemical measurements. However, the results apply to the organisms and detection method studied. They do not establish that similar performance would be achieved with other pathogens or under different agricultural conditions. Model errors also need careful attention because they can affect water-safety decisions. Overall accuracy may appear high even when a model fails to identify some contaminated samples, particularly where positive cases are uncommon. Sensitivity, specificity, false-negative rates and uncertainty should therefore be examined alongside comparisons with suitable reference methods. Testing the model on independent data can show whether its performance extends beyond the original dataset. Differences in seasons, water sources and environmental conditions may still affect its reliability. For pre-harvest safety, ML is best used to support decisions rather than independently certify irrigation water as safe. Depending on its intended and validated purpose, it can flag unusual readings, help prioritise samples for further testing or interpret signals from pathogen-specific sensors. Predictions based on indirect water-quality indicators should not replace microbial testing or established water-safety procedures. What matters is not simply how accurately a model predicts, but whether its predictions are reliable enough to support the decisions farmers need to make.

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Edge–Cloud Architectures and Real-Time Irrigation Decisions

The value of AI-based water monitoring depends not only on sensor accuracy or model performance, but also on how quickly the results can guide irrigation decisions. Edge–cloud architectures divide processing between local devices and remote platforms. Edge devices process data close to the sensors, while cloud platforms support data storage, model training and the analysis of longer-term patterns. This allows some decisions to be made quickly without losing the benefits of more detailed analysis (Bouziane et al., 2026; Badr & Noor, 2026). The two levels of processing serve different purposes. A microcontroller or gateway can check readings against predefined limits and trigger a local alert, even when internet access is unavailable. Cloud processing is more suitable for analysing historical records and running computationally demanding models. Badr and Noor (2026) demonstrated the potential of this arrangement for agricultural monitoring and irrigation management. However, their focus on water–energy management and crop production does not establish whether the system can detect microbial hazards in irrigation water.

Bouziane et al. (2026) examined water-quality monitoring more directly. They developed an IoT–edge–cloud architecture that calculated a water-quality index at the edge and used a stacking ensemble model to predict changes from physicochemical measurements in Morocco's Moulouya River Basin. The reported coefficient of determination () of 0.945 indicates strong predictive performance under the study conditions. However, simulation-based testing and the use of physicochemical measurements leave questions about long-term field performance and pathogen detection. A model that predicts a water-quality index accurately cannot, on that basis alone, confirm whether specific pathogens are present. The processing arrangement should match the decision being made. Local alerts can flag unusual readings quickly, while forecasting may require historical data and cloud-based analysis. Microbial detection presents a different challenge. Some methods require sample preparation and pathogen-specific testing, and faster computing cannot remove the time needed for these procedures. The system must support the detection method rather than be expected to replace it.

In practice, connectivity and maintenance can also cause problems. Poor internet access may interrupt cloud analysis, sensor failures can leave gaps in the data, and incompatible communication protocols may prevent devices from exchanging information. Cloud services can also add recurring costs and data-security concerns. Nsoh et al. (2024) identified interoperability, standardisation and cybersecurity as challenges in IoT-based irrigation management. These limitations may be particularly difficult for farms with weak infrastructure or limited technical support. A more reliable system would keep essential monitoring and alert functions available locally, flag missing or questionable readings, and synchronise stored data when the connection returns. Recording when measurements are taken, processed and communicated would help reveal delays that could affect decisions. Access controls, data backups and careful model updates are also needed to maintain dependable operation. For pre-harvest safety, edge–cloud computing provides the infrastructure for monitoring and decision support, but it does not guarantee that irrigation water is safe. Its usefulness depends on reliable measurements, validated predictions and clear procedures for responding to alerts. Field testing should examine response times, communication failures, maintenance needs and whether users can interpret the information correctly. This is especially

important where internet access is unreliable or suspected microbial contamination requires separate confirmation.

Reliability, Explainability and Transferability of AI-Based Monitoring

The reliability of AI-based water-quality monitoring depends on more than how accurately a model performs during testing. It also matters whether the model can produce dependable results across different water sources, seasons and operating conditions. A model developed using data from one location may perform less well elsewhere because water composition, environmental conditions and sensor characteristics can vary (El Bilali & Taleb, 2024). Mustapha et al. (2025) also raised concerns about localised datasets, inconsistent water-quality indices and limited real-time monitoring. Good results from one dataset do not necessarily mean that a model is ready for wider use. Model performance should be assessed using measures that suit the task. For regression models, the coefficient of determination (), mean absolute error (MAE) and root mean square error (RMSE) can show how closely predictions match observed values. Classification models require other measures, including sensitivity, specificity and false-negative rates. The latter is particularly important when missed detections could allow contaminated water to be used for irrigation. Testing with independent data from different locations or periods would also provide stronger evidence of transferability than simply dividing the original dataset into training and test sets. The consequences of errors differ too: inaccurate physicochemical predictions may lead to poor water-management decisions, while a false-negative microbial result may leave a pathogen undetected. It is also useful to understand how an AI model arrives at its predictions. Techniques such as SHapley Additive exPlanations (SHAP) can show how individual input variables contribute to a model's output. Bouziane et al. (2026), for example, incorporated SHAP into an IoT–edge–cloud framework for water-quality prediction. This can make results easier to interpret, but an explanation does not prove that a prediction is correct. A model may identify influential variables and still perform poorly when used with unfamiliar data or under different field conditions.

Reliable monitoring also has potential links with the Sustainable Development Goals (SDGs). Better-informed irrigation decisions may support SDG 2 (Zero Hunger) through safer agricultural production, SDG 3 (Good Health and Well-being) by helping to reduce food-safety risks, and SDG 6 (Clean Water and Sanitation) through improved water-quality management. Affordable, maintainable technologies are relevant to SDG 9 (Industry, Innovation and Infrastructure), while reducing contamination risks in fresh produce relates to SDG 12 (Responsible Consumption and Production). These contributions should not be assumed simply because a digital system has been developed. They depend on whether it works reliably and is used effectively in practice. Farmers must also be able to understand and maintain the systems. Confusing alerts, high maintenance costs, poor connectivity and incompatible technologies can discourage adoption, even where a model performs well during testing. Wei et al. (2024) highlighted the importance of human-centred design and understandable outputs, while Nsoh et al. (2024) discussed interoperability, standardisation and cybersecurity challenges. These practical issues can determine whether a monitoring system remains useful beyond an initial trial. For pre-harvest safety, AI predictions should support risk-based management rather than be treated as proof that irrigation water is safe. Where microbial contamination is a concern, appropriate testing for relevant pathogens or indicator organisms remains necessary. Wider application also requires transparent reporting, independent validation and clear

guidance on the limits of the predictions. Users need to know not only what a model indicates, but also when its results are uncertain and when further testing is required.

RO3: Research Gaps and Implementation of Digital Monitoring for Pre-Harvest Safety

Methodological and Validation Gaps

The studies reviewed in Sections 3.1 and 3.2 show progress in IoT-based sensing, rapid biosensors and machine learning for water-quality assessment. However, not all this evidence directly addresses pre-harvest food safety. Many systems focus on physicochemical parameters or general water-quality indices, while pathogen-specific detection serves a different purpose. A model may predict water quality accurately without showing whether irrigation water contains microbes that could contaminate fresh produce. One major gap is the limited evidence on sensor performance under actual agricultural conditions. De Camargo et al. (2023) identified weaknesses in the evaluation of low-cost IoT water-quality sensors, including limited comparisons with reference instruments and uncertainties about calibration and long-term performance. Short-term experiments may not show how well sensors perform across different water sources or after prolonged use. Field studies need to examine fouling, calibration drift, maintenance needs and changes in performance over time. Another concern is the difference between indirect water-quality indicators and direct microbial detection. Turbidity, pH and electrical conductivity can reveal changes in water conditions, but they cannot independently confirm the presence of a particular pathogen. Rapid biosensors and molecular methods offer more targeted detection, although their performance in complex environmental samples also needs to be established (Nnachi et al., 2022; Khodaparast et al., 2024). Studies should clearly distinguish between measuring general water quality, estimating contamination risk and detecting specific microbial targets. Without this distinction, the food-safety value of a digital system may be overstated.

Machine-learning studies raise further questions about prediction targets and transferability. Mokhtar et al. (2022) and Omeka et al. (2024a, 2024b) demonstrate the use of statistical and machine-learning methods to assess water-quality parameters or irrigation suitability. However, these applications do not establish that the models can detect pathogens. El Bilali and Taleb (2024) emphasised data reliability and uncertainty, while Mustapha et al. (2025) identified limited generalisability and localised datasets as continuing challenges. Models need to be tested with independent data from different locations and seasons, rather than relying only on random splits of the original datasets. The choice of evaluation measures also matters. A model may report high overall accuracy but still miss contaminated samples, especially when contamination events are uncommon. Classification studies should report sensitivity, specificity and false-negative rates, alongside uncertainty and comparisons with appropriate reference methods. These results would help establish whether a system can be trusted to support water-safety decisions, rather than simply perform well during testing. Finally, good technical performance does not automatically lead to better food safety. A sensor may measure water conditions accurately, or a model may predict a parameter successfully, without showing that the information leads to appropriate action or reduces contamination of fresh produce. Yi et al. (2023) and Qian et al. (2023) represent progress towards more direct microbial detection, but their findings remain specific to the methods and conditions studied. Further research should examine the full process, from detecting a potential hazard to issuing an alert and

taking action. This includes whether alerts are reliable, how users respond and whether those responses actually reduce contamination risks. Such evidence is needed to determine the practical value of digital monitoring for pre-harvest food safety.

Technical and Practical Barriers to Adoption

Good technical performance does not guarantee that digital monitoring systems will remain useful on farms. Equipment costs, electricity supply, network coverage, maintenance and access to technical support all affect whether farmers can use them over time. De Camargo et al. (2023) identified gaps in the evidence on the reliability of low-cost sensors for specific applications. Although these devices may be cheaper to purchase, calibration, repairs and replacement parts add to the long-term cost. Connectivity and compatibility can also cause problems. IoT systems rely on communication between sensors, devices and software platforms. Network interruptions may delay alerts or leave gaps in monitoring records, while incompatible technologies can make data sharing difficult. Nsoh et al. (2024) identified interoperability, standardisation and cybersecurity as important challenges in IoT-based irrigation management. Monitoring platforms should be able to flag missing or unreliable readings instead of treating incomplete data as evidence that water conditions are satisfactory.

Rapid microbial detection methods have their own limitations. Some biosensors and molecular techniques require sample preparation, specialised materials, trained personnel or additional equipment. Khodaparast et al. (2024) highlighted sample preparation and nucleic-acid extraction as important considerations in rapid molecular testing. These requirements may make routine use difficult where laboratory facilities and technical support are limited. The practicality of a method therefore depends on the full testing process, including sample collection, analysis, interpretation and any action needed afterwards. Farmers and water managers also need to understand how to use the information provided. They should know what each sensor measures, what an alert means and when further testing is required. Without adequate training, users may mistake indirect water-quality measurements for evidence of a particular pathogen or place too much trust in automated recommendations. Clear operating procedures, defined responsibilities and access to technical guidance can help prevent these problems.

There is also the question of what happens after an alert. Detecting a possible hazard may have little practical benefit if alternative water supplies, confirmatory testing or suitable treatment options are unavailable. On the other hand, repeated false alarms can lead to unnecessary testing or interruptions to irrigation. The Codex Alimentarius Commission (2023) supports a risk-based approach to determining water suitability for its intended use in food production and processing. Monitoring results should therefore guide appropriate responses based on the potential risk, rather than trigger the same action whenever a sensor reading changes. These barriers often overlap. A sensor may be accurate but become unreliable without regular maintenance. An affordable platform may also offer little benefit if farmers cannot understand the results or take action when needed. Pilot studies should therefore assess running costs, equipment failures, connectivity, user experience and access to follow-up testing, alongside technical performance. This would help establish whether digital monitoring is practical beyond short-term demonstrations and what support is needed to keep it working on farms.

Practical Pathways for Integrating Monitoring into Water-Safety Management

The gaps identified in the preceding sections suggest that digital monitoring should be part of a wider water-safety management process, not a stand-alone solution. Implementation should start by defining what needs to be monitored and which hazards are of concern. A system designed to track general water-quality changes will require different measurements and validation from one intended to detect specific pathogens. Sensor selection, testing methods and decision thresholds should reflect the intended use of the water and the decisions the results are expected to support. One practical approach is to combine frequent physicochemical measurements with planned microbiological testing and additional tests when risk indicators change. IoT sensors can track variations in turbidity, pH and electrical conductivity, helping users identify conditions that need investigation. However, these measurements cannot confirm microbial contamination on their own. Where specific pathogens are a concern, validated biosensors or molecular methods can provide more direct evidence about the target organisms (Nnachi et al., 2022; Khodaparast et al., 2024). This combination allows digital monitoring to provide frequent updates while retaining appropriate microbial testing.

Machine learning could also help identify unusual patterns, predict selected water-quality parameters or prioritise samples for further investigation. Its use must match the task for which the model was developed and validated. El Bilali and Taleb (2024) and Mustapha et al. (2025) highlighted concerns about data reliability and the ability of models to perform across different conditions. A model trained to predict physicochemical indices should not be treated as a pathogen-detection tool unless it has been specifically developed and validated for that purpose. Users also need clear information about prediction targets, uncertainty and limitations. Clear procedures are needed for responding to monitoring results. A change in general water-quality parameters may call for repeat measurements, equipment checks or additional microbial testing. A confirmed pathogen detection may require more immediate action, depending on the organism and intended use of the water. Procedures should state who reviews alerts, how unexpected results are confirmed and when irrigation should be reconsidered. These decisions should follow documented risk assessments rather than depend on isolated sensor readings. The Codex Alimentarius Commission (2023) provides international guidance for risk-based water-safety management in food production and processing.

Implementation should begin with testing and progress towards routine use only when the evidence supports it. Initial assessments should compare sensor readings and microbial test results with suitable reference methods. Pilot studies should then examine how the complete system performs under actual operating conditions, including calibration needs, sensor fouling, data loss, communication delays, false alarms and missed detections. Longer-term assessments should also consider seasonal changes, maintenance costs and access to technical support. Researchers, extension services, laboratories, technology providers and relevant authorities could work together to address these practical needs. Governance and local conditions also matter. Guidance should cover sampling frequency, data quality, record keeping, interpretation and responsibility for responding to possible hazards. In Nigeria, implementation should reflect applicable national regulations, local water sources, laboratory access and farmers' technical capacity. Although Codex guidance provides an international reference, it should not automatically be treated as binding Nigerian law. Evaluation should go beyond counting installed sensors

or recorded measurements. More useful indicators include detection sensitivity, false-negative rates, alert response times, system availability, maintenance costs and the suitability of management decisions. Claims that digital monitoring improves pre-harvest food safety also need evidence linking monitoring results to actions and reductions in contamination or exposure risks. Combining validated sensors, appropriate microbial testing, carefully evaluated predictive models and clear response procedures provides a stronger basis for managing irrigation-water safety.

Synthesis of Selected Literature

The studies reviewed in Sections 3.1–3.3 show three main areas of development in digital water-quality monitoring: connected sensors for regular monitoring, rapid methods for detecting microbial hazards, and artificial intelligence (AI) for analysing data and supporting irrigation decisions. However, the studies do not all address pre-harvest food safety directly. Some examine sensor performance, others focus on detecting specific pathogens, while several AI studies predict physicochemical water-quality parameters or assess irrigation-water suitability. Good results in one area do not necessarily mean that a system can reliably detect microbial hazards or reduce produce contamination. Table 1above brings together selected studies and reviews, comparing their methods, main findings, limitations and relevance to pre-harvest food safety. Looking across the evidence helps show where the approaches agree, how they differ and which gaps remain. It also helps distinguish findings supported by direct pathogen-detection studies from those whose contribution to food safety is still indirect or needs further validation.

Critical Synthesis of the Evidence

The studies in Table 4 show growing interest in using digital sensors, artificial intelligence (AI) and rapid detection methods to monitor irrigation water. However, their relevance to pre-harvest food safety varies. IoT systems and low-cost sensors allow water conditions to be checked more frequently (Glória et al., 2020; de Camargo et al., 2023), while biosensor reviews focus more directly on detecting microbial hazards (Nnachi et al., 2022; Kotsiri et al., 2022). Both have a role to play, but monitoring general water-quality parameters cannot confirm that water is free from harmful microorganisms. Machine learning is also being used to predict water-quality parameters and assess whether water is suitable for irrigation. Mokhtar et al. (2022) compared machine-learning models with regression methods, while Omeka et al. (2024) examined predictive modelling and spatial assessment in Nigerian agricultural settings. El Bilali and Taleb (2024) and Mustapha et al. (2025) discussed the potential of data-driven methods, alongside concerns about data quality, model reliability and practical use. These approaches can support water management, but predicting physicochemical parameters or a water-quality index is not the same as detecting pathogens. Differences in the data, prediction targets and validation methods also make it difficult to compare model performance or assume that a model will work equally well in other locations. Rapid microbial detection methods have a more direct link to pre-harvest safety. Nnachi et al. (2022), Kotsiri et al. (2022) and Khodaparast et al. (2024) examined different biosensing and molecular methods, while Qian et al. (2023) investigated machine-learning-assisted aptasensing for pathogenic Escherichia coli O157:H7 in hydroponic irrigation water. Yi et al. (2023) also explored AI-enabled biosensing and reported promising results under the conditions tested. These findings are encouraging, although they do not show that the methods will perform consistently across different pathogens, water sources or farm settings. Sample preparation, interference from other substances and independent validation still need

attention. One issue runs across much of the literature: good technical results do not necessarily translate into better food safety. Sensors need suitable calibration and continued performance checks, while AI models and rapid detection methods must be tested under conditions that reflect their intended use. Even when a system produces accurate readings or timely alerts, its value depends partly on how people interpret and respond to the information. Integrating IoT monitoring with validated microbial testing and carefully assessed AI tools is therefore more defensible than relying on any single technology. Further research needs to establish how reliably these integrated systems perform under field conditions and whether the information they provide leads to appropriate management decisions. It is also important to determine whether those decisions help reduce microbial exposure or contamination risks. Evidence on these practical outcomes would give a clearer picture of the contribution digital monitoring can make to pre-harvest food safety.

Gaps in the Literature

The reviewed studies show growing interest in combining Internet of Things (IoT) sensors, rapid biosensors and artificial intelligence (AI) for water-quality monitoring. However, there is still limited evidence on how well these technologies can support pre-harvest food safety in practice. The main issue is whether they can reliably identify microbial hazards and provide information that helps farmers make appropriate irrigation decisions. One important gap is the difference between general water-quality monitoring and detecting specific pathogens. Many IoT systems measure physicochemical parameters, while machine-learning models predict water-quality indices or classify water according to its suitability for irrigation. Although these approaches can reveal changes in water conditions, they cannot independently confirm whether specific pathogens are present. De Camargo et al. (2023) also identified weaknesses in comparisons with reference instruments, sensor calibration and evidence of long-term performance. More research is needed to show how these monitoring systems can work alongside validated microbial tests without treating indirect indicators as proof of microbiological safety. The reliability of these technologies under actual farming conditions also needs further investigation. A sensor or detection method that performs well in a controlled experiment may not produce the same results across different water sources, seasons and agricultural environments. Fouling, calibration drift, interference from other substances and communication failures can affect performance. Rapid detection methods need careful assessment too, including their detection limits, sensitivity, specificity and the time required to produce a result that can guide action. Longer-term field studies using suitable reference methods would help establish how dependable these technologies are beyond initial testing.

AI model transferability is another concern. Models developed using data from particular locations may perform less well elsewhere, especially when water conditions, measurement procedures or data quality differ. Independent testing and clearer reporting of uncertainty would help determine whether predictions remain reliable under changing conditions. It is also worth examining how farmers and water managers understand these predictions. An accurate model may offer little practical benefit if its alerts are confusing or users are unsure how to respond. The link between technical performance and actual food-safety improvements remains unclear in the literature reviewed. Faster detection or more accurate prediction does not, by itself, show that pathogen exposure has been reduced or that produce is safer. Studies need to examine whether monitoring leads to timely action and better water-safety management, rather than

reporting technical results alone. Research in Nigeria and similar agricultural settings is also needed to assess affordability, network access, maintenance requirements and suitability for local water sources. These factors will influence whether digital monitoring can be used reliably beyond controlled trials.

Contribution of the Current Review

This review brings together research on Internet of Things (IoT) sensors, rapid biosensors, artificial intelligence (AI) and digital decision-support systems, with a focus on pre-harvest food safety. Previous studies have examined these technologies from different angles, but their value depends on the water-safety problem they are meant to address. Rather than simply describing new developments, this review examines what each approach can do, where its limitations lie and how the technologies might work together in agricultural water management.

First, the review distinguishes between general water-quality monitoring and the detection of specific pathogens. IoT sensors can measure parameters such as pH, electrical conductivity, turbidity and temperature at regular intervals. Rapid biosensors and molecular methods, on the other hand, can target selected microorganisms or their genetic material. AI models that predict water-quality indices serve a different purpose and should not automatically be treated as pathogen-detection tools. This distinction helps clarify which methods are suitable for particular monitoring needs and prevents general water-quality results from being mistaken for evidence of microbiological safety.

Second, the review examines how these technologies can complement one another. Connected sensors provide regular information about water conditions, rapid biosensors can detect selected microbial hazards, and AI can help interpret sensor signals, identify patterns or predict certain parameters. Qian et al. (2023) and Yi et al. (2023) illustrate progress in combining microbial detection with computational analysis. However, combining technologies does not necessarily make a system more reliable. Each component must perform well, and the integrated system needs to be tested under the conditions in which it is intended to operate.

Third, the review considers practical requirements alongside technical performance. Calibration, validation, uncertainty, model transferability, maintenance and network access all affect whether a monitoring system can be used reliably on farms. The review also draws attention to what happens after a reading or alert is produced. Monitoring is of limited value if users cannot interpret the results or take appropriate action, such as arranging further testing or changing water-management practices.

Fourth, the review considers Nigerian research alongside international evidence. Omeka (2024) and Omeka et al. (2024) illustrate the use of data-driven methods to assess water-quality parameters and irrigation-water suitability. These applications offer useful insights into water management, but they do not by themselves establish microbiological safety. Their wider application also depends on validation in other locations and under different conditions. The Nigerian context brings practical concerns into focus, including affordability, maintenance, connectivity and access to suitable testing facilities.

The review therefore provides a critical assessment of how IoT, rapid biosensors and AI may contribute to pre-harvest water-safety management. It identifies areas where the evidence is promising and where further work is needed, particularly in field validation and the link between monitoring results and actual food-safety outcomes. Its contribution is an evidence-based synthesis and direction for future research, rather than the development or experimental validation of a new monitoring system.

CONCLUSION

This review examined how digital water-quality monitoring could support pre-harvest food safety, focusing on Internet of Things (IoT) sensors, rapid biosensors, artificial intelligence (AI) and machine learning (ML) in irrigation management. The literature covered connected sensing and microbial detection, AI-based water-quality prediction, and the technical and practical challenges that affect the use of these technologies in agriculture. The reviewed studies show that IoT sensors can provide frequent measurements of physicochemical parameters, transmit data remotely and help identify changes in irrigation-water conditions. However, their usefulness depends on accurate measurements, regular calibration, maintenance and reliable data transmission. More frequent readings do not necessarily mean safer water. Parameters such as pH, electrical conductivity and turbidity cannot independently confirm whether specific pathogens are present, so general water-quality monitoring needs to be complemented by appropriate microbial testing. Rapid biosensors and molecular methods offer a more direct way to detect selected microbial hazards and may reduce the time needed to obtain results. Combining these methods with AI also shows promise for interpreting complex signals and estimating pathogen concentrations. Still, performance can vary with the target organism, sample characteristics and testing conditions. Comparisons with suitable reference methods, field validation and careful assessment of false-positive and false-negative results are needed before these approaches can be relied upon for routine irrigation decisions.

AI and ML can help predict water-quality parameters, identify unusual patterns and support irrigation management. Their limitations must also be recognised. Predicting physicochemical characteristics does not establish microbiological safety, and a model that performs well with one dataset may not work equally well elsewhere. Data quality, independent validation, uncertainty and changing environmental conditions all affect reliability. The literature reviewed also provides limited evidence that digital monitoring, by itself, leads to less contamination of fresh produce or measurable improvements in food safety. The findings support combining connected sensors, validated microbial testing and appropriately evaluated AI tools within a risk-based water-safety management approach. Clear procedures are needed to interpret alerts, confirm suspected hazards and decide what action to take. In Nigeria and similar agricultural settings, further work should focus on affordable technologies, local validation, longer-term field testing, maintenance requirements and evidence that monitoring leads to effective interventions. Digital monitoring may also contribute to the Sustainable Development Goals (SDGs). Better-informed water management could support SDG 2 (Zero Hunger), while efforts to reduce food-safety risks relate to SDG 3 (Good Health and Well-being). Improved water-quality management is relevant to SDG 6 (Clean Water and Sanitation), the development of affordable and maintainable technologies to SDG 9 (Industry, Innovation and Infrastructure), and the prevention of contamination in fresh produce to SDG 12

(Responsible Consumption and Production). These contributions, however, depend on how well the technologies work in practice and whether their use leads to better water-safety management. Their adoption alone is not evidence of improved food safety.

Recommendations

Based on the findings of this review, the following recommendations are proposed to improve the use of digital water-quality monitoring for pre-harvest food safety.

1. Combine physicochemical monitoring with microbial testing. Agricultural water-monitoring programmes should use IoT sensors to track general water conditions and include validated microbiological or molecular tests where microbial hazards are a concern. Changes in pH, turbidity or other indicators may signal the need for further investigation, but they should not be treated as proof that pathogens are present or absent.
2. Improve field testing and quality assurance. Researchers and technology developers should compare sensors and rapid biosensors with suitable reference methods using representative agricultural water samples. Testing should cover accuracy, sensitivity, specificity, detection limits, repeatability, and false-positive and false-negative results. Longer-term field trials are also needed to assess calibration drift, sensor fouling, equipment failures and maintenance needs.
3. Make AI models more reliable across different settings. AI and ML models should be tested with independent datasets and, where possible, data from different water sources, locations and seasons. Researchers should report suitable performance measures and explain the uncertainty and limitations of their predictions. A model that predicts physicochemical parameters should not be presented as a pathogen-detection tool unless that ability has been specifically demonstrated and validated.
4. Link monitoring alerts to clear actions. Digital platforms should provide guidance on what to do when unusual readings or suspected hazards are detected. This may involve checking the equipment, repeating measurements, arranging confirmatory testing or reconsidering the use of the water, depending on the risk. Farmers and water managers also need training to interpret results and understand system limitations. Affordability, electricity supply, network access, maintenance and data security should be considered when choosing and installing these systems.
5. Give greater attention to local research and field application. Researchers in Nigeria and similar agricultural settings should test these technologies across different irrigation-water sources and farming conditions. Studies should consider purchase and running costs, maintenance requirements and ease of use, as well as technical performance. They should also investigate whether monitoring leads to quicker, more appropriate decisions and better water-safety practices. Accurate sensor readings or strong model predictions alone are not enough to demonstrate reduced contamination risk.

Putting these recommendations into practice would help ensure that monitoring technologies are selected for the hazards they are intended to assess, tested under relevant conditions and used as part of wider water-safety management. They may also support SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-being) and SDG 6 (Clean Water and Sanitation) through safer agricultural production, reduced food-safety risks and better irrigation-water management. Developing suitable technologies and local technical capacity is relevant to SDG 9 (Industry, Innovation and Infrastructure), while preventing irrigation-water contamination from affecting fresh produce relates to SDG 12 (Responsible Consumption and

Production). Progress should be judged by evidence of reliable monitoring, appropriate responses and improvements in water-safety practices, rather than by technology adoption alone.

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