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Emerging trends in IoT for aquatic systems: a systematic literature review

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Climate change, pollution, and the overexploitation of water resources have intensified global water scarcity, particularly in arid and semi-arid regions. This systematic literature review analyzes 458 peer-reviewed articles published between 2015 and 2025 to identify the main IoT-based technological strategies applied to the monitoring and management of surface and groundwater systems. Following PRISMA guidelines, the studies were categorized into four thematic areas: IoT applications in aquatic environments, data transmission technologies, algorithms for process optimization and data analysis, and sensor fusion techniques. The results show that LoRa is the most widely adopted transmission technology due to its long-range coverage, scalability, and low energy consumption. Emerging innovations such as remote IoT, satellite-assisted sensing, and digital twins are also gaining relevance as transformative tools for real-time hydrological monitoring. Overall, the findings reveal a shift toward more integrated and intelligent IoT frameworks and include a recommended architecture for aquatic systems. Despite these advancements, the review highlights the need for more accessible, affordable, and interoperable IoT solutions to enable broader adoption, particularly in resource-constrained regions, and to support sustainable water resource management.

KEYWORDS

Internet of Things, sensor fusion, systematic literature review, water quality, water resources

1 Introduction

Water is one of the most vital resources for sustainability on the planet. Over 70% of the Earth's surface is covered by surface water, complemented by a substantial amount of groundwater. However, this distribution is globally altered owing to climate change and the degradation of numerous water sources contaminated by various factors (Pointet, 2022). Consequently, this essential resource is becoming increasingly scarce, affecting both human consumption and ecosystems that rely on its potability (Shemer et al., 2023). In response, numerous global strategies have been implemented to protect these resources. These initiatives range from the conservation of mangroves and their habitats to environmental regulations aimed at safeguarding rivers, wetlands, specific water sources, and seas, all of which aim to reduce pollution and overexploitation (Kumar and Choudhury, 2024).

Put simply, the core problem is that climate change, pollution, and overexploitation are reducing the availability of safe water. This motivates the search for new tools that can monitor and manage water resources more efficiently. This study aims to identify and analyse the application of the Internet of Things (IoT) and related technologies are being applied in this field, highlighting their applications, strengths, and challenges. In doing so, the review seeks to provide an integrated perspective that can guide both researchers and policymakers in designing more sustainable and accessible solutions. Countries such as the United States, China, and Canada, as well as various regions of Asia (Wang and Xu, 2024), have intensified their conservation efforts, recognizing the growing challenges that future generations may face owing to population growth and current environmental issues (Aiche et al., 2024). In parallel, the development of IoT has witnessed significant growth over the past two decades (Yalli et al., 2024). Originally designed to interconnect devices and facilitate various aspects of daily life, the IoT has valuable applications in monitoring and controlling water sources (Rahu et al., 2024). Although some countries have managed hydrological data for decades, many developing nations lack such historical data, limiting their ability to make informed decisions regarding water management. Furthermore, the integration of the IoT with areas of artificial intelligence (AI) has expanded the scope of these technologies, enabling a deeper understanding of the current state of water resources and the formulation of strategies for their sustainable management (Miller et al., 2025).

This article presents a Systematic Literature Review (SLR) aimed at identifying the main Internet of Things-based models applied to the monitoring of surface and groundwater resources in the last decade. It provides a detailed examination of the sensor technologies, transmission systems, and monitoring platforms used to record variables related to water quality, pollution, and water level. Particular emphasis is placed on emerging trends, with a deliberate focus on groundwater studies, given their limited representation in the existing literature, despite their critical role as a strategic resource in arid and semi-arid regions worldwide, where they offer key solutions to address the water scarcity (Bouchaou et al., 2024).

Supplementary Figure S1 highlights the growing interest in implementing electronic tools for monitoring and managing water resources. To obtain these results, the Scopus and Web of Science (WoS) databases were queried using a logical equation that included terms related to sensor networks, algorithms, groundwater, and surface water. The analysis revealed a remarkable increase in publication rates, with growth in both cases exceeding 900% between 2017 and 2025. These findings underscore the contemporary relevance of the topic and the increasing need to integrate technological resources for the sustainable and effective management of water resources.

The core contributions of this study can be divided into three main points:

(a) Identification of the most relevant IoT technologies for effective water resource monitoring
(b) Classification of key domains within AI and IoT as enabling tools for monitoring and sustainable management of surface water and groundwater systems.
(c) Analysis of prevailing global trends in the development of sensor networks, computational algorithms, and communication technologies tailored for aquatic environments.

The remainder of this article is structured as follows: Section 2 outlines the methodological framework adopted for this systematic review. Section 3 presents the findings of the cluster analysis performed using the CiteSpace tool (https://citespace.podia.com/). Section 4 offers an in-depth discussion of the identified research trends, followed by Section 5, which addresses the specific research questions established at the outset. Section 6 introduces an IoT-based architecture applicable to both shallow and deep aquifer systems. Finally, Section 7 presents the main conclusions and recommendations to guide future research directions.

2 Research methodology

2.1 The SLR process

SLRs have gained popularity over the past seven decades (Barrios-Ulloa et al., 2022). This trend reflects their ability to delve deeply into various areas of knowledge, facilitating the identification of research gaps and shortcomings that often remain unnoticed in the academic community. Furthermore, these reviews outline the challenges and opportunities faced by researchers, practitioners, and other stakeholders. In terms of significance and impact, review studies are increasingly valued for their capacity to save researchers substantial amounts of time. This is particularly important given the vast volume of information available, which makes the process of searching, classifying, and organizing articles, conference papers, book chapters, and other resources relevant to their field of study increasingly challenging (Butler et al., 2024).

The structure of this document is primarily based on the PRISMA methodology, complemented by additional methodological elements proposed by various authors (Rana et al., 2022; Sonbul and Rashid, 2023; S. Shukla, 2023) and the methodological framework outlined in Marzi et al. (2025). This combined approach enabled the establishment of search criteria aimed at identifying, evaluating, and synthesizing studies that addressed specific research questions. These questions, designed to delineate the scope of the study, facilitated the formulation of inclusion and exclusion criteria, along with an evaluation process that optimized the selection of relevant studies.

The Research Questions (RQs) and Specific Objectives (SOs) are defined and organized in Supplementary Table S1, serving as a framework to guide the analysis conducted in this systematic review. The initial logical search equations yielded thousands of results, including journal articles, conference papers, and book chapters retrieved from the WoS and Scopus databases. To refine the search, reduction and focusing techniques were applied (Barrios-Ulloa et al., 2022), adjusting the criteria according to the most impactful areas of interest, technologies and applications in the field.

The keyword combinations included terms such as Internet of Things, surface and groundwater sources, water monitoring, wireless sensor networks (WSN), sensors, and contemporary concepts such as sensor fusion. These terms are specifically associated with the deployment of sensors to monitor water quality and levels. Finally, in the WoS database, the logical equation ("Sensor fusion" OR IoT) AND (Water OR Groundwater) was applied, yielding 830 records. More specifically, as shown in Supplementary Figure S2, the SLR process followed a sequential structure: initial database search, application of filters by language, time frame, and subject area, definition of inclusion and exclusion criteria, and final classification of selected articles into four main categories. At each stage, the number of retained documents is reported, thereby reinforcing the transparency of the process.

To delineate the search areas in this SLR, relevant fields such as engineering, computer science, and information science were meticulously and manually selected, whereas other areas such as medicine, chemistry, and earth sciences were excluded, as they were deemed misaligned with the objectives of this study (Supplementary Table S1). Furthermore, the search was restricted to English-language articles published in journals between 2015 and 2025, as this period was identified as the most productive for the chosen topic. Under these criteria, the initial database query yielded 458 records. The same filtering process was applied to the Scopus database using identical requirements and filters. Initially, the search using Scopus produced 8,645 documents for review. However, after applying filters for subject area, language, and time range, the number of results was reduced to 1,603 documents. This methodology ensured a more precise and relevant selection of studies, focusing exclusively on those that directly contributed to the specific objectives of the SLR.

Subsequently, the information retrieved from both databases was manually examined and cross-checked by applying the selection criteria and specific subareas outlined in Supplementary Figure S2 (IoT, communication, algorithms, and sensor fusion) with strict rigor. This meticulous filtering and comparison process yielded a final sample of 458 documents. To broaden and enrich the coverage of relevant studies and ensure the comprehensiveness of the review, additional specialized databases such as IEEE, DBLP, and ACM were also incorporated. A thorough analysis was conducted to prevent duplication, thereby enhancing the representativeness and depth of the selected studies in the research domain under consideration. It is important to note that this review focuses exclusively on freshwater sources.

The initial article selection process was based on a rigorous examination of titles, keywords, abstracts, and conclusions, ensuring that each document was aligned with the primary objective of the research. Moreover, the selection was restricted to articles published in scientific journals ranked between the first and fourth quartiles (Q1–Q4) according to the Scimago Journal Rank (SJR) and Journal Citation Reports (JCR) indices. Articles not indexed in these systems were excluded from the analysis (Supplementary Figure S3).

2.2 Scientometric analysis

Scientometrics is a scientific discipline that employs quantitative methods to measure and analyse scientific output. Through a set of indicators and metrics, scientometrics enables the evaluation of progress, impact, and current state of knowledge in a specific field, as well as the evolution of research trends and collaboration between institutions and countries (Zhang et al., 2024).

The following scientometric information was quantified and recorded for each of the 458 selected references: journal name, author names, quartile ranking in Scopus and WoS, journal country of origin, citation count by country, study country of origin, and authors' institutional affiliations.

The growth and relevance of this research field are evident, as the number of publications on this topic has increased significantly in recent years, highlighting its importance in IoT applications. This trend reflects the growing awareness of the need to invest in ensuring the quality of potable water resources worldwide.

The literature reveals three key areas of focus.

(1) Application of sensors in freshwater sources to monitor contaminants and water levels.
(2) Development of low-power data transmission technologies that enhance the autonomy of sensor devices.
(3) New machine learning (ML)-based algorithmic models are aimed at resource optimisation and improved data processing for analysis, management, and prediction.

Supplementary Figure S4 displays a scatter plot illustrating the number of articles published per year (left vertical axis). The peak in publishing activity was recorded in 2022, followed by a slight decline, possibly attributable to the rising interest in other emerging fields employing similar technologies, such as groundwater and brackish water monitoring. This trend underscores the importance of the IoT in developing sustainable technologies for water resource management, while also highlighting the diversification of its applications within the water and environmental sectors. Moreover, the horizontal axis represents the evaluation period ("Year"), while the size of each data point indicates the total number of citations ("Total Citations, TC"), which is also represented using a color scale.

China leads the list of countries with the highest number of citations, amassing over 1,400, as shown in Supplementary Figure S5. This is followed by South Korea, Spain, India, the United Kingdom, the United States, and Italy—countries that have made significant advancements in technology, particularly in the development of IoT and its applications for water resource management. Many of these countries face critical challenges related to their water sources, whether due to contamination, overexploitation, or population growth, underscoring the relevance and urgency of research in this area. These factors have driven both academic interest and scientific contributions to the development of technological solutions for sustainable water management in recent years. Supplementary Figure S6a highlights the most influential authors in this field of research, drawing attention to the most frequently cited scholars (Saheed et al., 2025; Qiao et al., 2024; Maia et al., 2022), and those with the highest number of publications in high-impact journals focused on IoT applications in water resource management. The prominence of Dr. Jaime Lloret from the Universitat Politècnica de València (Spain), followed by Dr. Rashid Mirzavand from the University of Alberta (Canada) reflects the concentration of scientific output around specific academic figures and institutions. However, this concentration also suggests a reliance on consolidated research hubs, which may constrain methodological diversity and hinder the contextual adaptation of solutions to local environments. Supplementary Figure S6b illustrates a co-authorship map generated with VOSviewer, where each node represents an author and the links indicate collaborations in publications on IoT applied to water reservoirs, based on data from WoS and Scopus. The size of each node reflects the author's productivity or impact (in terms of the number of publications and citations), while the colors distinguish different collaboration clusters. Well-defined groupings can be observed, highlighting the presence of specialized research communities with strong internal interactions, particularly those centered around authors such as Lloret, Nayyar, and Lin, among others. Complementarily, Supplementary Table S2 presents the journals with the highest volume of publications and the most active institutional affiliations, thereby revealing prevailing patterns of productivity and the dominant research lines in this field. Nevertheless, a significant gap remains in the participation of institutions in developing regions, particularly those most directly affected by water-management challenges.

A particularly relevant finding of this review is the limited participation of institutions from developing regions, despite these areas concentrating some of the most pressing challenges in water resource management and conservation. This absence generates a bias in the scientific literature, as most documented models, architectures, and technological approaches originate from countries with well-established infrastructure and high innovation capacity, thereby restricting their applicability in contexts constrained by limited infrastructure and funding availability. Likewise, the lack of institutional and territorial representation has contributed to the under-documentation or marginalization of local solutions–those based on low-cost technologies, community-driven practices, and context-specific regulatory frameworks–within the global scientific discourse. This gap not only perpetuates technological dependency but also heightens the risk of exacerbating critical issues, such as overexploitation, pollution, and inequality in access to safe water sources, particularly in fragile ecosystems and developing regions. To bridge this gap, we recommend fostering international collaborations that actively include institutions from developing regions, strengthening technology transfer networks, and promoting the publication of local case studies in indexed journals. Such efforts would enhance methodological diversity and ensure that IoT solutions for aquatic systems are effectively tailored to the realities of the most vulnerable territories.

2.3 Technical analysis

Supplementary Figure S7 illustrates the classification of the main aquatic systems used in this study. To narrow the scope of this review, studies on marine systems were excluded, as they focused on the analysis of freshwater systems, including surface and groundwater. Four major categories were established to facilitate their classification and evaluation in the analysis of the studies included in the SLR. The categories are as follows:

(a) Internet of Things and its applications in aquatic systems, which were categorized as Research Area 1 (RA1).
(b) Models and data transmission technologies in IoT devices classified as Research Area 2 (AR2).
(c) Algorithms aimed at optimizing processes, energy consumption, and data analysis were categorized as Research Area 3 (AR3).
(d) Applications of sensor fusion in aquatic systems, categorized as Research Area 4 (AR4).

Thus, SLR primarily focuses on the use of IoT-based monitoring tools, the data transmission methods employed for measurement collection, whether *in situ* or remotely, and the algorithmic systems applied for analysis and forecasting in these aquatic systems. The compiled databases included 219 articles in AR1, 113 in AR2, 100 in AR3, and 26 in AR4. The following sections highlight the main contributions of the selected studies in each category.

2.4 Key technologies and contributions identified

Supplementary Table S3 summarizes the contributions of the reviewed literature, highlighting the technologies employed for collection, integration, analysis, and decision-making support in water resource management. The most notable contributions of this study are as follows:

- Distributed sensors and IoT systems: IoT emerges as a central technology, utilizing sensors to monitor physical variables such as temperature, humidity, water level, pH, and dissolved oxygen. Commonly used devices include control boards such as ESP32 (Abdulbaqi and Hashim, 2024), Arduino (Bamini et al., 2024), and Raspberry Pi (Ghazali et al., 2024). These devices facilitate data collection from strategic points and are interconnected through wireless networks.
- Satellite systems and remote sensing: remote sensing is utilized in hard-to-access environments, offering temporal data with limited precision (Friedmann et al., 2024). However, its effectiveness is improved when complemented by *in situ* measurements obtained from local sensors (Arias-Rodriguez et al., 2020). A new concept, the "Remote Internet of Things" (Kinman et al., 2023; Barsha et al., 2025; Choudhary, 2025), has recently emerged, integrating high-precision sensors into modern satellite systems. This advancement significantly enhances the range and accuracy of the data collection.
- Digital twins (DT): these virtual platforms facilitate real-time simulation and forecasting of surface water reservoirs and aquifer dynamics (Yin et al., 2024). Their architecture integrates heterogeneous data streams from IoT-based monitoring nodes, Earth observation satellites, and spatially distributed *in situ* sensors, thereby enabling high-resolution spatiotemporal modeling (Venkatesh et al., 2025). By coupling these datasets within predictive analytics frameworks, platforms become critical decision-support tools for advanced, adaptive, and resilience-oriented water resource management (Cohen et al., 2025).

Several authors have underscored IoT-Cloud as a pivotal technology for the interconnection and management of data within IoT-based systems. This technology offers a robust infrastructure that supports the storage and processing of collected data and enables efficient analysis and management. Furthermore, IoT-Cloud seamlessly integrates advanced tools, such as Big Data analytics, Machine Learning algorithms, and scalable storage architectures, thereby facilitating the transformation of raw data into actionable, high-value insights that inform and optimize decision-making processes (Bhati et al., 2024).

Supplementary Figure S8 presents a consolidated synthesis of the findings derived from the consulted databases, underscoring the most significant technological developments and methodological approaches in the application of IoT for water resource management. As shown in Supplementary Figure S8a, the most prevalent platforms combine IoT with IoT-cloud infrastructure, reflecting their widespread adoption owing to their capacity for scalable data integration and processing. Supplementary Figure S8b illustrates the most frequently deployed data transmission technologies, among which the following stand out.

- LoRa: preferred for long-range networking requirements combined with low energy consumption.
- MQTT: valued for its lightweight messaging protocol, enabling efficient, low-overhead communication between IoT devices.
- WiFi: typically used in urban contexts or in areas with reliable local network coverage.
- ZigBee: employed in scenarios demanding low data rates, minimal energy usage, and mesh network configurations.
- NB-IoT: recognized for its broad coverage, low power requirements, and moderate data transmission capabilities.
- GSM: leveraged to ensure connectivity in regions with extended cellular network availability.

These findings emphasize the technological diversity in IoT-based water monitoring solutions and the deliberate selection of transmission protocols to match the operational constraints and environmental conditions of each deployment. Regarding the types of sensors used (Supplementary Figure S8c), the review indicated that temperature measurement was the most frequently implemented type. This is consistent with its importance in aquatic systems, as water temperature directly influences oxygen solubility, which is a key factor in maintaining adequate levels of dissolved oxygen essential for aquatic life. Among the most widely adopted temperature sensors are the DS18B20 and DHT22, which are selected primarily for their cost-effectiveness and operational reliability.

Similarly, pH sensors, such as SEN0161 and those developed by Atlas Scientific, are widely employed because of the critical role of pH in determining water acidity or alkalinity, which is a fundamental indicator of water quality. Turbidity, which reflects the concentration of suspended particles, is often measured using SEN0189 and TSD-10 sensors. For total dissolved solids (TDS), the gravity analog TDS and SEN0244 are among the most frequently used devices for measuring TDS.

Supplementary Figure S8d reveals that approximately 59% of the reviewed studies incorporated ML techniques, with a marked increase in adoption over the last five years. These techniques are predominantly applied to real-time data visualization, front-end interface development, predictive analytics, and the generation of future scenarios. This trend highlights the strategic relevance and growing impact of ML-enabled approaches in advancing research and supporting the sustainable management of aquifers and other water resources (Dharmarathne et al., 2025; Drogkoula et al., 2025).

2.5 Analysis of author contributions by area

To ensure clarity and analytical coherence, the reviewed contributions are grouped into five main subthemes: (i) IoT applications for water monitoring; (ii) data transmission technologies used to connect sensors and platforms; (iii) algorithms applied to process optimization and data analysis; (iv) sensor fusion techniques that combine multiple information sources to improve accuracy; and (v) digital twins that enable real-time simulation of aquatic system behavior.

This analysis was conducted using the Bibliometrix package in R Studio (https://www.bibliometrix.org/ and CiteSpace, which facilitated the organization, visualization, and thematic co-occurrence analysis of the selected studies. The following sections provide a balanced discussion of each area, emphasizing both the strengths and limitations of the reviewed technologies.

2.5.1 IoT

The integration of WSN and IoT has been extensively studied as an effective solution to address various challenges in sectors such as logistics, agriculture, and environmental monitoring. According to Rueda and Talavera (2017), WSNs are composed of sensor nodes that collect and transmit data via wireless or wired communication. However, these networks face significant limitations in terms of transmission range, processing capacity, and energy efficiency, which directly affect their lifespan and functionality in IoT applications. IoT, as defined by ITU-T, is a global infrastructure that connects physical and virtual objects through technological interoperability, enabling data acquisition and processing to deliver advanced services across diverse contexts while ensuring security and privacy.

Mutunga et al. (2024) proposed a WSN based on RFID, LoRa, and GSM to detect pesticides in groundwater in Kenya, emphasizing its accessibility and reliability in data transmission. Alobaidy et al. (2024) introduced a hybrid model (FSPL-STW-EBT) that enhances prediction accuracy in LoRa IoT networks in rural and suburban environments, achieving an accuracy rate of 87% to 96% by accounting for dense vegetation and uneven terrain. Jabbar et al. (2024) designed an IoT system combining LoRa/LoRaWAN and Wi-Fi for real-time water quality monitoring, enabling data access via platforms such as ThingSpeak.

Promput et al. (2023) implemented temperature, TDS, pH, and turbidity sensors on a wireless boat, achieving precise data transmission over distances of up to 2.0 km. Moiroux-Arvis et al. (2023) developed an IoT platform called SoLo, which employs low-power sensors and LoRaWAN networks to send data to a cloud for advanced analysis. Wang and Xu (2024) proposed an interoperability framework for IoT-based water conservation systems, integrating hydrometric stations, conservation equipment, and management systems using smart technologies and digital twins to optimize information exchange between components. Kumar et al. (2024) designed a real-time monitoring system for ponds, employing an aquatic boat capable of collecting water samples from various locations, such as the center and edges of ponds. This system records parameters such as pH, turbidity, and total dissolved solids (TDS) and uploads the collected data to the cloud for real-time analysis via a mobile application, AquaSpecs.

Mohaimenuzzaman et al. (2016) proposes an innovative model to transform aquatic transport systems into intelligent infrastructures based on IoT. This approach includes the design of a prototype that leverages a machine-to-machine (M2M) protocol based on IPv6, ensuring efficient interconnection between devices. The selection of 3G telecommunications technology is notable for its extensive coverage in the analyzed region, whereas the IEEE 802.15.4 network standard plays a crucial role in enabling wireless communication within the system. The data generated by the system are stored in the cloud, facilitating the centralized and scalable management of the collected information. Furthermore, data analysis was performed using a pretrained decision model capable of predicting the real-time status of moving aquatic vehicles. This model represents a significant step toward the digitalisation of aquatic transportation, with potential applications in logistics, safety, and environmental monitoring within aquatic ecosystems.

In the field of water quality monitoring, Bhati et al. (2024) proposed a cost-effective and energy-efficient solution that integrates electrochemical sensors with machine learning algorithms, such as decision trees and Naive Bayes, to assess water quality in distribution systems. This approach enables the detection of deviations from the parameters defined by the World Health Organization, issuing alerts to mitigate health risks. Similarly, Adeleke et al. (2023) developed an IoT-based system utilizing artificial neural networks (ANN) and support vector machines (SVM) to predict contaminant levels in water (Prabu et al., 2025). They concluded that ANN models offer superior accuracy, positioning them as pivotal tools for IoT applications in water-management. From an energy efficiency perspective, Olatinwo and Joubert (2020) introduced an innovative approach to IoT-SN systems that maximizes energy harvesting through wireless power sensor networks (WPSN) and advanced scheduling algorithms such as non-orthogonal multiple access (NOMA). This approach addresses the inherent energy constraints of WSNs by optimizing their potential for water quality monitoring applications. Similarly, Du et al. (2015) proposed a scheduling scheme based on compressive sensing that activates a minimal subset of sensor nodes during each time interval, thereby reducing energy consumption and enhancing system efficiency. Both studies underscore the importance of adopting energy-sustainable strategies to ensure the long-term viability of IoT networks in critical monitoring environments.

Supplementary Figure S9 presents a general overview of the key water quality parameters most frequently utilized by various authors, which have been integrated into IoT platforms through specialized sensors. These parameters are categorized into three main groups: physical, microbiological, and chemical, offering a comprehensive approach for evaluating and monitoring water quality in real time.

2.5.2 Data transmition in IoT

Advancements in IoT transmission technologies have enabled the development of specialized solutions for real-time water monitoring, thereby overcoming the limitations of traditional analysis methods. Aliagas et al. (2022) highlights the use of LoRaWAN, an LPWAN protocol that combines low energy consumption and long-range data transmission, particularly effective in rural areas with limited infrastructure. Similarly, Mutunga et al. (2024) proposed a system that leverages LoRa for long-distance transmissions and GSM to send real-time SMS notifications to users, thereby extending the impact of these technologies in vulnerable communities. These innovations, coupled with the modularity of platforms such as those presented by Slaný et al. (2020) and Moiroux-Arvis et al. (2023), illustrate how the IoT is diversifying its scope through hybrid protocols and flexible architectures to optimize data transmission in varied environments.

Moreover, the design of efficient IoT networks depends not only on transmission protocols but also on the implementation of intelligent algorithms. Masood et al. (2023) introduces a Q-learning-based approach that optimizes real-time routing to prioritize critical data in IoT networks, while Du et al. (2015) employs a compressive sensing (CS) scheme to minimize data transmission and reduce energy consumption. Meanwhile, Alobaidy et al. (2024) enhanced the accuracy of path-loss prediction models using hybrid ML techniques tailored to tropical environments. These contributions demonstrate that the integration of advanced algorithms with transmission technologies not only improves energy efficiency but also enhances the reliability and accuracy of IoT networks.

Complementarily, the integration of technologies such as LoRaWAN, Zigbee, and Wi-Fi, along with hierarchical and distributed architectures, is revolutionizing water quality monitoring. Truong et al. (2021) proposes a heterogeneous sensor network that combines Zigbee's advantages for short-range data transmission with LoRa's capabilities for long-range communication. Similarly, Kombo et al. (2021) introduced a groundwater monitoring system that leverages both LoRaWAN and GSM, capitalizing on the strengths of each to ensure continuous and reliable monitoring. These networks, in addition to being energy-efficient, offer the flexibility required for deployment across various settings and scales, ranging from rural communities to advanced industrial systems.

In terms of cloud-based services, the ability to analyse and visualize data in real time is increasingly critical in IoT water management systems. Promput et al. (2023) employs Node-RED to build interactive dashboards that display real-time water quality data, further integrating GPS to track device locations. Similarly, Adeleke et al. (2023) utilized the ThinkSpeak platform for cloud-based sensor data visualization, whereas algorithms hosted on Google Cloud analyzed the data to identify contamination patterns and propose corrective measures. These solutions highlight the growing importance of cloud computing and intuitive interfaces for informed decision-making in water management.

The future of IoT transmission technologies is centered on the integration of advanced techniques and optimisation of existing networks. Manjakkal et al. (2021) and Olatinwo and Joubert (2020) underscore the role of emerging technologies such as Wi-Fi HaLow, NB-IoT, and hybrid networks that merge LPWAN protocols with traditional communication methods for environmental monitoring applications. Additionally, energy-harvesting techniques, such as solar panels and RF energy collection, promise to extend the operational lifespan of the sensor nodes in remote IoT systems. These innovations, coupled with ML for prediction and optimisation, solidify the IoT's role as an essential tool for sustainable and efficient monitoring of water resources on a global scale. The most relevant data transmission technologies identified in this SLR are compared in Supplementary Figure S10. In terms of usability (Supplementary Figure S10a), the analysis focuses on the Quality of Service (QoS), defined as the ability to ensure that data traffic and critical applications operate reliably (Yahya et al., 2022). The results indicate that while technologies such as LoRaWAN and SigFox have certain limitations, ZigBee and, in particular, NB-IoT, exhibit superior performance.

Regarding energy efficiency and battery independence, LoRaWAN and SigFox have emerged as the most favorable options owing to their optimized designs for low-power IoT applications. Additionally, in terms of coverage and range, these technologies excel, making them the most effective solutions for IoT applications that require long-range communications. Scalability, defined as the ability of an IoT system to transition smoothly from prototyping to mass production, showed the best results with NB-IoT and LoRaWAN. Their architectures are specifically designed to support seamless and efficient deployment in advanced development stages. For latency and payload length, NB-IoT is the clear leader, closely followed by ZigBee, owing to its ability to handle larger data volumes with optimal response times. Finally, the construction costs associated with these technologies were assessed as critical factors for implementing IoT systems. In this area, ZigBee and LoRaWAN stand out as the most viable options for projects requiring low-cost devices, offering a balance between functionality and economic accessibility.

To complement this analysis, Supplementary Figure S10b presents a comparison based on the selection of essential parameters for various data transmission technologies. LoRa is particularly noteworthy for its energy efficiency, coverage, mobility, and data transmission range, even in scenarios involving obstacles or line of sight interference. Conversely, technologies such as GSM provide significant advantages in terms of coverage, mobility, and range, but face substantial limitations regarding energy consumption and spectrum availability. Based on the data presented and the analysis of the designs and implementations reviewed in the articles, it was concluded that the most widely used technology with the highest average performance for IoT applications focused on water quality and level management is that of LoRa. This technology not only outperforms others in several key parameters but also offers a superior cost-benefit ratio (Tu et al., 2022), establishing itself as the most suitable and efficient option in this field of study.

2.5.3 Algorithms

The primary types of algorithms and methodologies used by researchers in IoT applications for aquatic environments can be classified as follows:

Algorithms for intelligent traffic management and energy optimization: various studies emphasize the application of ML algorithms and optimization techniques in IoT to enhance efficiency and resource management in distributed systems. Masood et al. (2023) proposes a framework that integrates algorithms, such as Random Forest (RF) and Decision Trees (DT), with Q-learning (QL) to classify traffic in IoT agricultural networks. This approach not only improves the accuracy of managing critical data traffic but also optimizes real-time routing, reducing latency. Similarly, Du et al. (2015) introduced the SACC algorithm based on compressive sensing to extend the lifespan of a WSN by selectively activating nodes and prioritizing energy efficiency. This algorithm combines dynamic programming and greedy search strategies to balance node residual energy and maximize network performance (Prabu et al., 2025).

Machine learning for water quality prediction and monitoring: ML algorithms have proven to be key tools in predicting critical parameters for water quality monitoring systems. Singh et al. (2023) employs predictive models based on trees, such as M5 and Random Forest, to optimize aquaculture management, achieving a correlation exceeding 87% in the prediction of parameters like dissolved oxygen and pH. Similarly, Bamini et al. (2024) implemented artificial neural networks optimized with a hybrid Genetic Algorithm (GA) and particle swarm optimisation (PSO), achieving 91% accuracy in water quality prediction. These approaches highlight the effectiveness of predictive algorithms in enabling real-time decision-making and ensuring the sustainability of water resources.

Innovations in algorithms for IoT networks and monitoring systems: the integration of advanced algorithms has significantly enhanced the performance of IoT systems across various scenarios. Manjakkal et al. (2021) proposes the use of neural networks and AI techniques for analyzing multiparametric sensor data, merging information from sensors, satellite imagery, and social networks to predict water quality events. Olatinwo and Joubert (2020) develops a WPSN model with a focus on NOMA (Non-Orthogonal Multiple Access) and a PSO algorithm to optimize energy efficiency and data transmission (Prabu et al., 2025). These innovations not only ensure efficient management but also minimize energy consumption and enhance the scalability and functionality of IoT systems, cementing their role in critical applications such as water resource monitoring.

A critical comparison of the algorithms reviewed reveals that tree-based models such as Random Forest and Decision Trees are widely applied owing to their interpretability and robustness against noisy data. However, they tend to underperform in highly nonlinear environments compared with Artificial Neural Networks or hybrid models that integrate genetic algorithms or particle swarm optimisation. Conversely, Support Vector Machines (SVM) demonstrate strong predictive capabilities with small datasets but show limitations in scalability when processing large volumes of IoT data. Recently, ensemble methods that combine decision trees with reinforcement learning (for example: Q-learning) have gained attention for achieving a balance between accuracy and computational efficiency. This suggests that hybrid models may offer a superior trade-off between accuracy, resource consumption, and adaptability to heterogeneous aquatic systems.

2.5.4 Sensor fusion and data fusion in IoT applications

Sensor fusion and sensor data fusion have become essential tools for optimizing data processing in IoT systems (Saghir et al., 2025), particularly in environmental monitoring and infrastructure applications. Friedmann et al. (2024) demonstrates the potential of spatiotemporal fusion by integrating satellite data from MODIS Aqua/Terra, Landsat 5–9, and Sentinel 2 to generate products with a spatial resolution of 30 m across the contiguous United States (CONUS). This integration not only enhanced the accuracy of monitoring total suspended solids (TSS) but also increased the data update frequency, providing more reliable and near-real-time information. Furthermore, strengthening the database with *in situ* measurements reinforces the validation of the results, emphasizing the importance of combining remote sensing data and field measurements to ensure the quality and precision of IoT applications.

Conversely, Döring et al. (2022) focused on sensor data fusion to optimize surface moisture monitoring by applying various-feature selection algorithms. This study highlights the efficacy of combining transducers with different coatings to improve the performance of classifiers based on capacitive data. Among the evaluated algorithms, techniques such as Exhaustive Search (ES), Branch and Bound (BAB), and Sequential Forward Selection (SFS) have emerged as vital tools for identifying optimal feature subsets that maximize system accuracy.

The topic of sensor fusion has not been widely explored in water-related applications, according to articles reviewed from databases such as IEEE, WoS, and Scopus. To address this gap, the research was expanded to include additional sources, such as Google Scholar, revealing compelling results. For instance, Shen (2023) and Wang Y. et al. (2024) reported significant advancements: the former leveraged the Adaptive Weighted Data Fusion (AWDF) method and LSTM neural networks to integrate sensor data for water quality monitoring, and the latter employed a localization approach using an Unscented Kalman Filter on manifolds (UKF-M) for autonomous underwater vehicles (AUVs). Similarly, Priyanka et al. (2024) proposed a statistical model based on recursive estimation techniques that combined multiple sensors with Kalman filtering to evaluate lake water quality in India in real time. A noteworthy contribution was made by Lee et al. (2022), who developed a rapid detection system for ionic content in water through the fusion of ultraviolet spectroscopy (UVS) and electrochemical impedance spectroscopy (EIS) sensors. This system utilizes convolutional neural networks (CNNs) to analyse fused spectra, achieve precise predictions of ionic content, and offer promising solutions for salinisation monitoring.

Additionally, exploring databases such as DBLP (Computer Science Bibliography) and the ACM Digital Library uncovers further significant contributions. Liu (2021) presents an intelligent water quality monitoring system based on multi-level multisensory data fusion technologies, significantly enhancing system accuracy. Meanwhile, Zhang et al. (2023) proposed an online multisensory fusion system using MSP430 microcontrollers to improve the convenience and timeliness of water-quality monitoring. Similarly, Adriansyah et al. (2024) designed an IoT water-level monitoring system using node-integrating sensors for height, flow velocity, and rainfall measurements. This design combines hardware and software with fuzzy logic to estimate flood conditions in extensive areas, demonstrating the potential of sensor fusion in IoT systems for disaster prevention in water-related challenges.

With regard to sensor fusion, statistical methods such as Kalman Filters and their variants (e.g., Ensemble Kalman Filter) remain the most commonly employed due to their robustness and computational efficiency. However, these methods may be less effective when dealing with highly nonlinear or multimodal datasets, where machine-learning-based fusion approaches, such as Convolutional Neural Networks (CNNs) or LSTM-enhanced models, outperform traditional techniques. Although AI-based fusion methods increase predictive accuracy, they often require larger training datasets and higher computational resources, which limits their scalability in resource-constrained IoT deployments. Therefore, the choice between classical statistical fusion and AI-driven fusion approaches largely depends on the context: low-cost, real-time monitoring favors statistical methods, whereas high-resolution predictive modeling benefits from AI-based fusion. In conclusion, sensor fusion is emerging as a critical tool for water management and monitoring in IoT applications. From the real-time integration of sensory data to advanced techniques such as CNN's and fuzzy logic, advancements in this field provide innovative solutions to challenges such as salinisation, flood detection, and water quality assessment (Wang et al., 2025).

2.5.5 Digital twins

DT enables real-time connectivity between a physical object and its digital representation, facilitating automatic updates of the digital model based on observed changes in a real object (Manocha et al., 2024). This approach has proven to be a powerful tool in various water management fields, including irrigation systems (Zhang et al., 2025), flood control (Yin et al., 2024), early warning systems for leak detection and consumption optimisation (Syed et al., 2024), quality control in potable water networks (Baena-Miret et al., 2024), and wastewater treatment (Wang A. J. et al., 2024). However, in the realm of IoT applied to water quality management, DTs remain in an emerging stage, similar to research on DTs for disruptive technologies such as 5G networks (Hakiri et al., 2024). For instance, Primeau (2024) developed a framework based on a hydrodynamic model that integrates online sensor data to enhance the spatial and temporal understanding of water quality in a surface water body in Ålesund, Norway. Similarly, Ortega (2023) designed a DT application to dynamically monitor and manage groundwater levels in Enschede, the Netherlands, addressing climate challenges such as droughts and floods through pumping systems.

Wang and Xu (2024) introduced an interoperability framework for IoT-based smart water conservation systems that facilitates communication and information exchange among components such as hydrometric stations, conservation equipment (pumps, gates), and DT. Meanwhile, Anker (2023) developed a DT focused on the real-time monitoring of helical pumps used in groundwater extraction systems. This model combines sensor data from physical assets with digital simulations, thereby enabling the detection of failures that are historically difficult to identify using traditional methods.

In conclusion, while digital twins are becoming established as an effective technology in areas such as smart cities and infrastructure management, they remain largely unexplored with vast innovation opportunities in the context of IoT applied to monitor the quality and levels of freshwater in surface and groundwater systems (Kameswari et al., 2025). Leveraging advancements in IoT, hydrodynamic models, telecommunications, sensory technologies, and algorithm and software development form the foundation for building more robust and functional DT systems. This positions DT's as strategic tools with significant potential to address challenges in the efficient and sustainable management of water resources.

Moreover, the emerging 5G network is poised to serve as a critical enabler of the instantaneous connectivity of billions of devices within the IoT (Mahomed and Saha, 2025). This advancement will not only revolutionize device management but also act as a key driver for digital transformation in Industry 4.0, benefiting businesses, customers, and investors. A recent study (Omrany et al., 2023) projects that by 2026, 85% of IoT platforms will incorporate some form of DT, fuelling remarkable market growth from the current \$3.1 billion to \$48.2 billion over the next 5 years (Hakiri et al., 2024).

To conclude the analysis of the authors' contributions across the reviewed domains, a general reference framework for monitoring architectures is proposed, which synthesizes the current advances in the implementation of IoT technologies applied to aquatic systems. Supplementary Figure S11 illustrates a representative scheme of the most widely adopted architectures for IoT-based monitoring and water quality management developed in the reviewed studies. These architectures are typically organized into four fundamental layers: perception, transmission, platform, and application (Chen et al., 2021), which collectively enable the structured flow of information from data acquisition to analysis and integration into decision-making processes.

Perception layer: this layer encompasses sensors and control boards responsible for collecting, processing, and transforming data captured by sensory devices. Commonly used sensors for measuring water quality and level parameters include temperature, pH, turbidity, and conductivity. These sensors are often connected to controllers, such as ESP32 and Arduino (Kumar et al., 2024), which serve as intermediaries between the sensors and higher system layers. Sensor nodes are strategically placed in the target area and are frequently designed as autonomous wireless nodes capable of connecting to Wi-Fi terminals to send and download data in real time (Chen et al., 2023; Miao et al., 2022). This layer establishes the foundation for ensuring the accuracy and reliability of the collected data.

Transmission layer: in this stage, the collected data is transmitted using communication modules that leverage technologies such as LoRa (Ahmad et al., 2023), GSM (López-Muñoz et al., 2024), or WiFi, depending on the system's requirements for range, energy consumption, and costs. This layer not only facilitates data transfer but also organizes and packages the information to ensure efficient delivery to the next layer.

Platform layer: the transmitted data is stored and managed in centralized platforms, which can be hosted either in the cloud or on local physical servers (Morchid et al., 2025). These platforms provide tools for data analysis, aggregation, and structuring, enabling specific functionalities such as queries, visualization, and calculations. A commonly adopted model in this layer is cloud-based backend services (BaaS, Backend as a Service), which offer APIs, mass storage, notifications, and resource management, empowering developers to deploy applications efficiently and in a user-friendly way.

Application layer: in this final layer, processed data becomes accessible to end-users through visual interfaces and query tools. The monitoring system executes advanced functions such as data analysis, contamination alarms, local storage, node positioning, and real-time information visualization. This layer fosters informed decision-making and ensures seamless interaction between the data and users (Razaque et al., 2025).

These IoT architectures exhibit clear and well-defined hierarchies. The perception layer gathers detailed data directly from the environment of interest, whereas the transmission layer ensures connectivity and the flow of information among the distributed nodes. The platform layer acts as a backbone supporting the advanced applications and functionalities of the application layer, thereby completing the monitoring and management cycles (Saranya and Valarmathi, 2025). Together, these layers enable the implementation of reliable, scalable, and effective systems for water resource monitoring.

3 Cluster analysis

Cluster analysis was conducted using CiteSpace version 6.3.R1 Basic aims to identify groups of related articles based on their citation and co-citation patterns. This analysis was performed using a database of 458 documents, as previously mentioned. Supplementary Table S4 presents the four primary clusters associated with the topic *"Emerging Trends in IoT for Aquatic Systems"* obtained by applying the filters and restrictions outlined in the SLR methodology.

The largest cluster, named the IoT Sensor, comprised 16 nodes (articles) and was the most relevant in terms of connections. The table lists the most cited documents in this cluster identified by their respective Digital Object Identifiers (DOIs). This underscores the significant impact of IoT sensor-related topics in the analyzed publications. The second-largest cluster, Sustainable Water, included 11 nodes and focused on topics related to water sustainability. This highlights the growing interest in IoT technologies for sustainable water management. The third cluster, Water Quality Monitoring, contained eight nodes and was specifically linked to water quality. This suggests a more specialized and technical focus within the broader water domain. Finally, the Environmental Conservation cluster, which also comprised eight nodes, emphasized strategies for environmental preservation, including IoT applications and monitoring technologies for the safeguarding of water sources. Among the highlighted documents in this cluster is the most-cited article, "IoT based real-time water quality monitoring systems" (Chowdury et al., 2019).

The metrics obtained using CiteSpace provide valuable insights into the properties of clusters within a citation network, including authors, keywords, and titles. The most cited authors are Pasika and Gandla (2020) from Cluster #3, followed by Jamroen et al. (2020) from Cluster #2, and Jan et al. (2021) from Cluster #2. Additionally, CiteSpace identifies articles with *bursts* , which represent a sudden increase in the citation frequency of a node within a specific timeframe, signaling emerging topics or high-impact publications. Articles with bursts aligned with the most-cited works are listed in Supplementary Table S5.

In conclusion, by combining the metrics obtained, the most innovative and impactful articles were identified as key connectors of the research areas within this review. These studies included Wong et al. (2021), Dahane et al. (2022), Mukta et al. (2019), Pasika and Gandla (2020), and Kumar et al. (2023). These documents stand out not only for their high degree of connectivity and influence within the analyzed network but also for their contributions to advancing this research's thematic focus.

4 Thematic trend analysis

When analyzing the main current trends in the application of the IoT to aquatic environments, particularly freshwater systems, the following conclusions were drawn based on Supplementary Figure S12, which illustrates the evolution and variation of relevant topics over time (note that the size of the circle represents the frequency of mentions for each term, making it proportional to its relevance within the analysis).

The evolution of key IoT-related terms for related systems shows a steady increase in relevance between 2019 and 2023. Foundational terms such as *Internet*, *things*, and *IoT* have maintained consistent prominence, reflecting sustained interest in these areas because of their broad impact across sectors such as water resource management, sensing technologies, and monitoring applications. In the early years of the analysis period, concepts such as *management* and *city* stood out as practical application areas, suggesting an initial focus on specific solutions to problems. From 2022 onwards, more specialized terms such as *sensor*, *network*, and *protocol* gained greater relevance, indicating a shift toward technological infrastructure and data security as IoT matured.

The tabular data underlying Supplementary Figure S12 further reinforce this trend toward the consolidation of foundational technologies, with terms such as *Internet* (94 mentions), *things* (67 mentions), and *IoT* (51 mentions) leading to frequency. Although terms such as *smart* and *city* appear less frequently (six and five mentions, respectively), they represent emerging areas with growth potential, particularly in localized or specific contexts. The emergence and increasing prominence of the term *security* from 2022 onwards underscores concerns regarding data protection in IoT systems, highlighting the need for more robust protocols to support the interconnections of smart systems. Collectively, the analysis reveals the progressive maturation of the field, where fundamental technologies have been established, and the current focus is shifting toward network optimisation, security, and practical implementation in strategic sectors.

Supplementary Figure S13 complements the discussion by presenting a thematic map of the SLR structured on a Cartesian plane defined by two axes: density (Y-axis), representing the internal development of a theme, and centrality (X-axis), indicating its connection to other areas within the research network. The first quadrant is the *motor themes*, which serve as the main drivers of research and form the core of publications and collaborations. The second quadrant houses *niche themes*, characterized by high internal development but limited connections to other areas, indicating their relevance in specific contexts rather than within the broader scope of the SLR. In contrast, the third quadrant contains *emerging or declining themes*, which are identified by their low density and centrality. These terms reflect areas that are still nascent, with the potential to evolve into significant trends or lose prominence as contemporary approaches take precedence. Finally, the fourth quadrant includes *basic themes*, marked by high centrality but low density. Although not the focus of intensive research, these terms form the conceptual foundation of the field, acting as pillars to support more advanced and specialized studies. The analysis of the Thematic Map highlights a clear segmentation of trends related to the IoT and its application in water resource management. Within the motor theme quadrant, concepts such as *smart city*, *data analytics*, *ML*, *sensor fusion*, *groundwater*, *calibration*, and *sensors* have emerged as critical areas that drive, enhance, and specialize in aquatic system research. These concepts are not only central but also highly developed, underscoring their strategic importance in advancing research and their role as foundational elements in the implementation of advanced IoT systems. Additionally, terms such as *intelligent sensors* and *simulation* emphasize the role of advanced technologies and real-time predictive capabilities, paving the way for emerging approaches such as *digital twins* and the integration of *satellite technologies* into aquatic systems. These concepts strengthen current research and broaden the horizon for more innovative and multidisciplinary applications.

In the basic theme quadrant, concepts such as *IoT*, *NB-IoT*, *communication*, *LoRaWAN*, *WSN*, *design*, *antenna*, and *algorithms* stand out. These terms represent the foundational pillars upon which technological developments in the IoT domain have been built. Their high centrality underscores their strategic importance in a broader context, whereas their low density indicates that, although they are not the focus of intensive research, they form the theoretical and conceptual basis upon which early publications in the field were established.

In contrast, the niche theme quadrant includes terms such as *water stress*, *decision support system*, *autonomy*, and *encryption*. These represent specialized research areas with a high degree of internal development but limited connections to the main core of the LSR. These topics require further efforts in terms of integration and connectivity to achieve a greater influence within the broader research landscape of IoT in aquatic systems. The emerging or declining themes quadrant features concepts such as the *IoT Platform*, *smart grid*, *security*, *models*, and *microcontroller*. Depending on research priorities and advancements, these topics represent areas of opportunity that could either evolve into highly relevant lines of enquiry or lose prominence in the coming years. This broader analysis confirms that research on IoT applied to water systems is progressing toward the integration of intelligent technologies, predictive models, and sustainable approaches while solidifying the technological foundations required to support these implementations. It is also noteworthy that the basic themes have larger circles than the motor themes, as the bubble size is directly proportional to the theme's significance in the overall context. This observation may be attributed to the fact that the study area is strongly anchored to the foundational concepts of electronics engineering and communication. Moreover, terms such as energy efficiency and water quality monitoring are positioned near the center of the quadrants, highlighting their critical relevance. Although these terms are fundamental to the field's development, they present significant opportunities for further exploration and innovation.

From a prospective outlook, the trajectory of IoT-based water management research is expected to be shaped by the integration of high-impact technologies that, while still emerging, hold substantial promise. Future implementations will likely harness next-generation satellites, such as GRACE-FO, to derive groundwater storage variations through Earth's gravitational models (Karki et al., 2025), whereas advanced machine learning algorithms for satellite image downscaling are anticipated to refine the spatial and temporal resolutions of the recharge and extraction dynamics (Hamou-Ali et al., 2025). In addition, forthcoming generations of quantum, graphene-based, and self-powered sensors are poised to underpin high-resolution IoT networks and enhance measurement accuracy and autonomy in resource-constrained environments (Krishnamurthy and Milani, 2025; Ganguly and Sengupta, 2025). These developments will converge with progress in data fusion and cloud-based platforms, enabling the construction of digital twins augmented with artificial intelligence that can dynamically adjust operational parameters in real time (Alghamdi et al., 2025). Reinforcement learning techniques are also expected to play a decisive role in optimisation and planning by offering adaptive strategies for resilient groundwater governance (Kage et al., 2025). Simultaneously, the growing concern over cybersecurity will require the development of robust solutions to safeguard the integrity of these interconnected systems and to ensure their operational reliability and long-term sustainability (Alhamam et al., 2025). In this regard, the review identifies cybersecurity as a critical aspect in IoT systems applied to water resource monitoring, given the sensitivity of the generated information and the potential impact of vulnerabilities on management processes. Although several studies refer to basic security protocols, an in-depth analysis of vulnerabilities, threats, and mitigation strategies remains limited (Addow and Jimale, 2024). Data protection is crucial in this context, as information generated by sensors on water quality and availability is highly sensitive, and any alteration may compromise management decisions (Slany et al., 2025). Lightweight cryptography, multi-factor authentication, and intrusion detection mechanisms have begun to be integrated into IoT platforms to reduce risks (Dhanda et al., 2020; Garcia-Martin et al., 2023; Raphael et al., 2025), yet their adoption is still in its early stages (Ansari and Kumar, 2025). Moreover, AI-driven approaches for proactive anomaly and attack detection are emerging, although their scalability and efficiency in resource-constrained environments remain challenges (Ogenyi et al., 2025). This research gap underscores the need for future studies to explicitly integrate security and digital resilience as core components of IoT architectures for aquatic systems.

An emerging trend clearly identified in recent literature is the evolution of DT frameworks for water management, particularly in semi-arid environments and regions with limited infrastructure or financial resources. Recent studies have revealed a decisive shift toward hybrid and low-cost architectures, where the integration of IoT sensor data, satellite imagery, and hydrogeological records enables the development of dynamic models for monitoring and prediction. For instance, Cohen et al. (2025) proposed a cost-effective DT designed for semiarid zones in Colombia by combining IoT-based platforms, remote sensing, and *in situ* data. Similarly, Homaei et al. (2025) introduces an intelligent water management framework integrating LoRaWAN, machine learning, and blockchain infrastructure, thereby enhancing transparency and data security across distributed monitoring systems.

At a global scale, there is a clear move toward decentralized water monitoring through affordable and scalable IoT systems. In Sub-Saharan Africa, Kombo et al. (2021) demonstrated the viability of low-cost groundwater monitoring using LoRa-based sensors in Zanzibar, while more recent studies in Sinaloa (Ortiz et al., 2023), Timis (Bogdan et al., 2023), Chattogram (Rahman et al., 2025), Dakar (Gueye et al., 2025), and Albany (Lal et al., 2025) confirm the expanding adoption of accessible technologies for tracking physicochemical parameters and water levels. Collectively, these developments highlight a global trend toward the technological democratization of water monitoring, where energy efficiency, sensing accuracy, and long-range connectivity are becoming central pillars of innovation. However, persistent structural challenges related to scalability, interoperability, and system standardization remain, emphasizing the need for stronger technological governance frameworks and open data policies to facilitate the transnational integration of environmental information. In conclusion, Supplementary Table S6 synthesizes representative studies that document real-world implementations of the IoT applied to monitoring water quality and water levels across various geographic regions, particularly in low-resource environments.

5 Answers to questions set forth in the RSL

RQ1. What are the most popular IoT technologies and techniques applied to surface and groundwater?

The most popular IoT technologies applied for the monitoring of surface and groundwater include advanced sensors, communication networks, and data analysis techniques (El-Shafeiy et al., 2023). Among the essential components are sensors that measure key parameters, such as pH, dissolved oxygen, turbidity, water level, and temperature, for both surface and groundwater (Ortiz et al., 2023). These sensors provide real-time water quality and availability data, which are fundamental for managing aquatic ecosystems and water resources (Miller et al., 2023). In addition, WSNs play a critical role in collecting and transmitting data from multiple locations to base stations (Mohaimenuzzaman et al., 2016), utilizing communication technologies such as Zigbee (Kumar et al., 2024), LoRa, Sigfox, and NB-IoT, which are well-suited for long-range transmission and low energy consumption (Garcia-Martin et al., 2023). For data storage and analysis, cloud platforms and NoSQL databases enable the management of large volumes of information (Kumar et al., 2024), whereas Big Data techniques and ML algorithms are employed to detect patterns, predict water quality trends, and optimize usage (Lloret et al., 2016).

Emerging technologies, such as DT, are gaining prominence because they provide virtual representations of hydrological systems, enabling more efficient monitoring and optimized water resource management (Manocha et al., 2024). Security has evolved into a fundamental priority in IoT systems, particularly for safeguarding sensitive data and ensuring operational integrity (Aiche et al., 2024). Furthermore, interoperability between devices and platforms has been identified as a key factor in achieving integrated and efficient water resource management (Kumar et al., 2024). Collectively, these advancements have shaped a dynamic ecosystem in which the integration of intelligent tools and predictive models is transforming the monitoring and management of surface and groundwater, fostering sustainability, and strengthening data-driven decision-making. To synthesize the main findings related to RQ1, Supplementary Table S7 summarizes the IoT technologies and techniques applied to surface and groundwater monitoring, highlighting their contributions and limitations.

RQ2. Which are the most cited authors in recent years on IoT, WSN, sensor fusion applied to water?

See Section 2.2 Scientometric analysis; Supplementary Figure S6.

RQ3. How do WSNs operate in water sources? What are the most used algorithms for sensor fusion in both surface and groundwater applications?

WSNs are fundamental for monitoring water quality in both surface and groundwater systems. These networks operate by distributing multiple sensor nodes across specific areas, such as rivers and lakes (Mohaimenuzzaman et al., 2016) and aquifers (Ortiz et al., 2023), where each node is equipped with sensors to measure specific water parameters, including pH, temperature, turbidity, dissolved oxygen, and water level (Aliagas et al., 2022). The data collected by the nodes are transmitted wirelessly to a base station using communication technologies such as Zigbee, LoRa, Sigfox, NB-IoT, and 3G cellular networks (Garcia-Martin et al., 2023). The base station then aggregates the information and sends it to servers or cloud platforms for storage and analysis using tools such as NoSQL databases (Aliagas et al., 2022). These platforms enable the implementation of Big Data techniques and ML algorithms to detect anomalies, optimize water usage, and provide predictive analytics to enhance water resource management (Bamini et al., 2024).

Emerging technologies, such as sensor and data fusion, play critical roles in monitoring surface and groundwater systems by combining data from multiple sources to improve the accuracy, reliability, and understanding of hydrological processes (Jiazhe et al., 2025). The Kalman Filter (KF) is one of the most widely used algorithms owing to its ability to handle uncertainties in noisy data and adapt to real-time environmental changes (Priyanka et al., 2024). Its integration with hydrological and ecological models enables a deeper analysis of the dynamics that affect water quality. Variants, such as the Ensemble Kalman Filter (EnKF) and Distributed Kalman Filters, are emerging as essential tools for managing nonlinearity in complex systems and ensuring scalability in large sensor networks (Wang Y. et al., 2024). Additionally, statistical fusion methods are widely applied because they provide a comprehensive view by combining information from different sensors, thereby enabling the detection of long-term trends and anomalies in water quality (Mohammadi et al., 2024).

Another prominent approach involves the use of Markov chain-based models to identify temporal patterns in water quality and forecast future events, such as contamination episodes. These models, combined with techniques such as the Kalman Filter (KF), create a robust framework for managing the inherent uncertainty in sensor-derived data and enhancing prediction accuracy through advanced data fusion algorithms (Manzione and Castrignanò, 2019). In the field of image processing, pixel-level fusion improves spatial resolution and facilitates the detection of subtle features in water bodies by integrating images obtained from multiple satellite platforms (Friedmann et al., 2024). In contrast, decision-level fusion combines the outcomes of various models or algorithms to minimize uncertainties and significantly increase the accuracy of water quality classification and assessment (Li et al., 2023).

These trends are complemented by recent technological advancements that integrate sensors and data fusion within cloud-based platforms and sophisticated machine-learning techniques (Li et al., 2025). This integration enables the efficient analysis of extensive and heterogeneous datasets, driving the development and deployment of smarter, more robust, and sustainable systems for comprehensive water resource management (Rahu et al., 2024; Adeleke et al., 2023; El-Shafeiy et al., 2023). Supplementary Table S8 provides a structured synthesis of the findings associated with RQ3. It highlights how wireless sensor networks (WSNs) operate in aquatic environments and summarizes the main sensor fusion algorithms applied in both surface and groundwater monitoring, outlining their contributions and limitations.

RQ4. What is the technology trend for WSN applied to water sources?

WSN's are undergoing significant advancements toward more intelligent and efficient systems, driven by their integration with IoT (Barrios-Ulloa et al., 2022; Shen, 2023; Mastan Vali, 2024). This trend enables remote and real-time monitoring of water sources through low-cost wireless protocols and accessible hardware, facilitating the development of large-scale sensor networks (Ortiz et al., 2023). M2M communication between nodes within these networks further optimizes autonomy and data exchange. Concurrently, the development of low-cost, energy-efficient sensors is critical for extending battery life and ensuring sustainable deployment in rural and remote areas (Mastan Vali, 2024). Combined with new sensor designs and more robust materials, these innovations enhance the accuracy of continuous online monitoring (Manocha et al., 2024).

Another notable trend is the incorporation of mobile nodes, such as Unmanned Surface Vehicles (USVs) and Autonomous Underwater Vehicles (AUVs), which facilitate dynamic data collection in extensive and hard-to-reach areas (Wang M. et al., 2024). These mobile networks, along with Non-Terrestrial Networks (NTNs), extend the reach of WSNs, particularly in regions lacking traditional communication infrastructure (Hagh et al., 2024). It is worth highlighting that Digital Twins represent an emerging technology that has significantly gained recognition as an innovative alternative for the control, management, and maintenance of aquatic systems, particularly in complex and dynamic environments (Wang A. J. et al., 2024; Omrany et al., 2023; Hakiri et al., 2024). Their integration with hybrid systems, which combine fixed and mobile sensors, enables more adaptive and efficient monitoring, facilitating rapid and effective responses to critical events or emergencies (Alobaidy et al., 2024; Manjakkal et al., 2021).

Low-power wide-area network (LPWAN) technologies, such as LoRa, Sigfox, and NB-IoT, are also gaining popularity owing to their ability to transmit data over long distances with low energy consumption, making them ideal for groundwater monitoring in remote areas (Georgantas et al., 2025; Garcia-Martin et al., 2023). Additionally, intelligent data analysis using big data techniques and ML facilitates water quality prediction, anomaly detection, and optimisation of water resource management, establishing WSNs as a fundamental tool for efficient and sustainable water management (El-Shafeiy et al., 2023).

Finally, the security of IoT-based systems is becoming increasingly important because protecting sensitive data and ensuring system integrity are critical in water-monitoring applications (Hussain et al., 2024). Moreover, the implementation of specific sensors, such as optical sensors based on reflectance for turbidity measurements (Wang M. et al., 2024) and ultrasonic sensors for flood detection (Moreno et al., 2019), enables a detailed analysis of water conditions. Sensors, such as piezoresistive pressure sensors and electrical conductivity sensors, also play a key role in measuring piezometric levels and salinity in groundwater (Ortiz et al., 2023). Collectively, these technologies and advancements have positioned WSNs as essential tools for efficient and secure water resource management, aligning with the trends toward intelligent, sustainable, and resilient systems. Supplementary Table S9 synthesizes the findings associated with RQ4. It highlights the main technological trends shaping wireless sensor networks (WSNs) for water monitoring, including their benefits and limitations, ranging from IoT integration and LPWAN protocols to Digital Twins, mobile nodes, and specialized sensors.

6 Suggested IoT architecture for aquatic systems based on the contributions of the authors

After conducting a thorough review and analysis of the architectures proposed by various authors in this SLR, Supplementary Figure S14 presents a proposal for IoT platform solutions aimed at monitoring aquatic systems, including surface and groundwater. These platforms are designed to collect and analyse data related to the water level and quality in these sources (Boonsong et al., 2023; Gennaro et al., 2019).

For groundwater systems, two main approaches have been proposed for acquiring sensor data, encompassing parameters such as water level, temperature, pH, dissolved oxygen, and total dissolved solids (TDS). The first approach employs commercial sensors, such as AquaTroll 600, which are known for their scalability and ability to adapt to the specific needs of users, including the number of sensors, data transmission, and analysis capabilities (Moiroux-Arvis et al., 2023; Hagh et al., 2024; Koronides et al., 2024). The second approach leverages custom-designed sensors based on programmable electronic platforms, such as Arduino, ESP32, or Raspberry Pi, offering a more cost-effective solution that is widely utilized in non-commercial applications (Gennaro et al., 2019). In both cases, the collected data were transmitted from each well to a station, primarily using LoRa technology, which provides advantages in terms of low cost, extensive coverage, and energy efficiency (Bamini et al., 2024; Alobaidy et al., 2024).

For surface water monitoring, the use of autonomous devices, such as miniature navigation vehicles or floating sensors, is recommended to supplement the data collected by sensors deployed within the reservoir (Hagh et al., 2024). These systems are equipped with sensors similar to those used for groundwater (Mirzavand et al., 2017), with specific differences, such as the requirement to measure surface water temperatures. Data transmission and analysis rely on IoT-cloud-based infrastructures, which integrate IoT devices with cloud computing platforms to store, process, and analyse real-time data, enabling predictions of reservoir behavior over time (Moiroux-Arvis et al., 2023). Supplementary Figure S14 highlights the complementary use of remote sensor data, such as satellite imagery, which is effectively integrated with *in situ* data using advanced techniques, such as sensor fusion and data fusion (Friedmann et al., 2024). These tools enhance the accuracy and contextualization of the collected information (Olatinwo and Joubert, 2020; Vadone et al., 2025). Supplementary Figure S14 presents the proposed IoT architecture for aquatic systems, structured into four layers. (1) Perception Layer: A distributed network of sensors (commercial, NB-IoT, handmade, and LoRa-based) deployed in groundwater wells, rivers, and lakes collects water quality parameters such as pH, turbidity, dissolved oxygen, and water level. (2) Network Layer: Control cards, gateways, and LPWAN base stations transmit data through communication protocols, including Zigbee, LoRa, Sigfox, NB-IoT, and Wi-Fi. (3) Processing Layer: The collected information is aggregated in cloud-based platforms and databases, where Big Data, machine learning, and sensor fusion algorithms process and analyse the data. (4) Application Layer: dashboards, remote terminals, and decision support systems provide real-time monitoring, anomaly detection, and early-warning alerts for sustainable water management.

7 Conclusion

This systematic bibliographic review encompassed more than 458 publications retrieved from various databases, focusing on IoT technologies applied to water resource management from 2015 to 2024. The analyzed studies highlight the use of sensors in freshwater sources for monitoring contaminants and water levels, including distributed sensors and IoT systems. In this context, IoT has emerged as a pivotal technology, leveraging sensors to monitor physical variables such as temperature, humidity, water levels, pH, and dissolved oxygen.

Additionally, complementary techniques such as remote sensing and remote IoT have been explored, where satellite sensors periodically collect data in difficult-to-access environments. These temporal datasets, when combined with *in-situ* measurements, enrich analyses and improve monitoring precision. This review also underscores the advancements in low-power data transmission technologies that enhance the autonomy of sensory devices. Among these, LoRa stands out as the most widely adopted technology, particularly for IoT applications related to water quality and level monitoring in extensive surface water bodies and aquifers, owing to its broad coverage, long range, scalability, low energy consumption, and resistance to interference.

Finally, the integration of Digital Twins is highlighted as an emerging tool within virtual platforms, capable of simulating and predicting aquifer behavior in real time. These technologies are complemented by novel algorithmic models based on ML to optimize resources, improve data processing, and enhance analysis, management, and forecasting in water resource management.

While the findings of this review mark a significant step toward a more mature and integrated phase of IoT in aquatic systems, practical adoption remains limited. The major barriers include high implementation costs, technical complexity, interoperability issues, and limited accessibility in resource-constrained regions. In addition, the absence of universal standards leads to fragmentation and incompatibilities across platforms, while few studies report real-world large-scale deployments, especially in developing countries.

To address these challenges, future studies should prioritize:

- Developing low-cost, energy-efficient sensor networks tailored for rural and remote contexts.
- Designing interoperable platforms and open standards to reduce fragmentation across IoT solutions.
- Integrating cybersecurity frameworks to safeguard sensitive environmental data.
- Validating IoT and Digital Twin systems through pilot projects under real-world conditions.
- Strengthening collaborative research in developing regions to ensure inclusiveness and scalability.

By addressing these limitations and pursuing these practical lines of research, IoT can evolve into a mature, inclusive, and sustainable technology for safeguarding global water resources.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

CC-M: Formal analysis, Supervision, Writing – original draft, Data curation, Resources, Methodology, Visualization, Project administration, Conceptualization, Validation, Investigation, Writing – review & editing, Funding acquisition, Software. SC-L: Formal analysis, Visualization, Validation, Writing – review & editing, Methodology, Funding acquisition, Writing – original draft, Supervision. JV: Validation, Writing – review & editing, Formal analysis, Writing – original draft, Investigation.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frwa.2025.1699240/full#supplementary-material

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