CHAPTER TWO  
LITERATURE REVIEW

1. INTRODUCTION

This chapter presents a chronological review of significant literature that has contributed to the design and implementation of IoT-based sensor systems for water quality monitoring. The studies are presented in temporal order, revealing the progression from traditional laboratory-based methods to intelligent real-time sensing systems enhanced with artificial intelligence (AI), machine learning (ML), and geospatial tools.

1. CHRONOLOGICAL REVIEW OF RELATED WORKS

The chronological progression of research from 2013 to 2024 reveals a clear evolution in the methodologies and technologies applied to water quality monitoring. Initial studies focused on the development of foundational Water Quality Index (WQI) models grounded in conventional statistical and physio-chemical analysis. This phase laid the groundwork for standardizing water assessment techniques. As the field matured, machine learning algorithms were introduced, enabling more dynamic and predictive evaluations of water conditions. The incorporation of smart sensing technologies and Internet of Things (IoT) platforms between 2019 and 2020 marked a shift toward real-time, autonomous systems capable of continuous monitoring and remote data transmission. In subsequent years, researchers expanded these frameworks by integrating Geographic Information Systems (GIS) and cloud computing, enhancing spatial and temporal intelligence. By 2023, methodological reviews began synthesizing these innovations into comprehensive, scalable architectures. Most recently, context-driven studies in 2024 have emphasized modular, low-power, and regionally adaptable systems, demonstrating the global relevance of intelligent water monitoring solutions—particularly in underserved or infrastructurally limited regions. Collectively, these contributions provide a robust scientific foundation for the present research, which aims to design and implement an IoT-based water quality sensor system optimized for real-time, cost-effective, and locally deployable monitoring.

1. Foundations of Water Quality Index Modeling (2013–2016.

The period between 2013 and 2016 marked the foundational stage in the development of systematic methodologies for water quality assessment, particularly through the use of Water Quality Index (WQI) models. These early models primarily relied on traditional statistical and physio-chemical parameter analysis to quantify water quality in diverse environmental contexts. GG.S (2013) introduced a standardized framework for calculating the WQI by applying fixed numerical Q-values and corresponding weightage factors to essential water quality parameters such as pH, turbidity, dissolved oxygen, and total dissolved solids. This approach enabled the aggregation of multiple quality indicators into a single, interpretable index value, laying the groundwork for comparative water quality evaluation across regions. Dohare et al. (2014) expanded on this foundation by conducting a comprehensive physio-chemical assessment of water quality in Indore, India. Their study involved the evaluation of 27 parameters, including heavy metals, alkalinity, and microbial load, in accordance with the Indian Standard IS 10500:2012. The results highlighted significant spatial variability and reinforced the importance of multi-parametric data in accurate WQI computation.

In 2016, Lamare and Singh developed the Numerus Pollution Index (NPI), introducing a novel computational approach to quantify the pollution load in irrigation water. Their model incorporated six distinct machine learning algorithms for predictive classification, marking an early transition from purely statistical models to hybrid computational techniques. During the same period, Sutadian et al. (2016) introduced the Scottish Research Development Department Index, which provided an alternative method for evaluating surface water quality based on a regionally adapted set of indicators. This model gained widespread recognition for its applicability in surface water quality assessments, especially in temperate climate zones. Collectively, these foundational works established the essential concepts, parameters, and computational strategies that would later evolve into more sophisticated, real-time water quality monitoring systems.

1. Integration of Machine Learning into Water Monitoring (2017–2018)

The years 2017 to 2018 marked a transformative period in water quality assessment, characterized by the incorporation of machine learning (ML) techniques into environmental monitoring frameworks. These approaches offered more robust, data-driven models capable of uncovering complex, non-linear relationships among water quality parameters, thereby enhancing prediction accuracy and analytical depth. Wang et al. (2017) pioneered the application of fractional derivative methods in conjunction with Support Vector Regression (SVR) to estimate the Water Quality Index (WQI) based on remote sensing and spectral indices. Their model demonstrated a strong correlation between observed and predicted values, proving effective in mapping water quality variations across large aquatic systems. Similarly, Wu et al. (2017) classified water samples from Lake Poyang in China using 20 distinct parameters, employing multivariate statistical analysis to categorize water quality into three levels. Their findings highlighted the necessity of integrating multiple parameters for accurate ecological assessments.

In 2018, Ewaid et al. advanced groundwater quality prediction by applying linear regression models that evaluated pollutants such as nitrates and heavy metals. Their approach emphasized the spatial variability of contaminants and provided a foundation for predictive groundwater modeling. Also noteworthy was the work of Sun et al. (2018), who applied the Bascarron Index to improve the interpretation of turbidity—a key indicator of microbial and sediment-related pollution. This index refined the WQI by introducing more sensitive weighting techniques for turbidity-based parameters. Tiwari et al. (2018) took a multidisciplinary approach by combining geospatial analysis with hydrological modeling to trace contaminant migration in the urban groundwater environment of Panchkula, India. Their integration of GIS with environmental models demonstrated how spatial tools could enhance understanding of pollution pathways and potential mitigation strategies. These studies collectively signal the emergence of machine learning as a powerful complement to traditional water monitoring methods. By enabling the modeling of complex datasets and facilitating more accurate, real-time predictions, ML approaches have set the stage for the development of smart water quality monitoring systems.

1. Smart Sensing and Internet of Things (2019–2020)

The integration of smart sensing technologies and the Internet of Things (IoT) into environmental monitoring frameworks gained significant momentum between 2019 and 2020. This era marked a transition from data collection via manual sampling to real-time, automated systems capable of continuous monitoring, remote access, and intelligent decision-making. Liu et al. (2019) developed an IoT-enabled smart water quality monitoring system using Long Short-Term Memory (LSTM) neural networks. Their model was designed to process time-series data from sensors deployed in aquatic environments, enabling predictive analysis of parameters such as pH, temperature, turbidity, and dissolved oxygen. The system demonstrated strong forecasting capabilities, positioning LSTM as a reliable tool for trend detection in dynamic water systems.

Similarly, Yang et al. (2019) employed Support Vector Machine (SVM) models for short-term prediction of high-frequency water quality data. Their work underscored the importance of high-resolution temporal data in accurately capturing variations in water characteristics, particularly in fast-changing urban or industrial catchments. In 2020, Almetwally et al. introduced a cloud-integrated decision support system that combined IoT-based sensor data with automated rule-based processing for water quality regulation. The system featured onboard storage, historical data tracking, and threshold-based alert mechanisms, showcasing the practical advantages of deploying smart technologies in public health contexts. Chen et al. (2020) conducted a comparative study on ten machine learning algorithms applied to large-scale water quality datasets. Their findings highlighted the superior performance of ensemble models in terms of prediction accuracy and computational efficiency, especially when handling big data generated by sensor networks.

Additionally, Nayar (2020) contributed to the refinement of WQI classification by proposing a quality banding scheme based on a wide range of physio-chemical parameters, including transparency, sulfate concentration, chloride levels, and biological oxygen demand. This work bridged the gap between conventional WQI computation and modern sensor-driven data collection by offering an adaptable evaluation framework. Collectively, these studies exemplify the growing convergence of embedded systems, wireless communication, and intelligent algorithms in water quality monitoring. The adoption of IoT platforms not only improved measurement precision but also introduced scalability, energy efficiency, and cost-effectiveness—key factors for sustainable deployment in both urban and rural environments.

1. Advancements in Real-Time Monitoring and GIS Integration (2021–2022)

The period between 2021 and 2022 marked a significant advancement in the field of water quality monitoring, particularly through the fusion of real-time sensing systems, machine learning models, and geospatial information systems (GIS). These integrations enhanced the responsiveness, spatial intelligence, and predictive capabilities of smart water management systems. Wu et al. (2021) focused on refining Water Quality Index (WQI) computation by evaluating fifteen physio-chemical parameters to develop a fast-track model with reduced error margins. Their methodology streamlined parameter selection for real-time applications, ensuring balance between computational efficiency and accuracy. Sharma et al. (2021) contributed to predictive modeling by applying polynomial regression to IoT-acquired water data, enabling accurate WQI forecasting from real-time sensor inputs. Their model emphasized the use of edge computing for immediate processing and minimal latency.

Uddin et al. (2021) adopted a hybrid approach that integrated the Analytic Hierarchy Process (AHP) with machine learning techniques such as Long Short-Term Memory (LSTM) and Nonlinear AutoRegressive Neural Networks (NARNET). This architecture facilitated multi-criteria decision-making in classifying water quality, taking into account both quantitative sensor data and qualitative expert judgment. Their system was notable for its adaptability in diverse aquatic environments. In 2022, Sanya et al. demonstrated the practicality of deploying LoRaWAN-based water quality sensors for continuous monitoring in both urban and rural contexts. Their system highlighted the benefits of low-power wide area networks (LPWAN) in achieving long-range communication with minimal energy consumption—an essential requirement for remote deployments. Bell (2022) also implemented a real-time monitoring system using Arduino-based sensors and the ThinkSpeak IoT platform, offering cloud integration, automated alerting, and mobile access to water quality metrics. Further advancing the integration of geospatial tools, Azpilicueta et al. (2022) employed LPWAN technology to monitor groundwater quality in isolated regions. Their study validated the importance of spatial tracking in understanding subsurface water behavior. Herath and Mittal (2022) emphasized the role of AI and GIS in future smart city frameworks, advocating for data interoperability and multi-modal sensing infrastructures.

Moreover, Dawood et al. (2022) applied GIS tools to model and visualize the spatial distribution of pollutants in groundwater sources. Their work facilitated targeted policy interventions and infrastructure planning. In a related study, Arabameri et al. (2022) combined GIS and AHP to identify solid waste dump sites affecting aquifer recharge zones, highlighting how land use significantly impacts groundwater quality. These studies collectively reflect the maturation of smart monitoring systems, where sensor data is not only collected and processed in real-time but also mapped, analyzed, and acted upon through intelligent decision-support systems. The inclusion of geospatial intelligence has expanded the reach and impact of water monitoring technologies, especially in regions vulnerable to ecological and anthropogenic contamination.

1. Comprehensive Frameworks and Methodological Reviews (2023)

The year 2023 was characterized by a consolidation of prior technological advancements into more structured and comprehensive frameworks for water quality monitoring. Researchers moved beyond isolated component analysis toward developing holistic systems that integrate sensor networks, machine learning models, cloud platforms, and geospatial technologies into unified, scalable architectures. Jayaraman et al. (2023) presented a detailed review of existing studies that leveraged IoT, machine learning (ML), and Geographic Information Systems (GIS) in water quality analysis. The authors evaluated over 60 research articles, emphasizing the increasing deployment of smart sensor systems to monitor key parameters such as pH, turbidity, temperature, and dissolved oxygen. Their findings revealed that IoT-enabled systems demonstrated sensor accuracy of up to 95%, while ML algorithms—such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Long Short-Term Memory (LSTM), and Random Forest—significantly improved prediction reliability and early anomaly detection. The review also highlighted critical infrastructure challenges, such as data quality, training dataset limitations, and energy management in field deployments.

Akbarighatar et al. (2023) contributed a comprehensive bibliometric and taxonomic analysis of the field, classifying over 50 published studies based on hardware implementation, algorithmic design, and application domains. Their taxonomy covered sensor typologies (e.g., electrochemical, optical, and MEMS-based), machine learning paradigms, cloud integration techniques, and GIS applications. The authors identified recurring methodological gaps, including the lack of generalized frameworks for multi-environment deployment and inadequate real-time adaptability of existing Data Acquisition Systems (DAS). Their study underscored the need for modular and interoperable architectures that support seamless integration of hardware, software, and analytics across geographic and climatic regions. Kar and Varsha (2023) proposed a GIS-integrated hybrid modeling framework for Water Quality Index (WQI) prediction. Their methodology combined satellite imagery, spatial interpolation, and supervised learning algorithms to provide region-specific water quality forecasts. The model’s performance was validated across multiple watersheds, confirming the efficacy of combining geospatial intelligence with predictive analytics for environmental monitoring. This framework offered a strategic solution for environmental agencies seeking to optimize monitoring operations using both ground-level sensors and satellite data.

In a more application-focused study, Kothari et al. (2023) developed a mobile-integrated water quality alert system using GSM communication and Android interfaces. Their platform allowed real-time access to sensor readings via smartphone, offering public engagement and utility responsiveness. The system was notable for its low-cost design, making it suitable for municipal and rural deployments where infrastructure constraints limit traditional solutions. Collectively, the literature from 2023 reflects a maturation of smart water monitoring technologies into integrated platforms characterized by scalability, accessibility, and cross-disciplinary design. These frameworks not only bridge gaps between sensor hardware and data analytics but also lay the groundwork for responsive, community-centered water governance systems.

1. Contemporary Innovations and Regional Applications (2024)

The most recent contributions in 2024 reflect a strategic shift toward context-specific applications of intelligent water quality monitoring systems, with an emphasis on scalability, sustainability, and regional relevance. Innovations in artificial intelligence (AI), sensor miniaturization, and low-power embedded systems have advanced the design of next-generation monitoring frameworks, particularly in addressing water security challenges in developing countries. Pérez-Beltrán et al. (2024) conducted a comprehensive review on the integration of AI, particularly Artificial Neural Networks (ANNs), with spectroscopic techniques such as ultraviolet-visible (UV-Vis), infrared (IR), and Raman spectroscopy for water quality monitoring. Their work focused on the non-invasive detection of a wide range of contaminants—including heavy metals, pathogens, and organic pollutants—in drinking water, surface water, and wastewater systems. The authors demonstrated that coupling AI models with spectroscopic data enhanced accuracy, reduced laboratory processing time, and enabled real-time classification and prediction of water quality indices. Furthermore, the study introduced the concept of TinyML—machine learning deployed on microcontrollers—as a forward-looking solution for ultra-low-power, edge-based water monitoring systems.

In a study tailored to the Nigerian context, Isukuru et al. (2024) explored the application of IoT and AI in addressing the country’s growing water crisis. Their research identified the primary sources of water pollution in Nigeria, including industrial discharge, agricultural runoff, and poor waste management practices. The authors proposed a modular IoT-AI framework suitable for decentralized deployment in urban slums and rural communities, where traditional infrastructure is either lacking or poorly maintained. Key features of the proposed system included solar-powered sensors, GSM-based data transmission, and a mobile-friendly dashboard for government and community stakeholders. Their findings underscored the need for adaptable technologies that account for socio-economic limitations, regulatory gaps, and environmental variability in resource-constrained regions. These contemporary studies underscore a growing emphasis on context-aware innovation—where technological development is guided not only by engineering advancement but also by local environmental, economic, and policy considerations. They highlight the importance of modular, energy-efficient systems that can operate independently of large infrastructure, thereby broadening access to clean water through affordable, real-time monitoring.

1. Sensor Technology Review and Selection Rationale

Effective ammonia monitoring in aquaculture environments depends on the suitability of the sensing technology to detect contamination within aqueous systems. This section explores the iterative selection process that led to the adoption of the Apure NHN-206 submerged sensor probe. The review integrates both technical evaluation and contextual constraints, documenting how theoretical options were narrowed to a practical solution.

1. Initial Considerations: Gas-Phase Ammonia Sensors

The project initially investigated gas-phase detection systems, particularly the Manning EC-FX-NH₃ sensor manufactured by Honeywell. As an electrochemical leak detector, the EC-FX-NH₃ demonstrates high sensitivity to gaseous ammonia and is extensively deployed in industrial refrigeration and mechanical rooms. It supports 4–20 mA analog output and Modbus RTU communication, making it technically attractive for microcontroller integration.

However, further analysis revealed critical limitations:

* The sensor is optimized for ambient air monitoring, not for dissolved ammonia in water.
* Mounting requires dry, ventilated settings, and the enclosure is not IP-rated for submersion.
* It assumes a vapor-phase sampling method, conflicting with the aquatic deployment requirement of this project.

Thus, the Manning EC-FX-NH₃ was ruled out as unsuitable for submersible water quality applications.

2.3.2 Transition to Aqueous-Compatible Sensors

As the project evolved to accommodate the practical challenges and environmental demands inherent in aquaculture monitoring, attention shifted toward sensing technologies that could be submerged directly into water. This transition was driven by the necessity of selecting a sensor with a waterproof enclosure that could withstand full immersion, ideally rated at IP68. It was also essential to identify probes capable of detecting ammonium ions (NH₄⁺), due to their strong association with dissolved ammonia levels. Furthermore, the system required a digital communication interface—preferably using the RS-485 Modbus protocol—to ensure seamless integration with ESP32 microcontrollers. Affordability remained a crucial factor throughout the selection process, as the solution needed to be viable for local application and suitable within an academic research framework. Three candidate sensors emerged from this refinement:

* Apure NHN-206 (PVC-based ISE, Modbus RTU)
* WizSensor WS-OM-NH4-11A (multi-parameter compensation, high precision)
* Rika Sensors RK500-15 (analog + digital outputs, fast response time)

Table 1.0: Summary of Immersible RS-485-compatible probes

| Sensor Model | Technology | Measurement Range | Accuracy | Interface | Mounting | Protection | Unique Features |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Apure NHN-206 | PVC membrane ISE | 0–100 mg/L NH₄⁺ | ±10% or ±1 mg/L | RS-485 (Modbus RTU) | Submersible (¾" NPT) | IP68 | Temperature compensation; customizable cable length |
| WizSensor WS-OM-NH4-11A | Reagent-free ISE + smart logic | 0–100 mg/L NH₄⁺ (opt. 1000) | ±1% NH₄⁺ | RS-485 (Modbus RTU) | Submersible (¾" NPT) | IP68 | Triple compensation (pH, temp, ionic strength); 12–18 mo lifespan |
| Rika RK500-15 | PVC film ammonium ISE | 0–100 mg/L NH₄⁺ (opt. 1000) | ±5% FS | RS-485 + 4–20 mA | Submersible | IP68 | Fast response; auto temp compensation; low power (<0.5W) |

1. Comparative Review of Candidate Sensors for Submerged Ammonia Detection

Having established the need for submerged ammonia sensing in aquaculture systems, three commercially available RS-485-compatible probes were rigorously evaluated: Apure NHN-206, WizSensor WS-OM-NH4-11A, and Rika RK500-15. The selection criteria included sensing accuracy, interface compatibility, environmental protection, mounting configuration, and unique features supporting aquatic deployment.

1. Apure NHN-206

This sensor leverages a PVC membrane ion-selective electrode (ISE) to detect NH₄⁺ in water, offering a range of 0–100 mg/L with accuracy rated at ±10% or ±1 mg/L. Its RS-485 Modbus RTU interface ensures seamless digital communication with embedded controllers like the ESP32. A key strength lies in its temperature compensation feature, making it adaptable to fluctuating aquatic conditions. With IP68 protection and a ¾" NPT submersible design, the Apure probe is well-suited for continuous pond or tank monitoring. Additionally, the customizable cable length allows tailored installation based on site-specific needs.

1. WizSensor WS-OM-NH4-11A

The WizSensor offers advanced capabilities through smart logic and reagent-free operation. It supports an extended range up to 1000 mg/L and delivers ±1% accuracy, ideal for precision-critical applications. Its notable strength lies in triple parameter compensation—adjusting measurements for pH, temperature, and ionic strength, making it highly robust for chemically dynamic environments. Despite these advantages, the sensor's complexity and high procurement cost limit its practicality for simulation and academic prototyping. Its lifespan of 12–18 months also implies higher replacement overhead.

1. Rika RK500-15

Rika's model uses a PVC film-based ISE, measuring NH₄⁺ concentrations across the same nominal range. With ±5% full-scale accuracy and optional 4–20 mA analog output, it strikes a balance between digital flexibility and analog legacy systems. A fast response time, auto temperature compensation, and low power consumption (<0.5W) highlight its operational efficiency. While suitable for distributed or remote systems, it lacks multi-variable correction and high precision needed in variable aquatic ecosystems.

1. Selection Justification

After evaluating the sensors against performance criteria and budgetary constraints, the Apure NHN-206 was selected as the optimal choice for this project. It offers:

* Sufficient accuracy and resolution for real-time water quality simulation
* RS-485 Modbus RTU interface for digital integration
* Environmental resilience with IP68 waterproofing
* Economical pricing suitable for academic and localized deployments
* Reliable submersible installation via standard ¾" NPT threading

Thus, the Apure NHN-206 balances cost, performance, and integration requirements, validating its inclusion as the sensor of choice within this digitally simulated ammonia monitoring system.

1. SUMMARY OF TRENDS

A longitudinal review of literature and field technologies reveals several converging trends in water quality monitoring systems. Initially dominated by manual sampling and laboratory analysis, the field has progressively transitioned to sensor-based automation, emphasizing real-time responsiveness and decision support. This transformation is further enhanced by the rising deployment of machine learning techniques, such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVM), often embedded within hybrid models to improve detection accuracy and prediction reliability. Parallel to algorithmic advancements, the integration of Geographic Information Systems (GIS) has introduced spatial analytics and modeling into environmental monitoring frameworks. A growing emphasis on low-power and cost-effective IoT platforms underscores the necessity of scalable, remotely deployable systems—particularly relevant in decentralized or resource-limited communities. More recently, deep learning architectures have been increasingly applied to model complex hydrological systems, enabling dynamic adaptation in national-scale water management initiatives. Within this technological backdrop, the present study reflects an iterative design process shaped by real-world application constraints. While the project initially explored gas-phase ammonia sensors—such as the Manning EC-FX-NH₃, which demonstrated strong industrial capabilities—it became evident that such detectors lacked compatibility with aqueous deployment. This prompted a focused reevaluation of submersible probes capable of monitoring ammonium ions (NH₄⁺), the dissolved form of ammonia in water. The solution emerged in the form of RS-485-based submerged sensor probes, among which the Apure NHN-206 was selected. With its PVC membrane ion-selective electrode, integrated temperature compensation, and Modbus RTU compatibility, the Apure sensor aligned with both the digital and environmental requirements of the project. Its IP68 waterproof rating and economically viable specifications validate its role in simulation-based and field-ready monitoring systems. Together, these trends and technological evaluations establish the foundation for the current research—motivating the development of a locally adaptable, intelligent ammonia detection system designed for freshwater aquaculture environments.