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Aquatic quality watch informed by communities (AQWIC) facilitating the adoption of low-cost sensor systems for underserved communities: a review and tutorial†

Josiah Hacker,[a] Fatima Iqbal,[a] Matías Osuna,[g] Osely Perea,[c] Keiner Sánchez,[c] Christopher Page,[d] Jamie Torres,[e] Md. Nizam Uddin,[a] Hannah Walden,[f] Mikko Westerbeke,[f] Astana Woody,[a] Nazly Enith Rubio Murillo,[c] Francisco Cubas, [a] Farith A. Díaz-Arriaga [b] and Lewis S. Rowles *[a]

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This tutorial review addresses the growing need for accessible water quality monitoring in rivers, lakes, and other surface waters. While commercial monitoring systems effectively serve water utilities and regulatory agencies, many communities lack the resources for regular water quality assessment. We present approaches for developing low-cost monitoring systems specifically designed for community-based environmental monitoring programs, citizen science initiatives, and educational applications. Through systematic analysis of 84 peer-reviewed papers on low-cost water quality monitoring, we identify key implementation approaches, common challenges, and successful design strategies. This analysis informs our tutorial recommendations and provides evidence-based guidance for system development. Specifically, we introduce a web-based portal AQWIC – Aquatic Quality Watch Informed by Communities. This open-source portal includes (1) tutorials on how to construct, program, and deploy water quality sensor systems using commercially available, low-cost components; and (2) an interactive water quality database where users can input their collected water quality data with geolocation. We highlight the functionality of AQWIC and review a set of commercially available low-cost water sensors through several deployments both in the United States and Colombia. The sensor module used is capable of measuring conductivity, temperature, pH, and turbidity, providing a cost-effective alternative to traditional testing methods. Our findings demonstrate that the conductivity, temperature, and pH sensors offer reliable and consistent results, aligning with conventional testing methods over several week periods. However, we also observed limitations in the accuracy of the turbidity sensor, emphasizing the need for improved precision at lower turbidity levels. By offering a cost-effective and user-friendly approach to real-time water quality monitoring, this work aims to empower communities to monitor and characterize their water quality and makes significant strides toward ensuring equitable access to safe water for all.

Environmental significance

Access to clean water is a global challenge, with millions relying on untreated surface water. Traditional water quality monitoring methods are often expensive and time-consuming, limiting their application in resource-constrained settings. This research addresses this issue by developing and validating low-cost, open-source water quality sensor systems. By providing affordable and accessible means of continuous water quality monitoring, these systems empower communities to actively manage their water resources. Our findings demonstrate that low-cost sensors can reliably measure key parameters such as temperature, pH, and total dissolved solids, although challenges remain with turbidity measurements. This work contributes to democratizing water quality monitoring, potentially improving public health outcomes and environmental management in underserved areas worldwide.

[a]*Department of Civil Engineering and Construction, Georgia Southern University, Statesboro, Georgia 30458, USA. E-mail: lrowles@georgiasouthern.edu; Tel: +1 (912) 478-0772*

[b]*Department of Environmental Engineering, Universidad EIA, Envigado, Antioquia, Colombia*

[c]*Department of Environmental Engineering, Universidad Tecnológica Del Chocó, Quibdó, Chocó, Colombia*

[d]*Department of Computer Science, Georgia Southern University, Statesboro, Georgia 30458, USA*

[e]*Department of Electrical and Computer Engineering, Georgia Southern University, Statesboro, Georgia 30458, USA*

[f]*Department of Mechanical Engineering, Georgia Southern University, Statesboro, Georgia 30458, USA*

[g]*Department of Mechatronics Engineering, Universidad EIA, Envigado, Antioquia, Colombia*

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1 Introduction

Access to clean and safe water is a fundamental human right and a critical component of the United Nations Sustainable Development Goals (SDGs). However, despite the global commitment to ensuring universal access to safe and affordable drinking water by 2030 (SDG 6.1), progress has been slow, and many communities around the world continue to face significant challenges in accessing clean water.[1] This hurdle is largely due to a lack of adequate infrastructure, polluted water sources, limited financial resources, and insufficient monitoring and management of water quality.[2] To accelerate progress towards achieving the SDGs, an urgent need exists for novel, cost-effective, and user-friendly solutions that can empower communities to take control of their own water quality monitoring and management. These solutions must be accessible to those who need them most, particularly in low-income and resource-constrained settings, where the burden of poor water quality and water-related diseases is highest. In these communities, local residents rely on water sources for various essential purposes, including fishing, agriculture, and drinking water supply. Therefore, the introduction of new and accessible water quality monitoring devices is crucial to ensure the safety and sustainability of this vital resource.

Continuous water quality monitoring is a costly and time-consuming process, requiring specialized equipment and trained personnel.[2,3] These barriers have made it difficult for many underestimated communities, particularly those in low-income and resource-constrained settings, to regularly monitor their water quality and take action to address any issues.[4] However, recent advancements in sensor technology have opened up new possibilities for low-cost, real-time, and continuous water quality monitoring.[5–7] These sensors, when combined with Internet of Things (IoT) technologies, have the potential to revolutionize the way we monitor and manage water quality, making it more accessible and affordable for communities around the world.[5–7] IoT-enabled water quality monitoring systems can provide real-time data on key water quality parameters (*e.g.*, temperature, pH, turbidity, and conductivity) allowing for rapid detection of contamination events, identification of unidentified pollution sources, and timely interventions to protect public health.[8]

Despite the growing interest in water quality sensors and IoT technologies, the current literature on this topic is fragmented across various disciplines, with much of the research being conducted by those without water science backgrounds.[8,9] A need exists for greater involvement of water scientists and environmental engineers in the development and testing of these technologies to ensure that they are effective, reliable, and practical for use in real-world settings. Thus, these technologies can be more appropriately adopted for citizen science efforts. Understanding the accuracy and precision of commercially available low-cost sensors remains as well as their long-term performance in different environmental conditions can help to facilitate adoption pathways and optimization of these technologies. Without this knowledge, it is difficult to determine whether these technologies are suitable for use in water quality monitoring programs, particularly in resource-constrained settings where the need is the greatest.[4]

Low-cost water quality sensors are becoming increasingly available, thanks to advances in sensor technology and the growing demand for affordable monitoring solutions.[8,9] However, a great deal of uncertainty still remains regarding the accuracy and precision of many commercially available sensors, particularly when compared to traditional laboratory-based testing methods. This uncertainty can be a significant barrier to the adoption of these technologies by communities and water managers, who need to have confidence in the data being collected and used to inform decision-making.[2] To address this issue, more rigorous testing, validation of low-cost sensors, and the development of standardized protocols for their use and calibration may help to promote uptake by citizens.[5]

This tutorial review synthesizes current knowledge on water quality sensors and introduces AQWIC – Aquatic Quality Watch Informed by Communities, a web-based portal designed to facilitate adoption of low-cost monitoring systems. AQWIC provides comprehensive resources including tutorials on constructing, programming, and deploying water quality sensor systems using commercially components, alongside an interactive water quality database where users can contribute georeferenced data. To illustrate implementation principles and practical considerations, we present deployment examples from surface waters in the United States and Colombia, demonstrating how users can validate sensor performance against standard methods. Through these illustrative cases, we discuss key aspects of sensor selection, calibration approaches, and deployment strategies that users should consider when developing their own monitoring programs. This tutorial aims to enhance accessibility to water quality monitoring technologies, particularly for disadvantaged communities, by providing a structured framework for implementing low-cost sensor systems. By offering practical guidance for real-time water quality monitoring, this work contributes to empowering communities in monitoring and characterizing their water quality, advancing progress toward equitable access to safe water for all.

2 Background on low-cost water quality sensor systems

The convergence of climate change and urbanization presents a significant challenge to water quality, with extreme weather events like floods and droughts having substantial impacts on surface water quality.[10,11] These dynamic conditions create an urgent need for continuous, real-time monitoring solutions that can track rapid changes in water quality parameters. Floods increase loads of contaminants such as metals, nutrients, and other pollutants into surface water bodies *via* storm runoff, leading to deterioration in overall water quality of receiving water bodies.[5,11–13] Traditional grab sampling methods often miss these acute contamination events, highlighting the value of automated sensor systems that can capture temporal variations. For instance, recent research has highlighted the effects of hurricanes on drinking water quality, posing risks for the spread of waterborne diseases and public health.[14,15] While commercial monitoring systems can address these challenges, their high costs limit active citizen participation and widespread deployment, particularly in developing regions where water quality concerns are often most acute. Additionally, many water sources in developing countries are heavily polluted, primarily due to untreated wastewater discharges, improper solid waste disposal, and runoff from industrial, agricultural, and mining activities, among other factors. The complexity of these pollution sources demands multi-parameter monitoring capabilities, which become financially feasible only through low-cost sensor approaches. These water quality changes involve impacts on chemical composition, sediment loading, microbial quality, and total organic carbon concentration, resulting in declining water quality with significant implications for both environmental and human health.[15,16] The health risks associated with water contamination involve a wide range of diseases, such as cancer, respiratory disorders, microbial infections, neurological conditions, and several other diseases.[16] The development of affordable real-time monitoring systems is therefore crucial for public water systems, especially in less developed regions where financial constraints currently limit water quality surveillance and early warning capabilities.[17]

To address these challenges, a growing need exists for comprehensive and effective real-time water quality monitoring techniques that can provide sufficient data to support efficient decision making processes.[17,18] Conventional methods involving manual sample collection and laboratory analysis are time-consuming, costly, and often fail to detect sudden changes in water quality due to environmental conditions.[19] In contrast, the utilization of wireless sensor systems such as IoT and wireless sensor networks (WSNs) provide viable and cost-effective methodologies suitable for continuous monitoring water quality, particularly in remote and rural areas.[17,18,20] These systems use sensors that could be novel or off the shelf and consist of different microcontrollers and data logging methods, providing an economical approach that requires minimal allocation of human resources.[20] Numerous studies have been conducted to compare real-time monitoring with remote monitoring of water quality parameters, highlighting the benefits of real-time monitoring systems in facilitating prompt identification and responses to accidental or deliberate pollution in water systems, thus enhancing public health protection.[19]

The deployment of low-cost water quality sensors and IoT-based monitoring systems offers several advantages over traditional methods. These include real-time monitoring, early warning systems, and the ability to detect sudden changes in water quality due to environmental or anthropogenic factors.[19] Additionally, these systems are more cost-effective and require minimal human resources, making them suitable for long-term deployment in remote and resource-constrained areas.[20] However, deploying low-cost sensors for environmental monitoring also presents challenges and limitations. These include the need for proper calibration, regular maintenance, and data validation to ensure the accuracy and reliability of the collected data.[21] Furthermore, the selection of appropriate sensors, microcontrollers, and data logging systems based on the specific requirements of the monitoring application is crucial for the success of the deployment.[21,22] Careful consideration of factors such as the site environment, power supply, data transmission, and maintenance is essential to ensure the effectiveness and reliability of these monitoring systems. Finally, continuous application and optimization of current sensing technologies may lead to the development of more robust sensors, the expansion of their water quality monitoring applications, and the development of new sensors that can be used to quantify and characterize emerging constituents or pollutants of concern.

In summary, the increasing pressures on water quality due to climate change, urbanization, and industrialization necessitate the development and deployment of low-cost, real-time water quality monitoring systems. The integration of sensors, microcontrollers, and data logging systems through WSNs and IoT technologies provides a promising solution for addressing these challenges. By enabling timely detection of water quality issues and facilitating informed decision-making, these systems contribute to the protection of public health and the environment. However, careful consideration of the limitations and challenges associated with deploying low-cost sensors is essential to ensure the effectiveness and reliability of these monitoring systems. Proper planning, design, and maintenance of these systems, along with the involvement of relevant stakeholders, are crucial for their successful implementation and long-term sustainability.

2.1 Sensor types and characteristics

For clarity in this tutorial, we define key terms as follows: a 'sensing component' refers to the specific element that measures a parameter (*e.g.*, a pH electrode), a 'sensor module' combines a sensing component with supporting electronics (*e.g.*, a complete pH sensor unit with signal processing), and a 'monitoring system' describes the complete assembled device, including microcontroller, multiple sensor modules, and supporting hardware. When describing commercial products, 'off-the-shelf' refers to pre-built sensor modules ready for integration, while 'novel' refers to newly developed sensing approaches. Most systems discussed in this tutorial, including our example implementation, use off-the-shelf sensor modules combined into custom monitoring systems. It is notable that a global standardization of these terms could help to better facilitate adoption and deployment. Sensors are the key components of these monitoring systems, possessing the capability to collect and process data internally.[23] WSNs consist of nodes responsible for sensing, processing, and communication, and a base station for collecting and managing data from the nodes.[5,24] A node refers to a technological equipment that possesses the capabilities of sensing, processing, and communication, with its primary function being to measure parameters specific to a certain application.[24] IoT sensors (linked with control units, power systems, micro processing units, storage units, and wireless communication interfaces) are designed to observe the physical environment and capture real-time changes.[6] The fundamental element of the IoT data layer comprises a wide range of IoT sensors specifically designed for this purpose.[6] By monitoring parameters such as temperature, pH, turbidity, electrical conductivity, and oxidation–reduction potential, which act as markers to describe environmental systems and serve as predictive indicators of water quality, these sensor systems enable accurate inferences about overall changes in water quality. It has been shown that both chemical and biological contaminants exert a significant influence on multiple monitored water parameters (*e.g.*, temperature, pH, turbidity, total dissolved solids, dissolved oxygen levels, and oxidation–reduction potential).[6] Thus, by observing and identifying alterations in these water parameters, it is possible to make accurate inferences about water quality.

2.2 Micro-controllers integration

Microcontrollers play a crucial role in acquiring data from sensors and transmitting it to data loggers.[25] They function as the primary component responsible for systematically processing and analyzing the data obtained from sensors, which are linked to a microcontroller-equipped measuring node.[26,27] Microcontrollers are further equipped with data transmission modules that enable wireless communication.[26] Arduino and Raspberry Pi are popular open-source microcontroller platforms that offer cost-effective and compact solutions for receiving and transferring information.[25,28,29] Arduino is a well-known open-source platform that uses a hardware called Arduino Uno circuit board based on ATmega 328, encompassing all essential components required for microcontroller operation.[25,27] It can be easily linked to a computer *via* peripheral connection such as USB, which can be powered by an AC-to-DC adapter or battery source, with the use of rechargeable batteries powered by solar panels or sleep-mode libraries to reduce power consumption in situations where power supply is a concern.[27,30] Raspberry Pi, characterized by its small size and impressive capabilities in communication and computation, offers advantages such as built-in Wi-Fi and compatibility with various Linux operating systems.[28,29,31] It operates in a manner similar to that of a traditional personal computer, utilizing a keyboard and mouse for input commands, relying on an external power source, and connecting to a display device to provide visual output.[29,31] Additionally, there exists a variety of other microcontrollers like Atmel Atmega 328, ESP8266 and ESP32, Intel Edison, Intel curie and Omega2 that facilitate the reception and transmission of data.[28]

2.3 Data acquisition and storage methods

Data logging systems are essential for collecting, managing, and analyzing the data obtained from sensors. A standard data logger system comprises a control unit, memory storage, and sensor network.[32] They include data transmission modules like Zigbee and GSM for wireless communication, remote monitoring, and real-time notifications.[32] To address the constraints posed by technology and expenses, data loggers based on cloud computing, personal computers, and Wi-Fi connectivity have been developed to offer a cost-effective, dependable, and user-friendly monitoring solution.[33,34] Data loggers also ensure data redundancy through onboard secure data (SD) card modules, preserving crucial data even when instant network connectivity is unavailable.[35,36] Information can also be recorded on an SD card and transmitted wirelessly to nearby computers for immediate, real-time monitoring.[36] Data logging systems provide several other options for storing data, including short-term storage using specific cellular phone numbers, centralized database storage at the base station, and reliable backup storage assisted by onboard SD card modules for each sensor unit.[35]

Bluetooth low energy, a short-range wireless communication technology, enables data exchange in connected and advertising modes, making it suitable for low-cost and low-power applications.[33] It exchanges data in connected and advertising modes, with the generic attribute layer establishing a one-to-one data exchange link in connected mode and the generic access profile layer broadcasting data to nearby potential receivers in advertising mode.[33] Raspberry Pi also itself has the capability to work as an independent data logging device due to its built-in Wi-Fi functionality.[32] IoT-based monitoring systems also utilize cellular low power wide-area networks such as narrowband IoT, which offers expanded coverage, energy-efficient communication, and economically viable implementation for a diverse array of IoT applications.[34] It has the capacity to effectively monitor a specified system, encompassing the entirety of data collection required to meet user needs, and possesses the capability to proactively notify the user in the event of system problems or mistakes, guaranteeing prompt warning and response.[34] Also, a broad variety of other data loggers exist, such as the Decagon Em50 series, Solinst Levelogger, Digi XBee, Onset HOBO, and several others, that are making a significant contribution to the advancement of IoT applications with their ability to consistently collect and store data.[37]

3 Current state of knowledge

A systematic literature review was conducted to identify peer-reviewed papers that evaluated low-cost water quality sensor systems and their field applications. The review process began with a comprehensive search using Web of Science, covering articles' titles, abstracts, and keywords, limited to publications up to June 2024. The search employed the following Boolean terms: ALL=(“water”) AND ALL=(“quality” OR “pollut*”) AND ALL=(sensor*) AND ALL=(“low cost” OR “low-cost” OR “affordable” OR “cheap” OR “inexpensive” OR “economical”) AND ALL=(“surface water” OR “fresh water” OR “river*” OR “lake*” OR “pond*”). This systematic search yielded 252 literature articles, which were then manually screened for relevance based on inclusion criteria focused on low-cost implementations and field validation studies. The review examined parameters including sensor types used, microcontroller selection, data logging approaches, deployment settings, and study duration. Through this process, 84 literature articles were ultimately identified as relevant and formed the basis for our analysis. Additional details on how the literature review was conducted, all literature reviewed, and specific articles related to this work are included in the ESI Table S1.† This comprehensive review informs our subsequent discussion of sensor selection, system integration, and deployment considerations.

Our analysis of the literature reveals key trends and patterns in low-cost water quality sensor development, implementation approaches, and deployment strategies (Fig. 1). The sensor deployment system plays a vital role in environmental monitoring, with a focus on environmental health monitoring as the primary objective of approximately 65% of studies reviewed. The purpose of environmental health in this context refers specifically to ecosystem condition and ecological integrity, focusing on water quality parameters that indicate environmental sustainability and ecosystem functioning, distinct from direct human health outcome measurements. Other purposes include real-time monitoring, human health, climate change, and remote location monitoring. Key parameters such as pH, dissolved oxygen (DO), temperature, turbidity, total dissolved solids (TDS), and oxidation–reduction potential (ORP) are frequently measured, alongside other specific parameters. Temperature and pH are among the most commonly mentioned parameters, appearing in approximately 18% and 17% of studies respectively. Turbidity measurements are reported in about 12% of studies, while dissolved oxygen (DO) appears in 10%. Other parameters beyond ORP and those mentioned above represent approximately 33% of the total parameter measurements. Other parameters beyond ORP and those mentioned above represent approximately 33% of the total parameter measurements, including conductivity,[38,39] salinity,[40] heavy metals like cadmium,[41] nutrients such as nitrate and phosphate,[42,43] chlorophyll,[44] and chemical oxygen demand.[45] These findings reflect both the fundamental importance of these parameters for water quality assessment and practical considerations such as sensor availability and cost. Approximately 55% of the sensors used are novel, while the remaining 45% are off-the-shelf. Microcontroller usage varies, with around 24% of papers specifying the use of Arduino, and approximately 44% not mentioning any microcontroller for the setup. Wireless systems are the primary data logging method, utilized in about 26% of the papers. Other methods include SD cards, computers, and smartphones, while 21% of the papers do not specify the data logging method used. In terms of deployment, around 58% of times sensors were deployed in the field, 35% in lab settings, and 7% in both field and lab environments. Deployment durations varied, with 18% deployed for less than a day and around 20% deployed for more than a month.

Our review reveals three primary approaches to water quality sensor development in the literature: commercial off-the-shelf systems, custom-built systems using commercial components, and novel sensor developments. Commercial systems typically offer high reliability and manufacturer support but at substantially higher costs that may limit widespread deployment. Custom-built systems integrate commercial sensing components with open-source microcontrollers, offering a balance between performance and affordability that has proven particularly suitable for community-based monitoring. Novel sensor developments focus on specific applications or parameters, often prioritizing cost reduction or specialized measurements. The selection between these approaches involves key trade-offs in initial costs, maintenance requirements, calibration needs, and deployment duration. For instance, while commercial systems often include automated calibration features, custom-built systems may require more frequent manual calibration but enable broader deployment due to lower unit costs. These practical considerations significantly influence system selection and long-term viability, particularly for community-based monitoring programs.

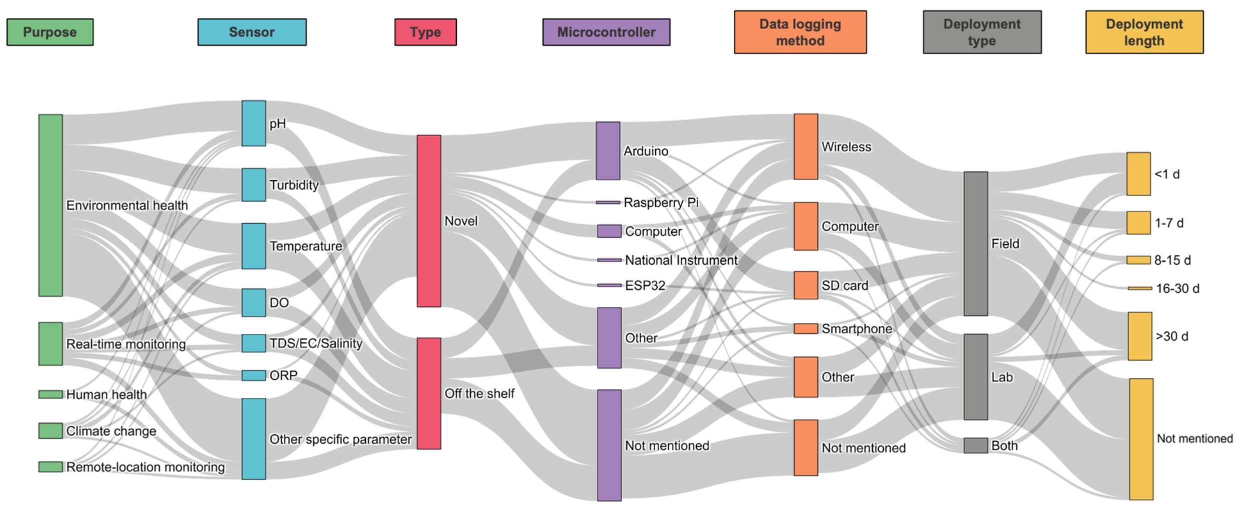

Fig. 1 Sankey diagram illustrating the current state of knowledge in low-cost water quality sensor systems based on a literature review of 84 relevant papers. The diagram shows the flow and distribution of key aspects in purpose sensor types, microcontroller usage, data logging methods, deployment settings, and deployment durations. The width of each flow corresponds to the percentage of papers addressing each aspect, providing a visual representation of trends in the field of low-cost water quality monitoring.

3.1 Sensors for surface water quality monitoring

The literature review reveals widespread deployment of sensors for measuring fundamental water quality parameters such as pH, DO, turbidity, temperature, TDS, and ORP in field settings. Specifically, pH and temperature have been mentioned approximately 17% and 18% of the time, while turbidity and DO have been mentioned around 12% and 10% of the time. Beyond these commonly measured parameters, additional water quality parameters represent approximately 33% of measurements in the reviewed studies. These additional parameters include conductivity,[38,39] salinity,[40] heavy metals like cadmium,[41] nutrients such as nitrate and phosphate,[42,43] chlorophyll,[44] and chemical oxygen demand,[45] utilizing both novel and off-the-shelf sensor technologies. Parameter selection is often driven by specific monitoring objectives, with environmental health monitoring being the primary application in approximately 65% of the assessed studies. The choice of parameters balances monitoring requirements with practical constraints including sensor reliability and maintenance needs.

Analysis of implemented sensor systems reveals important patterns in performance and reliability. Studies conducting long-term field validations demonstrate that temperature and pH sensors generally maintain stable readings with standard calibration protocols.[35,39] Comparative analyses of turbidity sensors show commercial and custom solutions each have distinct advantages depending on the measurement range and deployment environment.[46,47] Multi-parameter studies indicate that dissolved oxygen sensors often require more frequent validation compared to other parameters during extended deployments.[44,48] Our review indicates diverse opportunities for sensor development, with approximately 55% of reviewed studies focusing on novel sensor approaches. These developments address specific monitoring needs, from detecting emerging contaminants[41] to improving measurement accuracy[46] and enabling real-time data collection.[49]

Research efforts are directed towards the creation of novel sensors for detecting pathogens, pharmaceuticals and heavy metals, silicon nanoparticles, nutrients, microalgae, and antibiotics in water.[41,42,50,51] Real-time water quality monitoring through sensor deployment holds significant promise for enhancing human health in the future and has the potential to supplant conventional water quality monitoring methods.[8,49] This approach can save time and resources while enabling instant decision-making based on more reliable data. The advent of low-cost and easily assembled sensors could revolutionize and expand globally real-time water quality monitoring, ultimately enhancing the overall monitoring system and mitigating health hazards associated with poor water quality. The application of these systems varies significantly based on monitoring goals and resource constraints. Commercial systems dominate in regulatory compliance and industrial applications where high accuracy is essential. Custom-built systems have found widespread use in research, where specific applications are required. For community or citizen science deployment, the selection of appropriate sensor technology depends heavily on local context, including technical expertise, maintenance capability, and specific water quality parameters of interest.

3.2 Microcontrollers

The literature review reveals a notable lack of mention regarding the microcontrollers used in the water quality monitoring system. This lack of detailed reporting in many studies represents a potential methodological gap, with approximately 44% of reviewed papers not specifying the microcontroller used in their water quality monitoring systems, potentially limiting reproducibility and hindering comprehensive understanding of sensor system configurations. Among those that were mentioned, Arduino emerged as the most popular choice, being utilized in 24% of the cases, primarily due to its cost-effectiveness and open-source nature.[9,21,52] Other microcontrollers identified in the papers include Raspberry Pi, National Instrument, ESP32, and Teensy 2.0. Affordable and user-friendly microcontrollers have the potential to facilitate widespread utilization of sensors for water quality monitoring. The microcontroller is an essential component in water quality monitoring systems, serving as an intermediary platform between sensors and the data logging system. It plays a pivotal role in storing and processing data received from the sensors before transmitting it to the data logging system. Each platform presents distinct trade-offs between processing capability, power consumption, and development complexity, influencing their suitability for different monitoring applications. Advancements in this domain are poised to drive increased popularity of real-time water quality monitoring, enabling its use by mass people in the future. Evaluation of microcontroller implementations shows distinct trade-offs between platforms. Arduino-based systems dominate low-cost implementations due to their power efficiency and simplified integration with common sensor types.[21,52] While Raspberry Pi systems require more power, they offer advantages for applications needing on-site data processing and wireless connectivity.[53] The selection between platforms typically depends on deployment duration, power availability, and data processing requirements.[54]

3.3 Data logging

Data logging approaches fall into several distinct categories, each with different cost implications. Commercial data logging units (*e.g.*, HOBO loggers) typically cost \$500–2000 per unit but include integrated sensors and validated software. In contrast, open-source approaches using microcontroller-based logging (*e.g.*, Arduino with SD card storage) typically cost \$40–100 for the logging components, though requiring additional integration effort. Wireless logging systems span both categories, with commercial telemetry units at the higher end and DIY wireless solutions offering lower-cost alternatives. Recent investigations have highlighted advancements in data logging for affordable water quality sensors. The range of data logging techniques utilized in research, including wireless, computer-based, SD card, smartphone, and various other modalities. However, several studies lack comprehensive descriptions of their methodologies. Analysis of data logging methods across the reviewed literature shows wireless systems as the most commonly specified approach, used in approximately 26% of studies. Other documented methods include SD card storage (12%), computer-based logging (10%), and smartphone applications (8%). Notably, approximately 21% of studies did not specify their data logging method, while the remaining studies used various other approaches such as cloud storage and specialized data acquisition units. The prevalence of wireless systems reflects their advantage in enabling real-time data access, though each method presents different trade-offs between cost, complexity, and accessibility. This comprehensive analysis of data logging practices provides insights into the prevalent methodologies that are influencing the field of low-cost water quality sensor research. The continuous monitoring of the water quality parameters is of paramount importance as it helps to reduce the risks caused by pollution to both aquatic ecosystems and human health. This requires data logging methods that can consistently capture data for extended periods, ranging from days to months.[37,49,55] Despite recent technological advancements, there are still some challenges in using data loggers, particularly due to their high costs. This limits the deployment of a large number of units and results in incomplete information.[37] A study found that Arduino-based loggers have the advantage of monitoring the number of parameters simultaneously and are more cost-effective than conventional HOBO loggers.[21] However, deployment of Arduino-based loggers requires a higher level of expertise for sensor calibration and troubleshooting.[21] Moreover, the data logging methods discussed above, as reviewed in the articles, are of low-cost, rendering water quality monitoring more efficient and cost-effective. Field implementations demonstrate varying success with different data logging approaches. Wireless systems provide real-time data access but face connectivity challenges in remote locations.[49] SD card storage offers reliable data retention but requires regular site visits for data collection,[56] while smartphone-based systems provide an intermediate solution for accessible locations.[57] Long-term deployments often implement redundant logging methods to ensure data preservation.[21]

3.4 Deployment

The literature review identified a prevalent pattern in the use of sensors, with most of the studied articles emphasizing their primary application in field rather than laboratory. The deployment of sensors in a real-world environment enables the *in situ* collection of data where monitoring is imperative. Field deployment allows for the observation and measurement of variations in water quality over long periods of time, and offers a comprehensive view of environmental changes. An in-depth evaluation of study findings highlights the wide range of deployment durations, ranging from less than one day to more than a month. Some researchers even conduct analyses over several years, to capture the large datasets for their studies. The conventional approach of monitoring surface water quality, which involves collecting samples from specific locations and analyzing them in a laboratory, can be time-consuming and may provide limited information about the spatial and temporal dynamics of water quality. While these methods remain essential, particularly for microbial analyses and regulatory compliance, complementary continuous monitoring approaches can help capture rapid changes in water quality parameters.[58] The emergence of the IoT provides the opportunity to perform real-time monitoring that results in accurate and cost-effective measurement of water quality parameters. However, the deployment of multi-sensor systems in outdoor settings for a long time poses many difficulties. For a successful field deployment, it is crucial to address challenges related to fouling and properly calibrate aquatic sensors. In addition, it is necessary to utilize efficient techniques to reduce sensor drift, ensure effective incorporation of wireless technologies, and establish streamlined approaches for data aggregation.[22] Extended field studies have identified critical factors for successful deployment. Systems operating for multiple months demonstrate that regular sensor calibration and maintenance schedules are essential, particularly for chemical parameters like pH and conductivity.[44,59] Environmental conditions significantly impact maintenance requirements, with fouling rates varying based on water body type and local conditions.[43] Deployment configuration studies emphasize the importance of sensor positioning and protection from environmental interference.[39] Overall, trends from the review highlight the need of developing optimized monitoring systems using cost effective alternatives such as the use of novel sensors that can offset many of the challenges from traditional field sampling methods.

A comprehensive analysis of calibration and validation approaches in low-cost water quality monitoring revealed nuanced findings. Of the 84 papers reviewed, 63% reported completing sensor calibration, while 52% compared their results to standard equipment. However, the reporting of calibration methods was highly inconsistent, with significant variations in approach and detail. Many studies mentioned calibration was performed but failed to provide comprehensive protocols or specify clear acceptance criteria. Validation methods ranged from single-point comparisons to extended parallel deployments, creating challenges for systematic assessment and reproducibility. When commercial instrument comparisons were reported, procedures varied widely, highlighting the need for more standardized validation approaches. This variability in methodological reporting presents significant challenges for replicating and validating low-cost monitoring systems. Consequently, we have placed particular emphasis on detailed calibration and validation protocols in our tutorial guidance (Section 4.1). Our recommendations incorporate best practices from the most comprehensive studies, providing a framework for initial calibration and ongoing validation during field deployments.

4 Sensor system for temperature, turbidity, TDS, and pH

This section describes in a tutorial format our experience using temperature, turbidity, TDS, and pH sensors to assess the water quality of distinct environmental systems at two different locations. The overall experience is highlighted including successes and challenges so users are aware of common circumstances that are typically encountered in real field deployments. Although the information provided in this section doesn't come from the current literature, our results are compared and contrasted to other similar studies, to assess its validity, and thereby simultaneously contributing to the overall body of knowledge.

4.1 System development and calibration

The sensor system was constructed using an Arduino Uno microcontroller as the central processing unit, connected to a DS18B20 temperature sensor and DFRobot sensors for TDS, pH, and turbidity. An external battery was incorporated to provide a portable power supply, and an SD card reader was added for onsite data logging, enabling extended field deployments without the need for constant supervision. The components were carefully assembled following precise wiring diagrams to ensure proper connections, standardization, and optimal functionality. To protect the electronic components from environmental factors while allowing the sensors direct contact with water, the system was housed in a custom-designed waterproof enclosure. This enclosure was crucial for maintaining the integrity of the system during field deployments in aquatic environments. Programming of the Arduino utilized a combination of manufacturer-provided libraries and custom-written code to manage data acquisition from all sensors, process readings using calibration parameters, and log results to the SD card at specified intervals. The code was optimized to minimize power consumption, allowing for longer deployment periods between battery changes (see ESI Section S1† for complete Arduino code). Additionally, model numbers and website links to all parts are included in the published tutorials (described below).[60,61]

Calibration of the sensors was conducted systematically to ensure accuracy across the range of expected field conditions. The TDS sensor was calibrated using six standard solutions with conductivity values ranging from 0 to 1000 μS cm^{-1}, providing a comprehensive calibration curve (Fig. S1†). The pH sensor underwent a three-point calibration using standard buffer solutions of pH 4, 7, and 10, covering the typical range found in natural water bodies (Fig. S2†). The turbidity sensor was calibrated with four solutions of 0.02, 20, 100, and 800 NTU, accounting for the non-linear response often observed in turbidity measurements (Fig. S3†). For each sensor, voltage outputs were meticulously recorded for each standard solution, plotted on a spreadsheet, and analyzed using linear regression to derive the calibration equations. For calibration acceptance, we required R^2 values greater than 0.95, indicating strong correlation between voltage outputs and standard solutions. The TDS sensors achieved R^2 values of 0.997 across all three units, pH sensors achieved R^2 values between 0.998–0.999, and turbidity sensors showed R^2 values of 0.991 and 0.968 for the two functioning units. The resulting slope and intercept values were then incorporated into the Arduino code to convert voltage readings to their respective units of measurement. The temperature sensor, pre-calibrated by the manufacturer to ±0.5 °C accuracy, was verified against a certified thermometer to confirm its performance.

The calibrated sensor system was deployed for a 24 days field trial to assess its performance under real-world conditions. Throughout this period, the system continuously recorded measurements of temperature, pH, TDS, and turbidity at 5 minutes intervals, storing the data on the onboard SD card. This sampling frequency aligns with common practices identified in our literature review, where continuous monitoring systems typically collected data at intervals ranging from 1 to 15 minutes.[44,49] This high-frequency data collection allowed for the capture of both diurnal variations and rapid changes in water quality parameters that might be missed by less frequent sampling methods. To assess the accuracy and reliability of the sensor system, standard measurements were taken twice a week using certified laboratory equipment. A Myron L Ultrameter III (Carlsbad, CA) was used for measuring pH, TDS, and temperature, while an Oakton TN-100 Turbidity Meter (Vernon Hills, IL) was employed for turbidity measurements. These standard measurements provided a robust basis for comparison with the continuous data collected by the sensor system, allowing for evaluation of the system's performance and drift over time. The battery was monitored and replaced as needed during the trial to ensure uninterrupted data collection. This field deployment not only served to validate the sensor system's performance but also provided valuable insights into the practical challenges and considerations for long-term deployment of low-cost water quality monitoring systems in real-world settings.

4.2 Field testing

To illustrate key implementation principles, we present two example deployments of the described sensor system. These case studies demonstrate common challenges and solutions in real-world applications. The deployments highlight practical considerations including calibration stability over extended periods, power management strategies for long-term operation, environmental protection approaches for field conditions, and methods for data collection and validation. Detailed performance data and statistical analyses are available in the ESI.† In the United States, sensors were deployed at Eagle Creek in Statesboro, Georgia, a freshwater stream system that runs through the Georgia Southern University campus (Fig. 2c). In Colombia, the system was installed in a pond at the EIA University campus, which receives regular rainfall input and serves as part of the campus stormwater management system (Fig. S5†). These locations were selected to test system performance under different environmental conditions – a flowing stream *versus* a standing water body – and distinct climatic regimes.

A 24 days pilot study was conducted to test the accuracy of the sensor system by comparing its readings with standard sensors. The results show that the temperature, pH, and TDS sensors are functioning as intended, while the turbidity sensor is not as accurate (Fig. 3). The statistical analysis using the

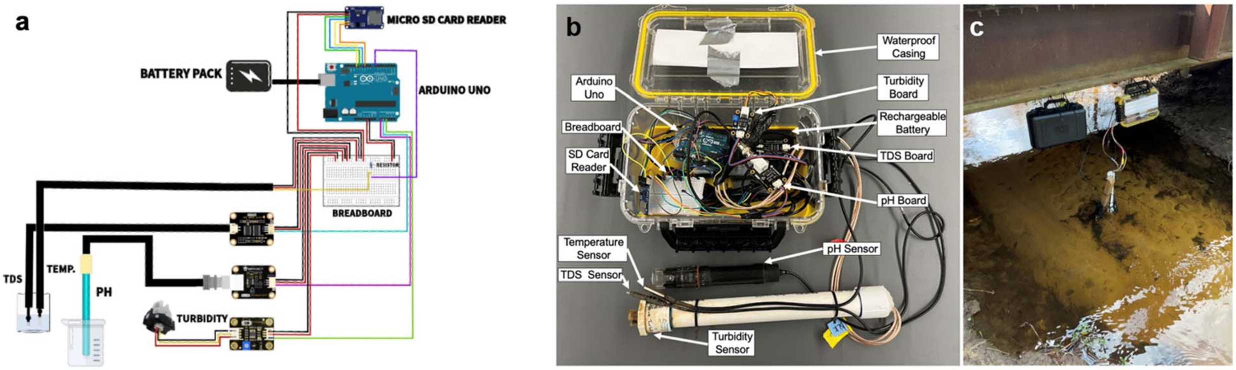

Fig. 2 Overview of the low-cost water quality sensor system. (a) Wiring diagram showing the connections between the Arduino Uno, sensors, and other components. (b) Photograph of the assembled sensor system prior to deployment, illustrating the compact and integrated nature of the device. (c) Image of the sensor system deployed in a field setting, demonstrating its practical application in real-world water quality monitoring.

Granger test, which is particularly suited for comparing time series data with different sampling frequencies, provides further insights into the accuracy of these sensors. The analysis compared 6652 measurements from the Arduino system (collected at 5 minutes intervals) with 8 discrete measurements from the standard equipment over the deployment period. The Granger test was selected for its ability to assess relationships between time series of unequal sample sizes while accounting for temporal dependencies in the data. The temperature sensor was found to be generally accurate through visual data inspection, although the Granger test produced a p-value of 0.8609. Despite this finding, the sensor system successfully captured

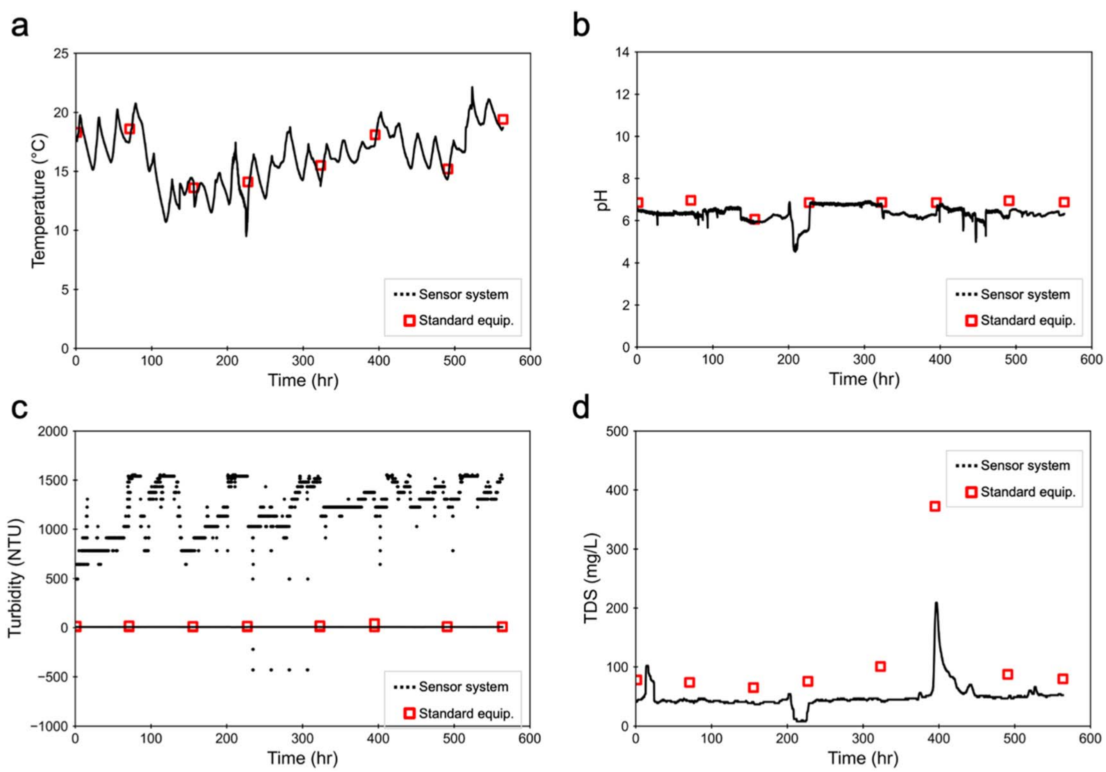

Fig. 3 Comparison of water quality parameters measured by the low-cost Arduino sensor system and standard field equipment during a 24 days field trial at Eagle Creek, GA. (a) Temperature, (b) pH, (c) turbidity, and (d) total dissolved solids (TDS) data are presented. Black lines represent continuous data collected by the Arduino system at 5 minutes intervals, providing high-resolution temporal monitoring. Red squares indicate discrete measurements taken twice weekly using calibrated standard field equipment for validation purposes. This comparison allows for assessment of the Arduino system's accuracy and reliability over an extended deployment period, highlighting both the capabilities and limitations of the low-cost sensor approach in real-world environmental monitoring scenarios. In panel c, the solid horizontal line represents the x-axis (0 NTU).

the natural temperature changes in water throughout the day. The pH sensor demonstrated good accuracy, with a *p*-value of 0.0393 from the Granger test, allowing the rejection of the null hypothesis and indicating that the standard sensors correlate with Arduino sensors. Observed shifts in pH have previously be attributed to various factors, such as pollution from industrial effluents, instream oxidation or reduction processes, runoff from agricultural lime, limestone gravel roads, cement production, and asphalt production.[62] For this deployment, we attribute the shifts in pH to debris from pine trees (*i.e.*, pine needles and sticks).

In contrast, the turbidity sensor showed inconsistencies between the standard readings and the Arduino readings, with a *p*-value of 0.8749 from the Granger test, failing to reject the null hypothesis (Fig. 3c). This discrepancy could be caused by issues during the calibration process and highlights an area for improvement in future work. The consistent near-zero turbidity readings from the standard equipment accurately represent the low turbidity conditions of the monitoring site. This environment provides a particularly challenging scenario for turbidity sensors, especially for low-cost systems that may struggle to provide precise measurements at very low turbidity levels. The low turbidity conditions emphasize the need for careful sensor calibration and validation, particularly when measuring parameters at the lower end of their detection range. This observation aligns with our broader findings about the limitations of low-cost turbidity sensors in detecting subtle changes in water clarity, especially in environments with minimal suspended particles. It is also noteworthy that submersible turbidity sensors are generally less accurate than portable ones, especially with low turbidity measurements.[63,64] Although the Arduino turbidity sensor data may not be reliable, the standard sensor readings provide general environmental observations, such as slight differences in turbidity measurements potentially caused by runoff sediment from rainfall. Higher turbidity levels are a concern as they can indicate an increase in pathogenic microorganisms in water.[65]

The TDS sensor showed consistent data between the standard readings and the Arduino readings, with a *p*-value of 0.04204 from the Granger test, rejecting the null hypothesis and indicating that the standard sensors are correlated with Arduino sensors. However, graphical gaps between the standard and Arduino values can be attributed to the Arduino sensor's lower sensitivity and the need for a warm-up period when first turned on. This issue could be mitigated in the future by improving the Arduino's battery life, as the batteries were changed on a weekly basis during the study. Changes in TDS values are caused by the presence of chemicals, salts, minerals, soil, or other organic matter containing carbonates, chlorides, sulfates, and nitrates, which can enter the watershed through dumping or runoff.[66]

Overall, these findings were consistent with those collected in Colombia (Fig. S4 and S5†). During that deployment, one sensor system monitored temperature, pH, turbidity, and conductivity, successfully capturing daily fluctuations and the impact of heavy rainfall on the monitoring location. The temperature sensor effectively recorded diurnal thermal cycles. The pH measurements revealed two periods of decreased levels, likely due to the introduction of debris. Although the turbidity sensor showed inconsistencies similar to the Georgia deployment, highlighting ongoing challenges with low-cost turbidity measurements. Notably, conductivity measurements demonstrated a gradual decrease over the monitoring period, attributed to the dilution effect of heavy rainfall. These results corroborate the findings from the Georgia deployment and also showcase the sensor system's ability to detect both short-term variations (such as daily temperature cycles and debris-induced pH changes) and longer-term trends (like rainfall-induced conductivity changes). This comprehensive data collection underscores the potential of low-cost sensor systems for continuous water quality monitoring, offering insights into water quality dynamics that might be missed by periodic manual sampling.

In summary, these pilot studies demonstrates that the temperature, pH, and TDS sensors of the developed system are functioning accurately when compared to standard sensors, while the turbidity sensor requires further improvement. The statistical analysis using the Granger test supports these findings, providing valuable insights into the performance of the sensor system. Future work should focus on enhancing the accuracy of the turbidity sensor and improving the battery life of the Arduino to ensure more consistent and reliable measurements.

The precision of the sensor system was evaluated by constructing and deploying three identical units under similar environmental conditions, with the results illustrated in Fig. 4. This approach allowed for an assessment of inter-unit variability and overall system reliability. Temperature sensors (Fig. 4a) demonstrated exceptional precision across all three units, with a mean coefficient of variation (CV) of 2.3% across all measurements. The graph shows three nearly overlapping lines, indicating that all sensors recorded very similar temperature values throughout the deployment period. This high level of consistency suggests that the temperature sensors provide reliable and reproducible measurements, which is crucial for accurate water quality monitoring. The pH sensors (Fig. 4b) also exhibited strong consistency among the three units, with a CV of 6.8% between units. While there are slight variations visible between the units, the overall trends and values remain closely aligned. This indicates good precision in pH measurements across different sensor units, supporting their reliability for field deployments. In contrast, the turbidity sensors (Fig. 4c) showed significant inconsistencies, a CV of 22.2%. Due to technical issues, data from only two of the three turbidity sensors were recorded during the deployment period. The two functioning sensors displayed a high degree of variability between units, with their measurements often diverging considerably. This level of variability is substantially higher than what was observed for the other sensors and suggests challenges in achieving consistent turbidity measurements with the current low-cost sensor design. The TDS sensors (Fig. 4d) demonstrated high precision and inter-unit consistency, with a CV of 1.4%. The graph shows three closely aligned lines, indicating that all TDS sensors produced very similar readings throughout the deployment. This consistency across units

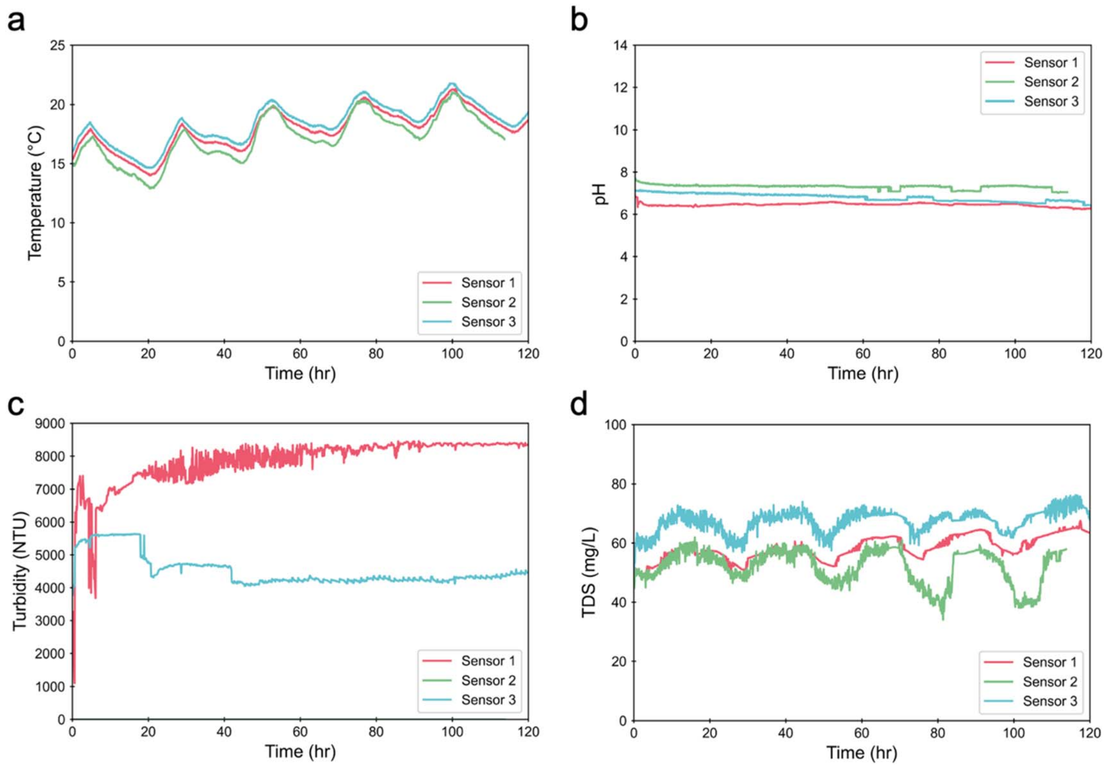

Fig. 4 Precision assessment of the low-cost water quality sensor system using three identical units deployed under similar environmental conditions. (a) Temperature, (b) pH, (c) turbidity, and (d) total dissolved solids (TDS) measurements from each unit are represented by different colored lines.

suggests that the TDS sensors provide reliable and reproducible measurements.

The disparate performance between sensor types underscores the varied challenges in developing low-cost water quality monitoring systems. While the temperature, pH, and TDS sensors demonstrate that high precision and inter-unit consistency can be achieved with affordable components, the turbidity sensor results highlight the ongoing difficulties in accurately measuring suspended particles in aqueous environments using low-cost optical sensors. These findings emphasize the need for further refinement in the design of submersible turbidity sensors for *in situ* use, more robust calibration procedures, or the exploration of alternative measurement techniques for turbidity in future iterations of this system. Additionally, the technical issues that prevented data collection from one turbidity sensor unit highlight the importance of system reliability in field deployments and suggest the need for redundancy or improved quality control measures in future designs.

4.3 Cost of sensor system

A primary objective of this project was to develop an affordable water quality monitoring system. As detailed in Table 1, the total cost of the assembled sensor system is $361.37, with a per-unit cost of $235.83 (as of the date of the materials list). This cost includes all components necessary for a fully functional unit, including the Arduino Uno microcontroller, temperature sensor, pH sensor, TDS sensor, turbidity sensor, SD card reader for data logging, and external battery for power. The cost breakdown reveals that the most expensive components are the sensors themselves, particularly the pH sensor at $64.90 and the turbidity sensor at $9.90. The Arduino Uno costs $32.00, while the 20 000 mA h USB battery pack, crucial for extended field deployments, costs $40.94. Another significant cost includes the waterproof case at $24.53. Despite these costs, the total system remains significantly less expensive than professional-grade water quality monitoring equipment. For instance, the Myron L Ultrameter III (Carlsbad, CA), which was used as a standard for comparison in this study, costs $2494.00.[67] Similarly, the Oakton TN-100 Turbidity Meter (Vernon Hills, IL), also used for comparison, is priced at $1374.45.[68]

This substantial cost difference highlights the potential of the developed system to democratize water quality monitoring. In a time when active community participation (schools, farmers, universities, private sector, citizen scientist, *etc.*) to monitor and preserve water resources to overcome the challenges of costly monitoring programs, the use of this type of sensors is becoming more common. The Arduino-based system could make continuous water quality monitoring accessible to a much wider range of users, including small communities, educational institutions, and citizen scientists who may not have the resources for expensive commercial equipment. In addition, this type of sensors with their application may have a great impact in developing countries and international

Table 1 Detailed cost breakdown of the low-cost water quality monitoring system. This table itemizes all components required to construct a fully functional unit, including the Arduino Uno microcontroller, sensors (temperature, pH, TDS, and turbidity), data logging equipment, power supply, and housing materials. Individual costs and quantities are provided for each item, along with the total system cost. Prices are as of June 1, 2024

Item	Total cost ($)	Per unit cost ($)	Number
Arduino Uno	32.00	32.00	1
USB type A to type B cable	13.99	13.99	1
Breadboard	8.99	1.50	1
Jumper wires	6.98	1.22	21 individual
4.7k Ohm resistor	6.99	0.03	1
Micro SD card	13.39	2.23	1
HiLetgo micro SD card reader	6.99	1.40	1
A 20 000 mA h USB battery pack	40.94	40.94	1
Waterproof case	24.53	24.53	1
1 ft of 1″ PVC pipe	6.99	6.99	1
1″ PVC cap	22.99	0.77	1
1–1/4-in. × 1-in. PVC bushing	1.45	1.45	1
6 ft of 16 AWG speaker wire	16.63	2.50	∼15 feet
Heat shrink tubing	12.99	0.19	6
PVC cement	9.99	2.00	A small portion
Silicone sealant	6.28	1.00	A small portion
Duct tape	6.69	1.00	A small portion
Flex tape	19.99	4.00	A small portion
Zip ties	4.98	0.50	∼10
DFRobot Gravity: analog turbidity sensor for arduino	9.90	9.90	1
DFRobot Gravity: analog TDS sensor/meter for arduino	11.80	11.80	1
DFRobot Gravity: analog pH sensor/Meter Pro Kit V2	64.90	64.90	1
DS18B20 waterproof temperature sensor	10.99	10.99	1
Total	361.37	235.83	

communities lacking the resources to establish a comprehensive water quality monitoring program. It's important to note that some components, such as the PVC pipe, cement, sealant, and various types of tape, are used in small quantities for each unit. Thus, the per-unit cost could potentially be reduced when building multiple systems, as these materials can be shared across units. Additionally, essential workspace requirements include basic electronics workbench with soldering equipment, access to tools for cutting and assembling PVC components, computer with appropriate software for Arduino programming, ventilated space for working with PVC cement and sealants, and testing area with access to water and power. Community organizations might consider partnering with local makerspaces, schools, or technical programs that can provide workspace access and basic technical support. The low cost of the system opens up possibilities for large-scale deployments and long-term monitoring projects that might be prohibitively expensive with commercial equipment. This could lead to more comprehensive datasets and a better understanding of water quality dynamics in various environments worldwide. In conclusion, while the developed sensor system may not match the precision of professional equipment in all aspects, its significantly lower cost represents a major step towards making water quality monitoring more accessible and widespread. This aligns with the project's goal of empowering communities and researchers with affordable tools for environmental monitoring.

5 Educational modules and interactive website

To facilitate the widespread adoption of low-cost water quality monitoring systems, two key educational resources were developed: an Autodesk Instructables guide and the AQWIC (Aquatic Quality Watch Informed by Communities) website.[60,61] The Autodesk Instructables guide (Fig. 5a) was created to provide a comprehensive, step-by-step tutorial for building, programming, and deploying the Arduino-based water quality monitoring system.[60] This guide, titled “Arduino Water Quality Monitoring System,” consists of 27 detailed steps with accompanying pictures. It covers everything from the initial software setup and hardware assembly to sensor calibration, field deployment, and data retrieval. The guide also includes a list of all necessary supplies, troubleshooting tips, and code snippets. By hosting this information on http://instructables.com/, a popular platform for DIY projects, the guide ensures accessibility to a wide audience of makers, citizen scientists, and environmental enthusiasts.

The AQWIC website (Fig. 5b) was developed as a more comprehensive resource center for the project. It features a detailed sensor materials list, providing an inventory of all components required to build the water quality monitoring system, including links to purchase options and estimated costs.[61] This helps users gather all necessary materials before starting the project. The website also includes a step-by-step

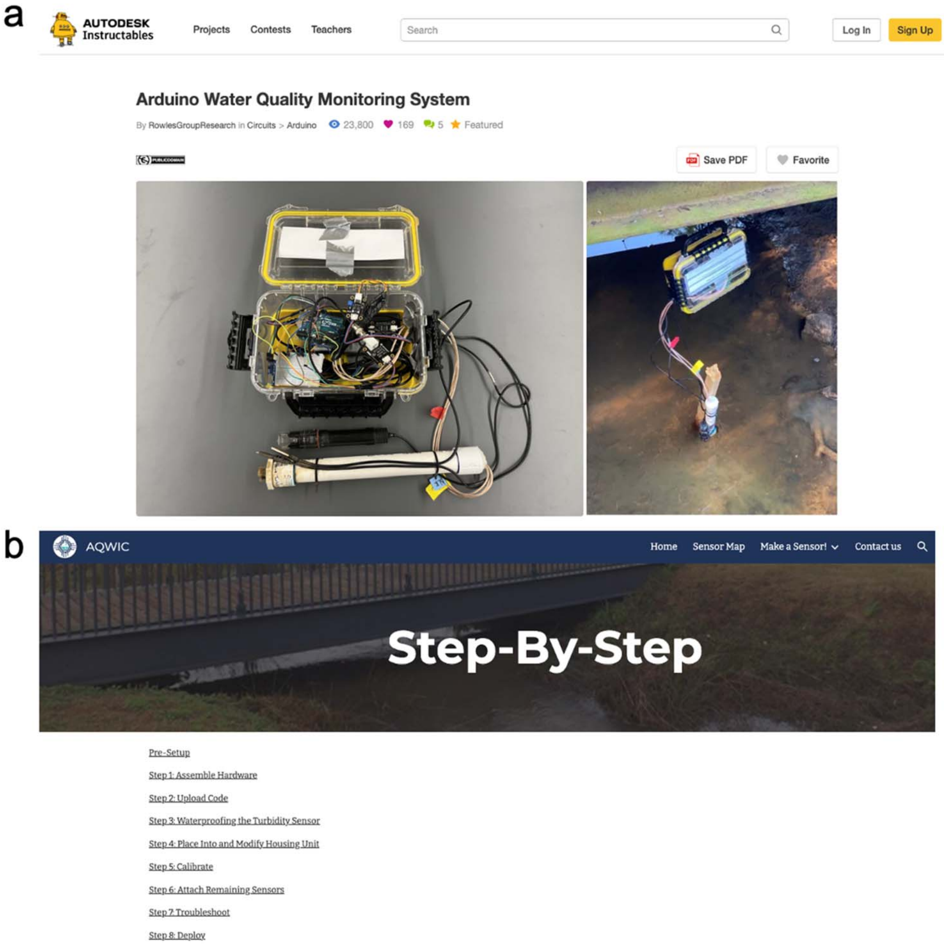

Fig. 5 Educational resources developed to facilitate the adoption of low-cost water quality monitoring systems. (a) Screenshot of the cover page for the "Arduino Water Quality Monitoring System" guide published on http://instructables.com/, providing a comprehensive, step-by-step tutorial for building and deploying the sensor system.[60] (b) Homepage of the AQWIC (Aquatic Quality Watch Informed by Communities) website, featuring resources such as a sensor materials list, step-by-step guide, Arduino code, and an interactive map for data upload. These educational modules aim to democratize access to water quality monitoring technology and encourage community-led environmental monitoring initiatives.[61]

guide, similar to the Instructables guide, but potentially with additional details or updates based on user feedback and ongoing development of the system. The full Arduino code required to operate the sensor system is provided on the website, allowing users to easily copy and paste or download the code for their own use. A unique feature of the AQWIC website is an interactive map where users can upload their collected water quality data. This crowdsourced approach to data collection has the potential to create a comprehensive, user-generated database of water quality information across various locations. The combination of the Instructables guide and the AQWIC website provides a robust educational framework for individuals and communities interested in monitoring their local water quality. The Instructables guide offers a hands-on, practical approach to building the system, while the AQWIC website serves as a central hub for resources, code, and data sharing.

By making these resources freely available online, the project aims to democratize access to water quality monitoring technology and encourage community-led environmental monitoring initiatives. Together, these educational modules empower users to not only build their own monitoring systems but also contribute to a larger community of citizen scientists engaged in water quality research to monitor and protect local water sources. The interactive map feature, in particular, has the potential to create a valuable dataset for researchers and policymakers, providing insights into water quality trends across different regions and over time.

6 Pathways to development and adoption of low-cost sensor systems

The development and adoption of low-cost water quality sensor systems involve a multi-step process that integrates technical innovation, community engagement, and educational outreach. This process, as illustrated in Fig. 6, provides a roadmap for researchers, community organizations, and citizen scientists to create, implement, and disseminate these technologies effectively. The first stage in this pathway is the technical development of the sensor system. This involves selecting appropriate

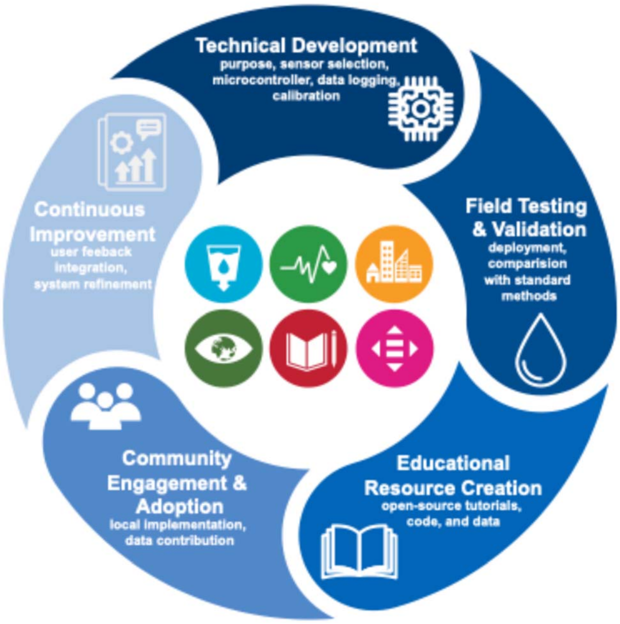

Fig. 6 Pathways for development and adoption of low-cost water quality sensor systems. The multi-step process involved in creating, implementing, and disseminating low-cost water quality monitoring technologies. The process begins with technical development, involving sensor selection, microcontroller integration, and system design. It progresses through field testing and validation, where the system's performance is compared against standard equipment. The next stage focuses on creating and disseminating educational resources, such as online tutorials and guides, to enable widespread adoption. Community engagement follows, involving local organizations and citizen scientists in implementing the systems. The final stage represents continuous improvement, incorporating user feedback and addressing technical challenges. This process aligns with several UN Sustainable Development Goals, shown in the middle of the figure.

sensors, microcontrollers, and data logging components based on the specific water quality parameters of interest and the environmental conditions of the deployment area. As demonstrated in our study, the Arduino platform offers a cost-effective and versatile foundation for building these systems. The development process also includes rigorous calibration and testing to ensure accuracy and reliability, as well as the design of weatherproof housing for field deployments, which is not different to the calibration of existing professional-grade equipment. The second stage focuses on field testing and validation. This crucial step involves deploying the sensor systems in real-world environments and comparing their performance against standard laboratory equipment. Our 24 days field trial exemplifies this process, revealing both the strengths and limitations of the low-cost sensors. This stage often leads to iterative improvements in the system design, particularly for challenging parameters like *in situ* turbidity measurement. The third stage emphasizes the creation and dissemination of educational resources. As demonstrated by our Autodesk Instructables guide and the AQWIC website, these resources are essential for democratizing access to water quality monitoring technologies. By providing step-by-step instructions, parts lists, and programming guides, these educational modules enable communities and individuals to build and deploy their own monitoring systems. The fourth stage involves community engagement and adoption. This includes working with local organizations, schools, and citizen science groups to implement the sensor systems. The interactive map feature of the AQWIC website plays a crucial role here, allowing users to contribute their data to a larger database, fostering a sense of community involvement and enabling broader environmental monitoring efforts. The final stage in this pathway is the continuous improvement and expansion of the technology. This involves incorporating user feedback, addressing technical challenges identified during deployment, and potentially expanding the range of measurable parameters. It also includes exploring ways to integrate these low-cost systems with existing water management infrastructure and decision-making processes.

The development and adoption of low-cost water quality sensor systems have significant implications for achieving several SDGs, particularly SDG 6: clean water and sanitation. By providing affordable and accessible means of monitoring water quality, these systems directly contribute to target 6.3, which aims to improve water quality by reducing pollution and increasing safe reuse. The community engagement aspect of this work also aligns with target 6.8, which seeks to support and strengthen local community participation in water and sanitation management. Furthermore, this work indirectly supports SDG 3: good health and well-being, by enabling early detection of water contamination that could lead to waterborne diseases. It also contributes to SDG 11: sustainable cities and communities, by providing tools for urban water management, and SDG 13: climate action, by facilitating the monitoring of climate change impacts on water resources. The educational components of this project, including the Instructables guide and AQWIC website, support SDG 4: quality education, particularly target 4.7, which aims to ensure that learners acquire knowledge and skills needed to promote sustainable development. By empowering communities with the knowledge to build and operate their own water quality monitoring systems, this work also contributes to SDG 10: reduced inequalities, helping to bridge the technological gap between developed and developing regions.

The pathways to development and adoption of low-cost water quality sensor systems presented here offer a comprehensive approach to addressing the global challenge of water quality monitoring. By combining technical innovation with community engagement and educational outreach, this approach has the potential to democratize access to water quality data and empower communities to take an active role in managing their water resources. Our findings demonstrate that while low-cost sensors can provide reliable measurements for parameters such as temperature, pH, and TDS, challenges remain in accurately measuring more complex parameters like turbidity. This highlights the need for ongoing research and development to improve sensor accuracy and reliability across all relevant water quality parameters. The success of the AQWIC platform and the Instructables guide in facilitating knowledge transfer and community engagement underscores the importance of open-source technologies and educational resources in promoting widespread adoption of these systems. The interactive map feature of AQWIC, in particular, shows promise in creating a global network of citizen scientists contributing to water quality monitoring efforts. However, it is important to note that the development and implementation of low-cost water quality sensor systems require a nuanced approach to performance assessment. Our field testing highlighted the critical importance of understanding sensor limitations across different measurement ranges and environmental conditions. The challenges in turbidity measurement, particularly at low concentrations, demonstrate that both low-cost and commercial sensors can have performance constraints.

Looking forward, the integration of these low-cost sensor systems with emerging technologies such as artificial intelligence and big data analytics could further enhance their capabilities, enabling predictive modeling of water quality trends and early warning systems for contamination events. Additionally, policy support and standardization efforts will be crucial in facilitating the integration of data from these systems into formal water management frameworks. In conclusion, while challenges remain, the pathways outlined in this study provide a clear direction for the continued development and adoption of low-cost water quality sensor systems. By following these pathways and addressing the identified challenges, we can move closer to achieving universal access to clean water and sanitation, contributing significantly to the realization of the Sustainable Development Goals.

Data availability

Data for this article, including reviewed articles and Arduino code are included in the ESI.†

Author contributions

J. H.: conceptualization, methodology, formal analysis, investigation, writing – original draft; F. I.: investigation (literature review), writing – original draft; M. O.: investigation (data collection in Colombia); O. P.: investigation (data collection in Colombia); K. S.: investigation (data collection in Colombia); C. P.: software, visualization (website and integrative map); J. T.: software (website development); M. N. U.: investigation (literature review), writing – original draft; H. W.: software, investigation (data collection in US); M. W.: software (website development); A. W.: software, investigation (data collection in US); N. E. R. M.: conceptualization, methodology; F. C.: conceptualization, methodology, writing – review & editing; F. A. D.-A.: conceptualization, methodology, writing – review & editing; L. S. R.: conceptualization, methodology, project administration, supervision, writing – review & editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

There are no conflicts to declare.

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References

1 UN Water, *Sustainable Development Goal 6: Synthesis Report 2018 on Water and Sanitation*, United Nations publications, United Nations: New York, New York, United States of America, 2018.

2 S. Behmel, M. Damour, R. Ludwig and M. J. Rodriguez, Water Quality Monitoring Strategies — A Review and Future Perspectives, *Sci. Total Environ.*, 2016, **571**, 1312–1329, DOI: **10.1016/j.scitotenv.2016.06.235**.

3 S. Gallaher and T. Heikkila, Challenges and Opportunities for Collecting and Sharing Data on Water Governance Institutions, *Contemp. Water Res.*, 2014, **153**(1), 66–78, DOI: **10.1111/j.1936-704X.2014.03181.x**.

4 J. Crocker and J. Bartram, Comparison and Cost Analysis of Drinking Water Quality Monitoring Requirements versus Practice in Seven Developing Countries, *Int. J. Environ. Res. Public Health*, 2014, **11**(7), 7333–7346, DOI: **10.3390/ijerph110707333**.

5 J. Dong, G. Wang, H. Yan, J. Xu and X. Zhang, A Survey of Smart Water Quality Monitoring System, *Environ. Sci. Pollut. Res.*, 2015, **22**(7), 4893–4906, DOI: **10.1007/s11356-014-4026-x**.

6 S. Geetha and S. Gouthami, Internet of Things Enabled Real Time Water Quality Monitoring System, *Smart Water*, 2016, **2**(1), 1, DOI: **10.1186/s40713-017-0005-y**.

7 E. Borgia, The Internet of Things Vision: Key Features, Applications and Open Issues, *Comput. Commun.*, 2014, **54**, 1–31, DOI: **10.1016/j.comcom.2014.09.008**.

8 S. O. Osman, M. Z. Mohamed, A. M. Suliman and A. A. Mohammed, Design and Implementation of a Low-Cost Real-Time In-Situ Drinking Water Quality Monitoring System Using Arduino, in *2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE)*, IEEE, Khartoum, 2018, pp 1–7, DOI: **10.1109/ICCCEEE.2018.8515886**.

9 W. Hong, N. Shamsuddin, E. Abas, R. Apong, Z. Masri, H. Suhaimi, S. Gödeke and M. Noh, Water Quality

Monitoring with Arduino Based Sensors, *Environments*, 2021, **8**(1), 6, DOI: 10.3390/environments8010006.

10 J. D. Miller and M. Hutchins, The Impacts of Urbanisation and Climate Change on Urban Flooding and Urban Water Quality: A Review of the Evidence Concerning the United Kingdom, *J. Hydrol. Reg. Stud.*, 2017, **12**, 345–362, DOI: 10.1016/j.ejrh.2017.06.006.

11 I. Delpla, A.-V. Jung, E. Baures, M. Clement and O. Thomas, Impacts of Climate Change on Surface Water Quality in Relation to Drinking Water Production, *Environ. Int.*, 2009, **35**(8), 1225–1233, DOI: 10.1016/j.envint.2009.07.001.

12 G. Qin, J. Liu, S. Xu and Y. Sun, Pollution Source Apportionment and Water Quality Risk Evaluation of a Drinking Water Reservoir during Flood Seasons, *Int. J. Environ. Res. Public Health*, 2021, **18**(4), 1873, DOI: 10.3390/ijerph18041873.

13 M. Bartos, B. Wong and B. Kerkez, Open Storm: A Complete Framework for Sensing and Control of Urban Watersheds, *Environ. Sci.:Water Res. Technol.*, 2018, **4**(3), 346–358, DOI: 10.1039/C7EW00374A.

14 Y. Lin, M. Sevillano-Rivera, T. Jiang, G. Li, I. Cotto, S. Vosloo, C. M. G. Carpenter, P. Larese-Casanova, R. W. Giese, D. E. Helbling, I. Y. Padilla, Z. Rosario-Pabón, C. Vélez Vega, J. F. Cordero, A. N. Alshawabkeh, A. Pinto and A. Z. Gu, Impact of Hurricane Maria on Drinking Water Quality in Puerto Rico, *Environ. Sci. Technol.*, 2020, **54**(15), 9495–9509, DOI: 10.1021/acs.est.0c01655.

15 M. R. Landsman, L. S. Rowles, S. H. Brodfuehrer, J. P. Maestre, K. A. Kinney, M. J. Kirisits, D. F. Lawler and L. E. Katz, Impacts of Hurricane Harvey on Drinking Water Quality in Two Texas Cities, *Environ. Res. Lett.*, 2019, **14**(12), 124046, DOI: 10.1088/1748-9326/ab56fb.

16 P. Levallois and C. M. Villanueva, Drinking Water Quality and Human Health: An Editorial, *Int. J. Environ. Res. Public Health*, 2019, **16**(4), 631, DOI: 10.3390/ijerph16040631.

17 T. P. Lambrou, C. C. Anastasiou, C. G. Panayiotou and M. M. Polycarpou, A Low-Cost Sensor Network for Real-Time Monitoring and Contamination Detection in Drinking Water Distribution Systems, *IEEE Sens. J.*, 2014, **14**(8), 2765–2772, DOI: 10.1109/JSEN.2014.2316414.

18 N. A. Cloete, R. Malekian and L. Nair, Design of Smart Sensors for Real-Time Water Quality Monitoring, *IEEE Access*, 2016, **4**, 3975–3990, DOI: 10.1109/ACCESS.2016.2592958.

19 M. V. Storey, B. van der Gaag and B. P. Burns, Advances in On-Line Drinking Water Quality Monitoring and Early Warning Systems, *Water Res.*, 2011, **45**(2), 741–747, DOI: 10.1016/j.watres.2010.08.049.

20 R. Martínez, N. Vela, A. el Aatik, E. Murray, P. Roche and J. M. Navarro, On the Use of an IoT Integrated System for Water Quality Monitoring and Management in Wastewater Treatment Plants, *Water*, 2020, **12**(4), 1096, DOI: 10.3390/w12041096.

21 K. Chan, D. N. Schillereff, A. C. Baas, M. A. Chadwick, B. Main, M. Mulligan, F. T. O'Shea, R. Pearce, T. E. Smith, A. Van Soesbergen, E. Tebbs and J. Thompson, Low-Cost Electronic Sensors for Environmental Research: Pitfalls and Opportunities, *Prog. Phys. Geogr.*, 2021, **45**(3), 305–338, DOI: 10.1177/0309133320956567.

22 B. O'Flynn, F. Regan, A. Lawlor, J. Wallace, J. Torres and C. O'Mathuna, Experiences and Recommendations in Deploying a Real-Time, Water Quality Monitoring System, *Meas. Sci. Technol.*, 2010, **21**(12), 124004, DOI: 10.1088/0957-0233/21/12/124004.

23 V. Garrido-Momparler and M. Peris, Smart Sensors in Environmental/Water Quality Monitoring Using IoT and Cloud Services, *Trends Environ. Anal. Chem.*, 2022, **35**, e00173, DOI: 10.1016/j.teac.2022.e00173.

24 M. Bhende, S. J. Wagh and A. Utpat, A Quick Survey on Wireless Sensor Networks, in *Proceedings of the 2014 Fourth International Conference on Communication Systems and Network Technologies; CSNT14*, IEEE Computer Society, USA, 2014, pp 160–167, DOI: 10.1109/CSNT.2014.40.

25 Y. A. Badamasi, The Working Principle of an Arduino, in *2014 11th International Conference on Electronics, Computer and Computation (ICECCO)*, IEEE, Abuja, Nigeria, 2014, pp 1–4, DOI: 10.1109/ICECCO.2014.6997578.

26 B. Paul, Sensor Based Water Quality Monitoring System, Thesis, BRAC University, 2018, http://dspace.bracu.ac.bd:8080/xmlui/handle/10361/10840, accessed 2024-03-24.

27 S. Gokulanathan, P. Manivasagam, N. Prabu and T. Venkatesh, GSM Based Water Quality Monitoring System Using Arduino, *Shanlax Int. J. Arts Sci. Humanit.*, 2019, **6**(4), 22–26, DOI: 10.34293/sijash.v6i4.341.

28 C. Z. Zulkifli, S. Garfan, M. Talal, A. H. Alamoodi, A. Alamleh, I. Y. Y. Ahmaro, S. Sulaiman, A. B. Ibrahim, B. B. Zaidan, A. R. Ismail, O. S. Albahri, A. S. Albahri, C. F. Soon, N. H. Harun and H. H. Chiang, IoT-Based Water Monitoring Systems: A Systematic Review, *Water*, 2022, **14**(22), 3621, DOI: 10.3390/w14223621.

29 M. S. Chavan, V. P. Patil, S. Chavan, S. Sana, C. Shinde, G. Scholer and U. G. Scholer, Design and Implementation of IOT Based Real Time Monitoring System for Aquaculture Using Raspberry Pi, *Int. J. Recent Innov. Trends Comput. Commun.*, 2018, **6**(3), 159–161, DOI: 10.17762/ijritcc.v6i3.1477.

30 R. S. Ferrarezi, S. K. Dove and M. W. van Iersel, An Automated System for Monitoring Soil Moisture and Controlling Irrigation Using Low-Cost Open-Source Microcontrollers, *HortTechnology*, 2015, **25**(1), 110–118, DOI: 10.21273/HORTTECH.25.1.110.

31 *Intelligent Computing in Engineering: Select Proceedings of RICE 2019*, ed. Solanki, V. K., Hoang, M. K., Lu, Z. and Pattnaik, P. K., Advances in intelligent systems and computing, Springer, Singapore, 2020.

32 T. Tavade and P. Nasikkar, Raspberry Pi: Data Logging IOT Device, *2017 International Conference on Power and Embedded Drive Control (ICPEDC)*, 2017, pp. 275–279, DOI: 10.1109/ICPEDC.2017.8081100.

33 R. N. Gore, H. Kour, M. Gandhi, D. Tandur and A. Varghese, Bluetooth Based Sensor Monitoring in Industrial IoT Plants, in *2019 International Conference on Data Science and*

Communication (IconDSC), 2019, pp 1–6, DOI: 10.1109/IconDSC.2019.8816906.

34 T. E. S. JÖNSSON, An Empirical Study of Cellular-IoT, https://odr.chalmers.se/server/api/core/bitstreams/2a0fdb3e-cdeb-4d92-b17a-0f633b37bb49/content, accessed 2024-03-24.

35 A. T. Demetillo, M. V. Japitana and E. B. Taboada, A System for Monitoring Water Quality in a Large Aquatic Area Using Wireless Sensor Network Technology, *Sustainable Environ. Res.*, 2019, **29**(1), 12, DOI: 10.1186/s42834-019-0009-4.

36 N. Harris, A. Cranny, M. Rivers, K. Smettem and E. Barrett-Lennard, Application of Distributed Wireless Chloride Sensors to Environmental Monitoring: Initial Results, *IEEE Trans. Instrum. Meas.*, 2016, **65**(4), 736–743, DOI: 10.1109/TIM.2015.2490838.

37 M. Gandra, R. Seabra and F. P. Lima, A Low-cost, Versatile Data Logging System for Ecological Applications, *Limnol. Oceanogr.:Methods*, 2015, **13**(3), 115–126, DOI: 10.1002/lom3.10012.

38 O. Postolache, J. D. Pereira and P. Silva Girão, Wireless Sensor Network-based Solution for Environmental Monitoring: Water Quality Assessment Case Study, *IET Sci., Meas. Technol.*, 2014, **8**(6), 610–616, DOI: 10.1049/iet-smt.2013.0136.

39 R. Tiberti, R. Caroni, M. Cannata, A. Lami, D. Manca, D. Strigaro and M. Rogora, Automated High Frequency Monitoring of Lake Maggiore through in Situ Sensors: System Design, Field Test and Data Quality Control, *J. Limnol.*, 2021, **80**(2), DOI: 10.4081/jlimnol.2021.2011.

40 D. Madeo, A. Pozzebon, C. Mocenni and D. Bertoni, A Low-Cost Unmanned Surface Vehicle for Pervasive Water Quality Monitoring, *IEEE Trans. Instrum. Meas.*, 2020, **69**(4), 1433–1444, DOI: 10.1109/TIM.2019.2963515.

41 J. Hu, M. Sedki, Y. Shen, A. Mulchandani and G. Gao, Chemiresistor Sensor Based on Ion-Imprinted Polymer (IIP)-Functionalized rGO for Cd(II) Ions in Water, *Sens. Actuators, B*, 2021, **346**, 130474, DOI: 10.1016/j.snb.2021.130474.

42 M. E. E. Alahi, X. Li, S. Mukhopadhyay and L. Burkitt, Application of Practical Nitrate Sensor Based on Electrochemical Impedance Spectroscopy, in *Sensors for Everyday Life*, ed. Mukhopadhyay, S. C., Postolache, O. A., Jayasundera, K. P. and Swain, A. K., Smart Sensors, Measurement and Instrumentation, Springer International Publishing, Cham, 2017, vol. 23, pp 109–136, DOI: 10.1007/978-3-319-47322-2_6.

43 E. O'Connor, A. F. Smeaton, N. E. O'Connor and F. Regan, A Neural Network Approach to Smarter Sensor Networks for Water Quality Monitoring, *Sensors*, 2012, **12**(4), 4605–4632, DOI: 10.3390/s120404605.

44 M. Makarov, I. Aslamov and R. Gnatovsky, Environmental Monitoring of the Littoral Zone of Lake Baikal Using a Network of Automatic Hydro-Meteorological Stations: Development and Trial Run, *Sensors*, 2021, **21**(22), 7659, DOI: 10.3390/s21227659.

45 Z. Zhang, X. Dai, G. Shan, G. Li, X. Li, X. Liu and F. Qin, A Low Cost UV-IR Dual Wavelength Optical Sensor with Chirp Modulation for in-Situ Chemical Oxygen Demand Measurements, *Sens. Actuators, B*, 2022, **371**, 132538, DOI: 10.1016/j.snb.2022.132538.

46 Y. Wang, S. M. S. M. Rajib, C. Collins and B. Grieve, Low-Cost Turbidity Sensor for Low-Power Wireless Monitoring of Fresh-Water Courses, *IEEE Sens. J.*, 2018, **18**(11), 4689–4696, DOI: 10.1109/JSEN.2018.2826778.

47 J. Droujko, F. Kunz Jr and P. Ö.-T. Molnar, 3D-Printed Open-Source Turbidity Sensor with Arduino Shield for Suspended Sediment Monitoring, *HardwareX*, 2023, **13**, e00395, DOI: 10.1016/j.ohx.2023.e00395.

48 W. Jo, Y. Hoashi, L. L. Paredes Aguilar, M. Postigo-Malaga, J. M. Garcia-Bravo and B.-C. Min, A Low-Cost and Small USV Platform for Water Quality Monitoring, *HardwareX*, 2019, **6**, e00076, DOI: 10.1016/j.ohx.2019.e00076.

49 A. T. Demetillo and E. B. Taboada, Real-Time Water Quality Monitoring For Small Aquatic Area Using Unmanned Surface Vehicle, *Eng. Technol. Appl. Sci. Res.*, 2019, **9**(2), 3959–3964, DOI: 10.48084/etasr.2661.

50 M. Alam, K. Kumar and V. Dutta, Analysis of Solar photovoltaic-battery System for off-grid DC Load Application, *Int. Trans. Electr. Energy Syst.*, 2021, **31**(1), 1–12, DOI: 10.1002/2050-7038.12707.

51 M. H. M. Facure, R. Schneider, D. M. Dos Santos and D. S. Correa, Impedimetric Electronic Tongue Based on Molybdenum Disulfide and Graphene Oxide for Monitoring Antibiotics in Liquid Media, *Talanta*, 2020, **217**, 121039, DOI: 10.1016/j.talanta.2020.121039.

52 Z. Tsiropoulos, E. Skoubris, S. Fountas, I. Gravalos and T. Gemtos, Development of an Energy Efficient and Fully Autonomous Low-Cost IoT System for Irrigation Scheduling in Water-Scarce Areas Using Different Water Sources, *Agriculture*, 2022, **12**(7), 1044, DOI: 10.3390/agriculture12071044.

53 W.-C. Hsu, P.-Y. Chao, C.-S. Wang, J.-C. Hsieh and W. Huang, Application of Regression Analysis to Achieve a Smart Monitoring System for Aquaculture, *Information*, 2020, **11**(8), 387, DOI: 10.3390/info11080387.

54 D. S. Simbeye, J. Zhao and S. Yang, Design and Deployment of Wireless Sensor Networks for Aquaculture Monitoring and Control Based on Virtual Instruments, *Comput. Electron. Agric.*, 2014, **102**, 31–42, DOI: 10.1016/j.compag.2014.01.004.

55 E. Serrano-Finetti, C. Aliau-Bonet, O. López-Lapeña and R. Pallàs-Areny, Cost-Effective Autonomous Sensor for the Long-Term Monitoring of Water Electrical Conductivity of Crop Fields, *Comput. Electron. Agric.*, 2019, **165**, 104940, DOI: 10.1016/j.compag.2019.104940.

56 E. F. Eidam, T. Langhorst, E. B. Goldstein and M. McLean, OpenOBS : Open-source, Low-cost Optical Backscatter Sensors for Water Quality and Sediment-transport Research, *Limnol. Oceanogr.:Methods*, 2022, **20**(1), 46–59, DOI: 10.1002/lom3.10469.

57 S. Srivastava, S. Vaddadi and S. Sadistap, Smartphone-Based System for Water Quality Analysis, *Appl. Water Sci.*, 2018, **8**(5), 130, DOI: 10.1007/s13201-018-0780-0.

58 F.-L. Chen, B.-C. Yang, S.-Y. Peng and T.-C. Lin, Applying a Deployment Strategy and Data Analysis Model for Water

Quality Continuous Monitoring and Management, *Int. J. Distrib. Sens. Netw.*, 2020, **16**(6), 155014772092982, DOI: 10.1177/1550147720929825.

59 L. W. Keenan and S. J. Miller, An Inexpensive, Low-Maintenance, Precision Amplifier, Dissolved Oxygen Sensor, and Miniature Data Logger System Designed for Long-Term Deployment in Riverine Systems, *Trans. Am. Fish. Soc.*, 2010, **139**(2), 593–597, DOI: 10.1577/T08-011.1.

60 RowlesGroupResearch, Arduino Water Quality Monitoring System, Instructables. https://www.instructables.com/Arduino-Water-Quality-Monitoring-System/, accessed 2023-03-27.

61 AQWIC, https://sites.google.com/georgiasouthern.edu/watersensors/home, accessed 2024-07-22.

62 US EPA, O. pH, https://www.epa.gov/caddis-vol2/ph, accessed 2023-03-26.

63 T. Matos, M. S. Martins, R. Henriques and L. M. Goncalves, A Review of Methods and Instruments to Monitor Turbidity and Suspended Sediment Concentration, *J. Water Process Eng.*, 2024, **64**, 105624, DOI: 10.1016/j.jwpe.2024.105624.

64 Turbidity measurement and monitoring in water quality analysis, https://www.ysi.com/parameters/turbidity, accessed 2024-12-18.

65 WHO-FWC-WSH-17.01-Eng.Pdf, https://apps.who.int/iris/bitstream/handle/10665/254631/WHO-FWC-WSH-17.01-eng.pdf, accessed 2023-03-21.

66 Ws_review.Pdf, https://www.iowadnr.gov/portals/idnr/uploads/water/standards/ws_review.pdf, accessed 2023-03-26.

67 L. Myronl, Ultrameter III Series 9PTKB-BD with bluDock. Cannon Water Technology, https://cannonwater.com/myronl-l-ultrameter-iii-series-9ptk-bda-with-bluDock/, accessed 2023-03-21.

68 Oakton TN-100 Turbidity Meter, Handheld, Waterproof, with Standards from Cole-Parmer. https://www.coleparmer.com/i/oakton-tn-100-turbidity-meter-handheld-waterproof-with-standards/3563500#eb-item-powerreviews, accessed 2023-03-21.