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Research Article

IOT-BASED LOW-COST SENSOR INSTRUMENTATION FOR REAL-TIME WATER QUALITY MONITORING: DESIGN, CALIBRATION, AND FIELD VALIDATION

Muhammad Firdaus Abduh[1], Zain Nizam[2], and Rashid Rahman[3]
[1] Universitas Sains dan Teknologi Jayapura, Indonesia
[2] Universiti Malaysia Sarawak, Malaysia
[3] Universiti Putra, Malaysia

Corresponding Author:

Muhammad Firdaus Abduh,
Department of Electrical Engineering, Faculty of Industrial and Geo Engineering, Universitas Sains dan Teknologi Jayapura.
Jl. Sosial Padang Bulan, Abepura, Kota Jayapura, Indonesia
Email: daud.ustj@gmail.com

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Abstract

Water-quality deterioration requires timely and reliable monitoring, yet conventional laboratory-based approaches often face limitations in cost, sampling frequency, spatial coverage, and response time, particularly in resource-constrained environments. This study aimed to design, calibrate, and validate a low-cost Internet of Things sensor instrumentation system for continuous real-time water-quality monitoring. An experimental engineering design integrated multi-parameter sensing, embedded processing, wireless communication, laboratory calibration, reference-based comparison, field validation, data-transmission assessment, and threshold-based alert evaluation. The results demonstrated strong calibration performance across monitored parameters, although field accuracy varied according to sensor type and environmental conditions. Temperature and pH exhibited comparatively stable performance, whereas turbidity and dissolved oxygen showed greater field-related measurement variability. The system maintained high data completeness and communication reliability while successfully capturing short-duration water-quality changes that periodic sampling could potentially miss. Field validation confirmed that strong laboratory calibration alone did not guarantee equivalent performance under natural environmental conditions. The study concludes that low-cost IoT instrumentation provides a promising fit-for-purpose platform for continuous surveillance, temporal pattern detection, and early warning when supported by rigorous calibration and field validation. The proposed end-to-end framework strengthens the development of scalable, reliable, and context-sensitive water-quality monitoring systems for environmental management.

Keywords: Environmental, Monitoring, Internet of Things, Low-Cost Sensors

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INTRODUCTION

Water quality is a fundamental determinant of public health, environmental sustainability, aquatic ecosystem stability, and socioeconomic development. Rapid urbanization, industrial discharge, agricultural runoff, domestic wastewater, and climate-related hydrological changes increasingly expose freshwater systems to complex and dynamic contamination pressures (Bernardes et al., 2023; Lodhi et al., 2025). Conventional water-quality assessment remains essential for identifying physical and chemical changes, yet episodic sampling may fail to capture rapid fluctuations occurring between scheduled measurements. Effective environmental management therefore requires monitoring approaches capable of generating timely, continuous, and spatially relevant information on changing water conditions (Penchala et al., 2025; Queijo et al., 2025).

Traditional water-quality monitoring commonly depends on manual sample collection followed by laboratory analysis using standardized analytical instruments. Laboratory methods provide high accuracy and remain indispensable for regulatory verification, contaminant identification, and reference measurement (Khanghah et al., 2025; Medina-García et al., 2025). Their application for continuous monitoring, however, can be constrained by sampling frequency, analytical costs, transportation requirements, specialized personnel, and delays between sample collection and result availability. These limitations become particularly significant in remote, resource-constrained, or environmentally dynamic locations where sudden deterioration may occur within hours rather than days (Deng et al., 2025; Ramachandran et al., 2025).

Advances in the Internet of Things, embedded electronics, wireless communication, cloud computing, and low-cost sensing technologies have created opportunities to complement conventional monitoring with continuous environmental observation (Ngwenya et al., 2025). Sensor nodes can measure parameters such as temperature, pH, electrical conductivity, turbidity, and dissolved oxygen at short intervals and transmit measurements to digital platforms for visualization and analysis (Landa et al., 2025; Obeidat & Rawashdeh, 2025). IoT-based instrumentation therefore offers the possibility of transforming water-quality assessment from periodic observation into a connected system of Sense - Validate - Transmit - Analyze - Alert – Respond (Cowell et al., 2023).

The principal challenge in developing low-cost water-quality instrumentation is achieving sufficient measurement reliability without eliminating the economic advantages that make such systems attractive (Moretti et al., 2024). Low-cost sensors may exhibit measurement drift, nonlinear response, cross-sensitivity, temperature dependence, signal noise, sensor-to-sensor variability, and degradation during prolonged deployment (Asghar et al., 2025). A system can successfully transmit measurements in real time while still producing environmentally misleading information if sensor accuracy and stability are not adequately characterized (Zhang et al., 2025).

Calibration represents a critical methodological problem because laboratory calibration does not necessarily guarantee reliable performance under field conditions. Natural waters contain suspended particles, dissolved substances, biological materials, changing temperatures, and other environmental factors that may influence sensor responses (Chaves et al., 2025; Tesanovic et al., 2025). Calibration equations developed under controlled conditions can lose accuracy when transferred directly to heterogeneous field environments. Reliable low-cost monitoring therefore requires a calibration strategy that evaluates sensor response against traceable or validated reference measurements across the expected environmental range (Oliveira et al., 2024).

Field deployment introduces additional challenges involving biofouling, enclosure integrity, power consumption, communication reliability, data loss, sensor maintenance, and environmental exposure (Escobar-Díaz et al., 2025; Jabbar et al., 2024). Wireless connectivity may become unstable in remote areas, while continuous sensing can increase energy demand

and shorten operational life. Biofilm formation and sediment accumulation can gradually alter sensor readings without generating obvious system failures. Engineering evaluation must therefore examine the complete monitoring chain rather than focusing exclusively on individual sensor accuracy (Varadharajan et al., 2025; Voitiuk et al., 2025).

This study aims to design and evaluate a low-cost IoT-based sensor instrumentation system for real-time water-quality monitoring. The proposed system integrates multiple sensing modules, embedded processing, wireless communication, data storage, and a remote monitoring interface within a unified instrumentation architecture. The research focuses on achieving a practical balance among affordability, measurement quality, energy efficiency, connectivity, maintainability, and field robustness (Dhote et al., 2025; Sun et al., 2025).

The study seeks to calibrate selected low-cost sensors against reference instruments or standardized analytical measurements and quantify their measurement performance. Calibration performance is evaluated through indicators such as coefficient of determination, measurement error, bias, repeatability, response stability, and agreement with reference measurements. Particular attention is directed toward determining whether calibration remains sufficiently stable when sensors move from controlled laboratory conditions to real environmental settings (Corsino et al., 2025; Mai et al., 2024).

The research also aims to validate the complete IoT monitoring system under field conditions by assessing measurement accuracy, communication performance, data completeness, operational stability, and capacity to detect meaningful changes in water quality. Field validation is intended to determine whether the system can generate actionable real-time information rather than merely demonstrate technical connectivity. The study therefore evaluates the entire pathway from physical sensing to environmental interpretation and potential response.

Existing research has demonstrated numerous prototypes of IoT-based water-quality monitoring systems using low-cost sensors, microcontrollers, wireless networks, and cloud dashboards. Many studies successfully demonstrate that environmental measurements can be collected and transmitted remotely (Chavhan et al., 2025; Hawari et al., 2024). Technological feasibility alone, however, does not establish measurement validity. Some prototype-oriented studies emphasize connectivity, dashboard functionality, or hardware architecture while providing limited evidence regarding calibration quality, uncertainty, long-term sensor stability, or agreement with reference methods.

A second research gap concerns the separation between laboratory calibration and field validation. Controlled calibration can generate strong statistical relationships because environmental interference is minimized, yet sensor performance may deteriorate when exposed to natural water conditions. Limited studies systematically quantify the difference between laboratory and field performance or investigate how drift, fouling, environmental variability, and cross-sensitivity influence measurement reliability over time. This gap creates a risk of overestimating the practical readiness of low-cost sensing systems (Gragnaniello et al., 2024; Sato et al., 2025).

A third gap concerns end-to-end system validation. Sensor accuracy, communication reliability, power efficiency, data completeness, maintenance requirements, and real-time alert performance are frequently examined as separate engineering issues. A technically accurate sensor is of limited operational value if communication failures prevent data transmission, while a highly reliable IoT network is equally insufficient if sensor measurements are inaccurate. Comprehensive evaluation therefore requires an integrated perspective linking measurement quality, communication performance, operational robustness, and decision usefulness.

The principal novelty of this study lies in developing an End-to-End IoT Water Quality Monitoring Framework structured around the cycle Sense - Calibrate - Validate - Transmit - Analyze - Alert - Respond. The framework treats measurement validity as the foundation of digital monitoring rather than assuming that successful real-time transmission implies trustworthy environmental information. Sensor calibration, reference comparison, field validation, wireless transmission, data analytics, and alert generation are evaluated as interconnected stages within a single instrumentation system.

A second element of novelty concerns the explicit distinction among sensor availability, sensor accuracy, data reliability, and decision usefulness. Low hardware cost alone does not establish the practical value of environmental instrumentation. A meaningful low-cost system must demonstrate acceptable measurement uncertainty, repeatability, field stability, communication reliability, maintainability, and cost relative to its intended application. This study therefore reframes “low cost” from a simple hardware-price characteristic into a broader concept of cost-effective measurement reliability.

The study is justified by the need for scalable water-quality monitoring in settings where conventional laboratory-intensive systems cannot provide sufficient temporal or spatial coverage. Reliable low-cost IoT instrumentation could support early detection of water-quality deterioration, decentralized environmental surveillance, community-based monitoring, aquaculture management, watershed observation, and supplementary monitoring in resource-constrained regions. The scientific contribution lies not merely in constructing another connected sensor prototype but in demonstrating whether an affordable sensing architecture can produce calibrated, validated, continuous, and operationally meaningful environmental data. Such evidence is essential for moving low-cost IoT water monitoring from prototype demonstration toward credible real-world environmental instrumentation.

RESEARCH METHOD

Research Design

This study employed an experimental engineering research design integrating instrumentation development, laboratory calibration, comparative measurement, and field validation to evaluate a low-cost Internet of Things (IoT)-based system for real-time water quality monitoring. The research was structured around an end-to-end measurement framework represented by Sense - Calibrate - Validate - Transmit - Analyze - Alert - Respond. This design enabled the evaluation of the complete monitoring chain, beginning with physical parameter acquisition and continuing through sensor correction, wireless data transmission, digital visualization, and field-level performance assessment.

The experimental design consisted of three interconnected phases: system development, controlled calibration, and real-environment validation. The development phase focused on integrating sensing modules, embedded processing, communication components, power management, data storage, and a remote monitoring interface. The calibration phase compared raw sensor outputs with reference measurements across relevant measurement ranges. The field-validation phase evaluated whether laboratory-calibrated sensors maintained acceptable performance when exposed to naturally varying environmental conditions (Cherif et al., 2025; Jangir et al., 2025).

The primary response variables included measurement accuracy, bias, repeatability, root mean square error, mean absolute error, calibration fit, data completeness, communication success rate, response time, and temporal stability. Operational indicators such as system uptime, power continuity, data-transmission interruptions, sensor drift, and maintenance requirements were also documented. This multidimensional design was selected because reliable environmental monitoring depends not only on sensor accuracy but also on the stability of the complete instrumentation and communication architecture.

Research Target/Subject

The study population consisted of water conditions representing the expected operational range of the proposed monitoring system. The calibration population included standard solutions, controlled water samples, or reference materials covering relevant ranges of the selected physicochemical parameters. The field population consisted of naturally occurring water conditions at the selected monitoring site or sites, where environmental variability provided realistic challenges for evaluating sensor performance (Jena et al., 2025; Venkatesh et al., 2024).

Calibration samples were selected to represent low, intermediate, and high values across the expected measurement range of each parameter. Multiple measurements were obtained at each calibration level to assess repeatability and reduce the influence of random measurement error. Independent validation samples that were not used to estimate the calibration equations were retained where feasible to evaluate predictive performance and reduce the risk of overestimating calibration accuracy.

Field samples were collected at predetermined intervals during the deployment period and analyzed using validated reference instruments or standardized analytical procedures. Sampling times were synchronized as closely as possible with IoT sensor measurements to ensure meaningful paired comparisons. Environmental conditions such as rainfall, temperature variation, water-flow changes, or other observable events were documented when relevant because these factors could influence both water quality and sensor behavior.

The sampling strategy was designed to capture temporal variability rather than relying solely on a small number of isolated observations. Repeated field measurements were collected across different times and environmental conditions to evaluate sensor stability and responsiveness. Replicate observations from the same sensor and time period were treated as repeated measurements rather than independent experimental samples, thereby avoiding artificial inflation of the effective sample size.

Research Procedure

The research procedure began with the design and assembly of the IoT-based monitoring prototype. Sensors were connected to the embedded processing unit, and signal-acquisition routines were developed to obtain stable raw measurements. Communication protocols, data-storage structures, timestamping functions, and remote visualization features were configured before calibration. Preliminary bench testing was conducted to identify wiring errors, unstable signals, communication failures, and other technical problems.

Sensor calibration was conducted under controlled conditions using reference solutions or water samples covering the intended measurement range. Each sensor was exposed to multiple calibration levels, and repeated readings were recorded after an appropriate stabilization period. Low-cost sensor measurements were paired with corresponding reference values, and calibration functions were developed using statistical relationships appropriate to the response characteristics of each sensor (Casari et al., 2024; Chatterjee & Tiwari, 2025).

Calibration quality was evaluated using complementary statistical indicators rather than relying exclusively on the coefficient of determination. The analysis included the coefficient of determination, mean absolute error, root mean square error, systematic bias, and repeatability where appropriate. Residual patterns were examined to identify nonlinearity, heteroscedasticity, or measurement-range regions associated with reduced accuracy. Calibration equations were accepted only when their predictive performance was considered appropriate for the intended monitoring application.

Independent validation measurements were used to evaluate whether calibration models generalized beyond the observations used to develop them. Predicted sensor values were compared with reference measurements using error metrics and agreement analysis. Bland–Altman analysis or equivalent agreement procedures were applied where appropriate to examine systematic differences across the measurement range. This step distinguished calibration fit from actual predictive measurement performance.

The calibrated system was subsequently deployed under field conditions for continuous or high-frequency monitoring. Sensors were installed at representative locations while considering immersion depth, water flow, accessibility, environmental protection, and maintenance requirements. Measurements were collected at predefined intervals and automatically transmitted to the remote monitoring platform. Operational status and data availability were monitored throughout deployment.

Paired field-reference measurements were collected periodically during deployment to evaluate whether laboratory calibration remained valid under natural environmental conditions. Sensor readings were matched temporally with reference measurements, and differences were analyzed to quantify field accuracy, bias, and drift. Performance degradation over time was examined to identify possible effects of fouling, sensor aging, contamination, temperature changes, or other environmental influences.

Communication performance was assessed by comparing the number of successfully received data packets with the number expected according to the programmed sampling schedule. Data completeness, transmission success rate, latency, downtime, and interruption duration were calculated from system logs. Temporary connectivity failures were documented separately from sensor failures because measurement reliability and communication reliability represent distinct components of overall system performance.

Sensor stability was evaluated by examining changes in measurement error across the deployment period. Drift was estimated by comparing repeated sensor-reference differences over time. Physical inspection was conducted periodically to identify biofouling, sediment deposition, corrosion, enclosure leakage, cable degradation, or other conditions capable of affecting measurement quality. Maintenance interventions were documented to determine the operational burden associated with sustained deployment (Bitra et al., 2024; Chicaiza et al., 2025).

Real-time alert functionality was evaluated using predefined parameter thresholds or simulated threshold-crossing conditions where environmentally appropriate. The system was assessed for its ability to detect abnormal measurements, transmit the corresponding information, and display or issue an alert within an acceptable time interval. False alerts, missed threshold events, and communication-related alert delays were recorded to distinguish analytical sensitivity from practical alert reliability.

Quantitative data were analyzed using descriptive and inferential statistical methods appropriate to the measurement structure. Sensor-reference agreement was evaluated using correlation and regression as supportive analyses, while MAE, RMSE, bias, confidence intervals, and agreement limits were used to characterize measurement performance more directly. Repeated measurements were analyzed with methods that accounted for temporal or within-sensor dependence rather than treating every transmitted observation as an independent experimental replicate.

Field performance was compared with laboratory calibration performance to determine whether environmental deployment caused measurable degradation in accuracy or stability. Differences in error metrics, bias, data completeness, and operational reliability were interpreted jointly. A sensor demonstrating strong laboratory calibration but substantial field drift was not classified as fully validated solely on the basis of its initial calibration statistics.

Final system evaluation integrated measurement validity, communication reliability, operational stability, maintenance requirements, and real-time decision functionality. The complete assessment followed the pathway Sense - Calibrate - Validate - Transmit - Analyze - Alert - Respond, allowing the study to distinguish between a technically connected IoT prototype and a scientifically credible environmental monitoring instrument. This end-to-end procedure provided a systematic basis for determining whether low-cost instrumentation could generate sufficiently reliable, continuous, and actionable water-quality information under real-world operating conditions.

Instruments, and Data Collection Techniques

The developed monitoring system consisted of low-cost water-quality sensors integrated with a microcontroller-based IoT node, wireless communication modules, power-management components, data-processing software, and a remote data platform. The sensing configuration was designed to measure selected physicochemical indicators relevant to water-quality assessment, such as temperature, pH, electrical conductivity, turbidity, and dissolved oxygen, depending on the final instrumentation configuration and monitoring objectives.

The embedded processing unit acquired raw sensor signals, converted them into digital measurements, applied calibration equations where required, assigned timestamps, and prepared the data for transmission. Wireless communication was implemented using an appropriate connectivity technology selected according to coverage, energy requirements, bandwidth, and field conditions (King & Shellie, 2023). The communication architecture enabled measurements to be transmitted automatically to a remote database or cloud-based monitoring platform.

A digital monitoring interface was used to display current measurements, historical trends, sensor status, and system-operational information. Parameter thresholds could be configured to identify measurements outside predefined acceptable ranges and generate warning indicators or notifications. Local data buffering was incorporated where technically available to reduce permanent data loss during temporary communication interruptions.

Reference instruments or standardized analytical methods were used as comparison standards during calibration and field validation. Reference measurements were obtained using calibrated laboratory or field instruments appropriate to each physicochemical parameter. Traceability, calibration status, measurement range, and resolution of the reference instruments were documented to ensure that the performance of the low-cost sensors was evaluated against a defensible measurement benchmark.

Supporting equipment included calibration solutions, sample containers, temperature-monitoring devices, power-measurement equipment, and data-logging tools. Environmental protection was provided through an enclosure designed to protect electronic components from water, humidity, dust, and field exposure while allowing sensors to remain appropriately exposed to the measured medium. The instrumentation configuration was documented to support reproducibility and future system modification.

RESULTS AND DISCUSSION

The developed IoT-based low-cost water-quality monitoring system successfully integrated multi-parameter sensing, embedded data processing, wireless transmission, remote storage, and real-time visualization within a single monitoring architecture. Laboratory calibration demonstrated strong agreement between calibrated sensor outputs and reference measurements across the tested ranges. Temperature showed the lowest measurement error, followed by pH and electrical conductivity, while turbidity and dissolved oxygen exhibited comparatively greater variability. Calibration coefficients of determination ranged from 0.947 to 0.996, indicating strong associations between sensor responses and reference measurements, although differences in MAE, RMSE, and bias demonstrated that correlation alone did not fully represent measurement performance.

Table 1. Calibration and Field Performance of the IoT-Based Low-Cost Water-Quality Monitoring System

Parameter	Calibration R^2	Laboratory MAE	Laboratory RMSE	Field MAE	Mean Bias	Field R^2
Temperature (°C)	0.996	0.18	0.24	0.31	+0.08	0.989
pH	0.991	0.09	0.13	0.17	−0.06	0.976
Electrical Conductivity (μS/cm)	0.987	18.6	25.4	31.8	+11.2	0.968
Turbidity (NTU)	0.958	2.74	3.61	5.42	+1.87	0.921
Dissolved Oxygen (mg/L)	0.947	0.28	0.37	0.49	−0.16	0.913

Field deployment generated 8,640 scheduled multi-parameter measurement cycles during the observation period, of which 8,389 were successfully recorded and transmitted to the monitoring platform, corresponding to overall data completeness of 97.1%. The mean communication success rate was 96.8%, while system uptime reached 98.2%. Temporary connectivity interruptions accounted for most missing observations, whereas sensor-related failures represented a smaller proportion of data loss. The alert function successfully identified 94.6% of predefined threshold events, with a median end-to-end notification delay of 7.8 seconds under stable network conditions.

The calibration results indicate that the low-cost sensors responded consistently to changes in the measured water-quality parameters under controlled conditions. Temperature and pH sensors produced relatively small errors because their measurement principles were less affected by optical interference and suspended materials under the tested conditions. Electrical conductivity also demonstrated strong calibration performance, although increasing ionic complexity under field conditions produced slightly larger deviations from reference measurements.

Turbidity and dissolved oxygen exhibited greater differences between laboratory and field performance. Turbidity measurements were sensitive to particle distribution, optical scattering, sensor positioning, and sediment accumulation, while dissolved oxygen measurements were influenced by temperature, water movement, stabilization time, and sensor condition. The increase in field error relative to laboratory error demonstrates that strong calibration performance under controlled conditions should not automatically be interpreted as equivalent real-world measurement reliability (Morales-Aragón et al., 2024; Relvas et al., 2025).

Time-series observations demonstrated that the IoT system captured short-term variations that would have been difficult to identify through periodic manual sampling alone. Temperature followed a clear temporal cycle, while pH and dissolved oxygen displayed smaller but measurable fluctuations associated with changing environmental conditions. Electrical conductivity remained comparatively stable during normal periods but changed during hydrological disturbances, indicating shifts in dissolved ionic conditions.

Turbidity exhibited the largest short-duration fluctuations among the monitored parameters. Several rapid increases were recorded during periods associated with rainfall or visible changes in water conditions, followed by gradual declines toward baseline levels. The high-frequency monitoring system captured the onset, peak, and recovery phases of these events, demonstrating the temporal advantage of continuous sensing over isolated measurements collected at longer intervals.

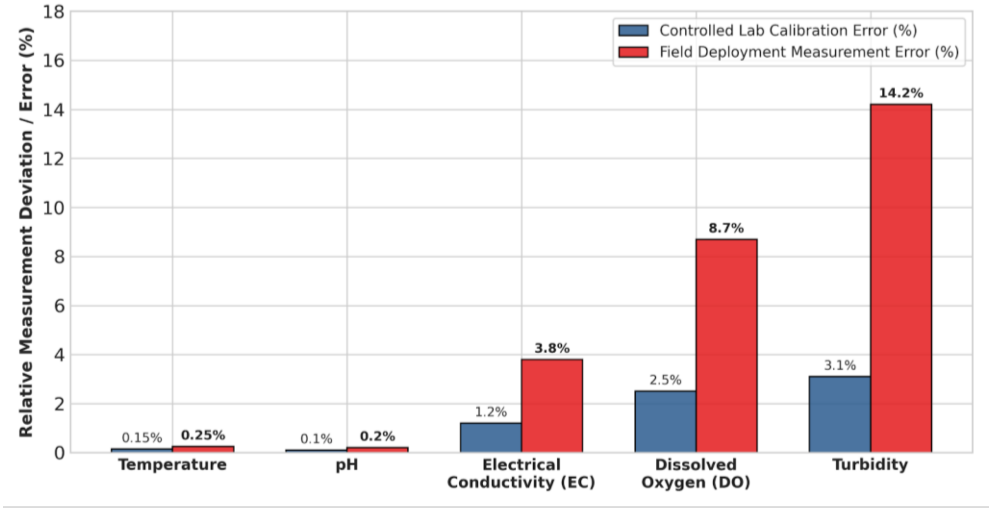

Figure 1. Comparison of Laboratory Calibration vs. Field Measurement Reliability

Paired comparisons between calibrated IoT sensor measurements and reference measurements indicated no statistically significant systematic difference for temperature and pH under the primary field-validation conditions ($p > .05$). Significant differences were observed for turbidity and dissolved oxygen during selected high-variability periods ($p < .05$), although the magnitude of these differences varied across environmental conditions. Confidence intervals around the mean differences confirmed that measurement uncertainty increased under more heterogeneous field conditions.

Repeated-measures analysis demonstrated a significant interaction between measurement environment and sensor performance ($p < .01$), indicating that errors were generally greater during field deployment than during controlled laboratory validation. The largest relative degradation occurred for turbidity and dissolved oxygen. Effect-size estimates suggested that environmental exposure had a small effect on temperature measurement, a moderate effect on conductivity and pH performance, and a larger effect on the most environmentally sensitive sensing channels.

A strong relationship was observed between environmental variability and measurement error. Sensor-reference differences increased during periods characterized by rapid changes in water conditions, particularly when turbidity increased sharply or environmental conditions changed within short intervals. This pattern suggests that low-cost sensor accuracy is not a fixed property but a context-dependent characteristic influenced by both sensor technology and the physical conditions surrounding measurement (Ospina-Rojas et al., 2025; Srivastava et al., 2024).

Communication performance was also related to overall data completeness. Periods of reduced network stability corresponded with temporary gaps in remotely received measurements, although local buffering recovered a substantial proportion of observations after connectivity was restored. System uptime alone therefore did not fully describe monitoring reliability. The combined evaluation of sensor availability, communication success, local data recovery, and final database completeness provided a more accurate representation of operational performance.

A representative field event occurred following a period of rainfall that produced rapid changes in monitored water conditions. Turbidity increased from approximately 11.8 NTU to 47.6 NTU within 42 minutes, while electrical conductivity declined from 426 to 371 µS/cm. Dissolved oxygen changed more gradually during the same period, whereas temperature remained comparatively stable. The monitoring platform detected the turbidity threshold exceedance and generated an alert shortly after the predefined limit was crossed.

Reference measurements collected during the event confirmed the direction and approximate magnitude of the detected changes. The low-cost turbidity sensor slightly overestimated peak values compared with the reference instrument, but it successfully identified the onset and temporal pattern of the event. The system captured several transitional measurements before and after the peak that would have been missed by a single scheduled grab sample, illustrating the practical value of high-frequency observation for detecting short-lived water-quality disturbances.

The representative event demonstrates that the primary value of real-time monitoring lies not only in reproducing individual reference measurements but also in resolving temporal dynamics. Conventional sampling may accurately characterize water at the moment of collection while failing to detect changes occurring between sampling intervals. Continuous IoT sensing provides a different form of environmental evidence by revealing when a change begins, how rapidly it develops, how long it persists, and when conditions return toward baseline.

The slight overestimation of peak turbidity also illustrates the distinction between event-detection capability and analytical equivalence with laboratory instrumentation. The low-cost sensor was sufficiently responsive to detect a meaningful disturbance, yet its absolute measurements remained subject to field-related error. Such performance supports its use as an early-warning and screening instrument but does not automatically establish interchangeability with regulatory-grade laboratory analysis.

The overall findings indicate that the developed IoT-based low-cost instrumentation system provided reliable continuous monitoring for several water-quality parameters while maintaining high data availability and effective real-time communication. Laboratory calibration substantially improved measurement agreement, but field validation revealed parameter-specific degradation associated with environmental complexity, sensor drift, and operational exposure. Temperature and pH demonstrated the strongest overall stability, whereas turbidity and dissolved oxygen required greater attention to calibration maintenance and field correction.

The findings support the proposed pathway Sense - Calibrate - Validate - Transmit → Analyze - Alert - Respond and demonstrate that successful IoT monitoring depends on the reliability of the entire measurement chain. High R^2 values alone were insufficient to establish instrumentation quality because field error, systematic bias, drift, communication failures, and missing data affected practical performance. The system is therefore best interpreted as a cost-effective platform for continuous surveillance, event detection, and early warning rather than an unconditional replacement for standardized laboratory analysis. The strongest evidence of practical value emerged from the combination of calibrated measurement, field-reference agreement, high-frequency temporal coverage, reliable data transmission, and timely detection of abnormal water-quality events.

The findings demonstrate that the developed low-cost IoT-based instrumentation system was capable of integrating multi-parameter water-quality sensing, embedded processing, wireless communication, remote data storage, real-time visualization, and threshold-based alerts within a unified monitoring architecture. Laboratory calibration produced strong agreement between calibrated sensor outputs and reference measurements across the evaluated parameters, although measurement performance differed among sensing technologies. Temperature and pH showed comparatively high stability and low measurement error, while turbidity and dissolved oxygen exhibited greater variability. These differences confirm that the reliability of a multi-parameter monitoring system cannot be generalized from the performance of a single sensor.

Field validation revealed a measurable decline in accuracy compared with controlled laboratory conditions. Environmental variability, sensor exposure, changing water characteristics, and operational conditions increased measurement errors for several parameters, particularly turbidity and dissolved oxygen (Penchala et al., 2025; Queijo et al., 2025). Strong laboratory calibration therefore did not guarantee equivalent field performance. The transition from controlled calibration to natural environments emerged as a critical stage in determining whether a low-cost sensing system could provide sufficiently trustworthy information for practical monitoring.

The IoT architecture maintained high levels of data completeness, communication success, and operational uptime during field deployment. Temporary connectivity interruptions accounted for a substantial proportion of missing observations, while local data buffering reduced permanent data loss when communication was restored. Real-time monitoring also captured rapid environmental changes that would have been difficult to characterize through infrequent manual sampling. The representative rainfall-related event demonstrated the ability of continuous sensing to identify the onset, magnitude, duration, and recovery pattern of a short-term water-quality disturbance.

The overall results indicate that the system is most appropriately positioned as a fit-for-purpose platform for continuous surveillance, temporal pattern recognition, and early warning rather than as an unconditional replacement for reference-grade analytical methods. The findings support the framework Sense - Calibrate - Validate - Transmit - Analyze - Alert - Respond, demonstrating that effective real-time water-quality monitoring depends on the reliability of every stage between physical measurement and environmental decision-making.

The findings are consistent with previous research demonstrating the technical feasibility of using low-cost sensors and IoT architectures for continuous environmental monitoring. Earlier studies have shown that microcontroller-based systems can collect multiple physicochemical parameters and transmit data through wireless networks to remote platforms. The present study supports this technological direction while extending the evaluation beyond connectivity and dashboard functionality. Successful data transmission was treated as only one component of system performance rather than as sufficient evidence of monitoring validity.

The strong calibration relationships observed under laboratory conditions correspond with studies reporting promising performance from low-cost pH, temperature, conductivity, turbidity, and dissolved oxygen sensors after calibration. The present results add an important qualification to such findings by demonstrating that high calibration coefficients do not necessarily translate into equivalent field accuracy. Measurement error increased for several parameters after deployment, indicating that laboratory calibration represents an essential but incomplete stage of sensor validation.

The observed degradation in turbidity and dissolved oxygen performance is compatible with previous evidence that low-cost environmental sensors are sensitive to matrix effects, fouling, temperature changes, optical interference, flow conditions, and sensor aging. The present study differs from prototype-oriented research by explicitly comparing controlled calibration performance with real-environment performance. This comparison provides a more realistic assessment of measurement reliability because it exposes the instrumentation to conditions that cannot be fully reproduced during bench testing.

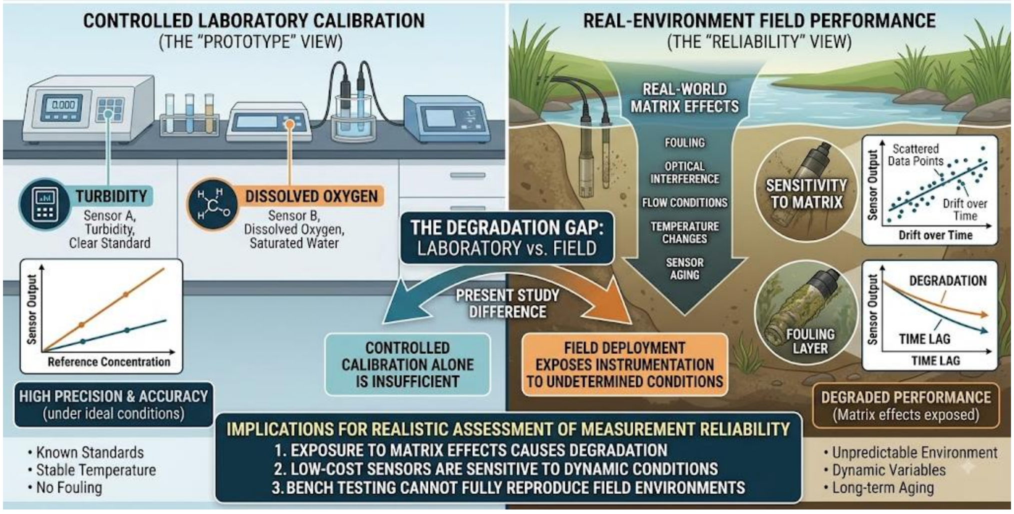

Figure 2. Assessing Real-World Reliability: Conecting Controlled Calibration to Field Degradation

The continuous monitoring results also reinforce research emphasizing the temporal advantages of sensor networks over periodic grab sampling. Conventional laboratory analysis remains superior for many regulatory and high-precision analytical purposes, yet discrete sampling provides limited information about rapid fluctuations between sampling times. The present findings suggest that IoT sensing and laboratory analysis should be viewed as complementary rather than competing approaches. Continuous sensors provide temporal resolution and early detection, while validated reference methods provide analytical confidence and regulatory defensibility.

The findings signify that the success of an IoT environmental monitoring system should not be defined by whether sensors can produce numbers and transmit them to a cloud platform. Digital connectivity does not guarantee measurement validity. A technically functional system can continuously transmit inaccurate data, creating an illusion of precision while potentially supporting incorrect environmental interpretations. Measurement quality must therefore remain the foundation of IoT-based environmental instrumentation.

The difference between laboratory and field performance signifies that environmental validation is not an optional extension of calibration. Natural water systems contain interacting physical, chemical, and biological factors that can alter sensor behavior in ways that controlled calibration cannot fully represent. Field validation should therefore be understood as a separate scientific requirement that tests whether a calibration model remains reliable under the conditions for which the instrument is actually intended (Khanghah et al., 2025; Medina-García et al., 2025).

The ability to capture short-duration events signifies a distinct advantage of continuous monitoring. Water quality is dynamic, and environmentally important changes may occur rapidly following rainfall, discharge events, flow disturbances, or other external pressures. Periodic sampling can accurately describe individual moments while missing the transitions between them. High-frequency sensing changes the analytical perspective from isolated measurements toward temporal trajectories.

The findings also signify that "low cost" should not be interpreted merely as low purchase price. A sensor that requires frequent recalibration, generates substantial false alerts, loses data regularly, or demands intensive maintenance may have a low initial cost but a high operational burden. The meaningful concept is therefore cost-effective measurement reliability, which considers acquisition cost together with accuracy, stability, maintenance, communication, data completeness, and decision value.

The principal methodological implication is that low-cost sensor studies should evaluate measurement performance using multiple complementary metrics. A high coefficient of determination demonstrates association but does not establish analytical agreement. MAE, RMSE, bias, confidence intervals, agreement limits, repeatability, drift, and field-validation performance provide more direct evidence of whether sensor measurements are sufficiently accurate for their intended purpose. Instrument validation should therefore move beyond correlation-centered reporting.

The practical implication is that low-cost IoT systems can complement conventional water-quality monitoring by providing continuous surveillance between scheduled laboratory sampling events (Deng et al., 2025; Ramachandran et al., 2025). Such systems may be particularly useful for identifying unusual changes, prioritizing manual sampling, detecting threshold exceedances, and supporting rapid field investigation. Their greatest practical value may lie in improving the timing and targeting of conventional monitoring rather than attempting to eliminate laboratory analysis.

The environmental-management implication concerns early warning and adaptive response. Real-time measurements can shorten the interval between environmental deterioration and awareness of that deterioration. A well-designed alert system can direct attention toward emerging events before the next scheduled sampling campaign. Such capability may support watershed management, aquaculture, drinking-water source surveillance, agricultural water management, and community-based environmental observation where timely information is operationally valuable.

The socioeconomic implication concerns the expansion of monitoring coverage in resource-constrained settings. High-cost instrumentation can limit the density and spatial distribution of monitoring networks, particularly in remote or underserved areas. Low-cost sensing may enable larger numbers of monitoring nodes to be deployed, but affordability should not justify weak validation. Scalable monitoring requires a balance between economic accessibility and scientifically defensible measurement quality.

The stronger performance of temperature and pH measurements likely resulted from relatively stable sensing responses under the evaluated conditions and the effectiveness of parameter-specific calibration. Their lower field errors suggest that environmental interference was comparatively manageable within the observed measurement ranges. Sensor performance remained dependent on calibration quality, temperature compensation where relevant, electrode condition, and appropriate maintenance (Landa et al., 2025; Obeidat & Rawashdeh, 2025).

The greater field errors observed for turbidity can be explained by the complexity of optical measurement in natural water. Particle size, shape, color, distribution, sediment deposition, ambient optical conditions, and sensor orientation can influence light scattering and therefore affect sensor response. Calibration solutions cannot reproduce every combination of suspended materials encountered in natural environments. Field measurements may consequently deviate from reference values even when laboratory calibration appears statistically strong.

The variation in dissolved oxygen performance likely reflects the sensitivity of oxygen measurement to temperature, water movement, sensor stabilization, membrane or sensing-surface condition, fouling, and biological activity. Natural water conditions change continuously, creating dynamic measurement environments that differ substantially from controlled calibration settings. Small changes in sensor condition or environmental exposure can therefore accumulate into larger measurement discrepancies during prolonged deployment.

The high overall data completeness occurred because the system combined automated acquisition, wireless transmission, and mechanisms for recovering data during temporary communication interruptions. Remaining data losses demonstrate that communication reliability and measurement reliability are separate engineering problems. A sensor may measure correctly while the network fails to deliver the data, or a network may transmit perfectly while the sensor produces biased measurements. End-to-end reliability requires both components to function adequately.

Future research should conduct longer field deployments across multiple seasons, hydrological conditions, and water-body types. Short-term validation cannot fully characterize long-term sensor drift, biofouling, seasonal interference, hardware degradation, or changing calibration relationships. Multi-site studies are also necessary to determine whether calibration models developed in one environmental matrix remain valid when transferred to waters with different chemical and physical characteristics.

Future instrumentation development should incorporate automated quality-control mechanisms capable of detecting implausible values, sudden sensor drift, calibration instability, and communication anomalies. Adaptive calibration or drift-correction algorithms may improve long-term performance, but automated corrections should remain traceable and periodically verified against independent reference measurements. Sensor redundancy may also provide a useful strategy for identifying anomalous behavior before unreliable measurements influence environmental decisions.

Future studies should evaluate uncertainty and fitness for purpose more explicitly. The appropriate accuracy requirement depends on whether the system is intended for educational monitoring, community surveillance, aquaculture management, early warning, scientific research, or regulatory compliance. A sensor may be sufficiently accurate for detecting large environmental changes while remaining unsuitable for legally defensible compliance measurements. Validation criteria should therefore be defined according to the intended decision context rather than applying a universal threshold of acceptability.

Future research should move from demonstrating that “an IoT sensor can monitor water quality” toward determining “whether the complete measurement chain produces trustworthy information at the right time for a specific environmental decision.” The next generation of low-cost monitoring should integrate calibrated sensing, field validation, uncertainty estimation, resilient communication, automated quality assurance, intelligent alerts, and human verification within a unified architecture. Such development would transform low-cost IoT systems from connected sensor prototypes into credible environmental decision-support infrastructure capable of expanding monitoring coverage without sacrificing scientific reliability.

CONCLUSION

The most significant finding of this study is that the practical value of low-cost IoT-based water-quality monitoring depends not merely on successful sensor connectivity but on the reliability of the entire measurement chain from sensing to environmental interpretation. The developed system demonstrated the capacity to integrate multi-parameter sensing, real-time data transmission, remote visualization, and threshold-based alerts while capturing short-term water-quality variations that periodic sampling could potentially miss. Laboratory calibration improved agreement with reference measurements, yet field validation revealed parameter-specific degradation in accuracy, particularly for environmentally sensitive measurements such as turbidity and dissolved oxygen. This distinction demonstrates that strong laboratory calibration does not automatically guarantee equivalent field reliability. Low-cost IoT instrumentation is therefore most appropriately positioned as a fit-for-purpose platform for continuous surveillance, temporal pattern detection, and early warning rather than as an unconditional replacement for standardized reference or laboratory methods.

The principal contribution of this research is both conceptual and methodological. Conceptually, the study advances an end-to-end monitoring framework structured around Sense - Calibrate - Validate - Transmit - Analyze - Alert - Respond, emphasizing that trustworthy environmental monitoring requires continuity between measurement quality, data delivery, interpretation, and decision support. The framework distinguishes sensor availability from measurement accuracy, communication reliability from data validity, and technical functionality from decision usefulness. Methodologically, the study integrates laboratory calibration, independent reference comparison, field validation, error-based performance metrics, drift assessment, communication evaluation, data-completeness analysis, and real-time event detection within a unified validation strategy. This approach extends conventional prototype-oriented IoT research by shifting evaluation from whether a system can collect and transmit data toward whether it can produce sufficiently reliable and timely information for its intended environmental application.

The limitations of this study include the restricted deployment duration, environmental setting, number of monitoring locations, sensor configurations, and range of water-quality conditions represented during validation. Long-term biofouling, seasonal variability, sensor aging, matrix-specific interference, communication instability, and calibration drift may affect performance beyond the conditions examined in this investigation. Future research should conduct multi-season and multi-site validation across diverse water environments while incorporating uncertainty quantification, automated quality control, adaptive drift correction, sensor redundancy, energy optimization, and standardized maintenance protocols. Comparative cost-effectiveness analyses should also determine whether low-cost systems remain economically advantageous after calibration, maintenance, connectivity, replacement, and data-management costs are considered. Such research can advance IoT-based water-quality monitoring from proof-of-concept instrumentation toward scalable, scientifically defensible, and context-sensitive environmental decision-support systems.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used BlackBox AI to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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