

IoT-Enabled Environmental Monitoring for Water and Air Quality: System Design, Field Deployment, and Data Analytics

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Abstract

Continuous monitoring of water and air quality is essential for the timely detection of environmental degradation and for protecting public health. This paper presents the design, field deployment and data-analytics framework of an Internet of Things (IoT) environmental monitoring network that simultaneously measures key water-quality parameters (temperature, pH, dissolved oxygen, turbidity and electrical conductivity) and airborne particulate matter (PM_{2.5} and PM₁₀) across three water and three air monitoring sites. Six low-power wireless sensing nodes were deployed for a combined study period of 90 to 120 days, transmitting data to a cloud platform through a LoRaWAN and 4G uplink. The results show that the network achieved a mean packet-delivery rate above 94 percent, with good temporal coverage of the targeted parameters. Water-quality measurements remained within typical freshwater ranges for most of the deployment, although episodic turbidity spikes were observed after rainfall. Air-quality measurements revealed that daily mean PM_{2.5} and PM₁₀ concentrations frequently exceeded the 2021 World Health Organization air quality guideline values. A field inter-comparison between the low-cost particulate-matter sensors and a reference monitor produced a coefficient of determination of 0.87 for hourly PM_{2.5}, confirming adequate performance after a relative-humidity correction. The findings demonstrate that low-cost IoT systems can deliver operationally useful environmental intelligence and support evidence-based management decisions, provided that careful calibration, data-quality control and network maintenance are sustained.

Keywords: internet of things, environmental monitoring, water quality, air quality, low-cost sensor, LoRaWAN, particulate matter, data analytics

1. Introduction

Freshwater resources and ambient air are fundamental to human well-being, yet both are increasingly stressed by urbanisation, industrial activity, agricultural runoff and climate variability. The degradation of water quality threatens drinking-water safety, aquatic ecosystems and irrigation-dependent livelihoods, while poor ambient air quality is associated with a broad range of adverse health outcomes, including respiratory and cardiovascular diseases, impaired cognitive development and premature mortality (World Health Organization, 2021). Reliable, timely and spatially dense environmental data are therefore essential for identifying emerging pollution problems, evaluating the effectiveness of mitigation measures and informing public policy at both local and national scales.

Conventional environmental monitoring relies on periodic manual sampling followed by laboratory analysis. Although these approaches provide high measurement accuracy and are well accepted by regulatory authorities, they are expensive, labour-intensive and offer poor temporal resolution. Outbreaks of contamination or short-lived pollution episodes may be missed entirely between consecutive sampling events, and the number of monitoring stations that can be operated is limited by budget and staffing constraints. As a result, the observational record in many regions is both sparse in space and coarse in time, which makes it difficult to attribute pollution events to specific sources or to respond rapidly when conditions deteriorate. These limitations are particularly acute in developing regions, where monitoring infrastructure is sparse and the pressures on environmental quality are often highest (Geetha & Gouthami, 2016).

The rapid maturation of the Internet of Things (IoT) has created new opportunities to overcome these constraints. Low-cost sensors, low-power wireless communication and cloud-based data platforms now enable continuous, near-real-time monitoring at a fraction of the cost of traditional instrumentation (Al-Fuqaha et al., 2015). The IoT paradigm connects physical sensors to digital services, allowing large volumes of environmental

measurements to be collected, transmitted, stored and analysed automatically. Wireless sensor networks have been applied to river and reservoir water-quality monitoring, and low-cost particulate-matter sensors have been deployed to increase the density of urban air-quality observation (Adu-Manu et al., 2017; Castell et al., 2017). When combined, these technologies can deliver a scalable environmental-monitoring fabric that supports both scientific analysis and operational decision-making.

Despite the promise of IoT environmental monitoring, several practical questions remain unresolved. The real-world reliability of low-cost sensors, the achievable data completeness of the underlying wireless network, and the consistency of sensor readings against reference instruments all require systematic field evaluation. Sensor drift, environmental interference and communication losses can compromise data quality if they are not managed carefully. Moreover, the integration of water- and air-quality monitoring within a single IoT architecture, together with the analytical procedures needed to convert raw observations into actionable information, has received comparatively little attention in the applied-sciences literature (Saravanan et al., 2018). Many published systems are demonstrated in laboratory or short-term settings, leaving an evidence gap regarding sustained field performance.

This paper addresses that gap by presenting the design, deployment and evaluation of an IoT-based environmental monitoring network that measures both water quality and airborne particulate matter. The specific objectives are: (1) to design and deploy a low-power IoT sensing network for water and air quality at six complementary sites; (2) to evaluate the data completeness and reliability of the wireless communication and data pipeline over an extended period; (3) to assess the performance of low-cost particulate-matter sensors against a reference instrument; and (4) to demonstrate how the collected data can be used to identify water-quality events and to benchmark air quality against health-based guidelines. By addressing these objectives, the study aims to provide transferable design guidance and quantitative evidence for agencies and utilities that are considering the adoption of low-cost IoT monitoring.

Beyond the immediate scientific value, the study also addresses a broader governance concern. Environmental monitoring is a prerequisite for environmental management, yet its cost is often prohibitive for lower-income communities and smaller municipalities. If the total cost of ownership of a monitoring network can be reduced by an order of magnitude while retaining adequate accuracy, the range of institutions that can participate in evidence-based environmental stewardship widens considerably. Demonstrating that such systems can be built from low-cost, openly documented components and can operate with modest technical support is therefore a contribution to environmental equity as well as to applied engineering. The choice to report data-quality metrics transparently, rather than presenting only the most favourable readings, is intended to give prospective adopters a realistic basis for assessing whether a low-cost network would meet their own requirements.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature on water-quality IoT monitoring, air-quality sensing, wireless network technologies and data-quality challenges. Section 3 describes the system architecture, sensor nodes, communication infrastructure, calibration protocols, deployment sites and analytical methods. Section 4 presents the results of the deployment, including network reliability, water-quality observations, air-quality observations and sensor validation. Section 5 discusses the interpretation of the findings, their practical implications and the limitations of the study. Section 6 concludes with a summary and recommendations for practitioners and for future research.

2. Literature Review

2.1 IoT-Based Water-Quality Monitoring

Water-quality monitoring has been one of the earliest and most successful application domains of wireless sensor networks. Early systems demonstrated that networked sensors could transmit measurements of physical and chemical parameters from rivers, reservoirs and distribution networks to central databases in near-real time (Adu-Manu et al., 2017). Key parameters typically measured include water temperature, pH, dissolved oxygen, electrical conductivity, turbidity and, in some systems, nutrient concentrations and heavy-metal levels. Each parameter informs a different aspect of environmental and public-health risk: temperature affects biological activity and dissolved-gas solubility, pH determines the mobility of many contaminants, dissolved oxygen reflects the health of aquatic ecosystems, and turbidity is a proxy for suspended solids and for the efficacy of water-treatment processes.

The review by Adu-Manu et al. (2017) systematically documented the state of the art in this field and highlighted both the technical advances and the persistent challenges, including energy constraints, sensor drift and the difficulty of maintaining calibration under harsh field conditions. Their analysis identified data quality and node energy management as the two most important factors governing the long-term viability of water-quality sensor

networks. Subsequent studies have confirmed that attention to these factors, rather than to raw sensing accuracy alone, largely determines whether a deployment yields trustworthy time series.

Subsequent deployments have moved from proof-of-concept prototypes toward operationally oriented systems. Adu-Manu et al. (2020) deployed wireless sensor nodes for real-time river-quality monitoring, using energy-efficient transmission scheduling and solar-energy harvesting to prolong node lifetime over a five-month period. Their work at an intake in Ghana demonstrated that continuous systems can sustain monitoring through seasonal variability and can flag changes in water quality that coincide with catchment activity. Geetha and Gouthami (2016) proposed an IoT architecture in which sensor readings were streamed to the cloud and made available through web interfaces, emphasising the value of open data access for stakeholders. Saravanan et al. (2018) integrated IoT-based water-quality measurements into supervisory control and data-acquisition (SCADA) environments, showing how streaming data can be fused with existing operational systems used by utilities.

These studies consistently report that continuous IoT monitoring can reveal short-lived events, such as pollution pulses and turbidity excursions, that would be invisible to intermittent grab sampling. However, they also underscore that data credibility depends on rigorous sensor validation, regular maintenance and clearly defined quality-control procedures. Without such safeguards, unattended instruments may silently drift or fail, generating data that appear plausible but are inaccurate. The literature therefore points toward a deployment model in which continuous IoT sensing is complemented by periodic reference sampling and by transparent reporting of data-quality metrics.

A further theme in the water-monitoring literature is the trade-off between measurement density and cost. Adding more parameters and more frequent sampling increases the information available but also raises energy demand, bandwidth use and servicing effort. Designers therefore face a practical optimisation problem: which parameters, at what sampling interval, and at how many locations will deliver the information needed for a particular management objective? In many applications, a small set of core parameters sampled every ten to thirty minutes provides most of the decision-relevant information at a fraction of the cost of a fully instrumented laboratory-grade station. This principle guided the selection of parameters and sampling intervals in the present study.

2.2 Air-Quality Monitoring With Low-Cost Sensors

Ambient air-quality monitoring has traditionally been performed by regulatory agencies using reference-grade instruments, which are accurate but costly and sparsely deployed. The emergence of low-cost optical particulate-matter sensors has stimulated considerable interest in densifying observation networks and in engaging citizen-science communities (Castell et al., 2017). These sensors estimate particle mass concentrations from the scattering of laser light and can be combined with small microcontrollers and communication modules to form compact, battery- or solar-powered monitoring nodes that cost a small fraction of a reference station.

Field evaluations have shown that low-cost sensors can provide adequate accuracy for daily-average PM_{2.5} concentrations, while hourly values are subject to greater bias. Tagle et al. (2020) tested a custom-built IoT sensor in Santiago, Chile, and reported coefficients of determination between 0.47 and 0.86 for hourly PM_{2.5} and between 0.63 and 0.87 for daily averages across multiple regulatory monitoring stations. Their work also documented meaningful inter-unit variability, which underlines the need for per-unit calibration. A recurrent finding across the wider literature is the influence of relative humidity: sensors tend to overestimate particulate concentrations when humidity exceeds roughly 75 percent, owing to the hygroscopic growth of particles, and to underestimate at low humidity.

Castell et al. (2017) evaluated commercial low-cost sensor platforms and concluded that, although they are not substitutes for regulatory instruments, they can make a valuable contribution to exposure assessment and to the spatial characterisation of pollution when appropriately calibrated and deployed. The practical implication is that low-cost networks are best understood as a complementary layer of observation that fills spatial and temporal gaps, while reference stations provide the authoritative anchor points for calibration and verification. This layered approach has been widely adopted in smart-city initiatives and citizen-science projects worldwide.

It is also worth noting that the value of an air-quality measurement depends not only on its accuracy but on its representativeness. A single reference monitor located at a city centre provides limited information about the very different concentrations found in residential streets, industrial zones and parks. Because low-cost sensors are inexpensive, dozens of them can be distributed across a city, revealing the spatial heterogeneity that a sparse reference network cannot capture. This spatial richness, in turn, supports more reliable estimates of population exposure and enables the identification of pollution hotspots that warrant closer investigation. The present deployment exploited exactly this property by placing sensors across urban, industrial and suburban locations.

2.3 Communication Technologies and Network Architecture

The choice of wireless technology governs the cost, energy consumption and spatial reach of an environmental monitoring network. Short-range options such as Wi-Fi, ZigBee and Bluetooth have been widely used, but they constrain node placement and require dense gateway infrastructure, which increases cost and limits deployment in remote locations. These technologies are well suited to indoor or campus-scale applications but are less attractive for dispersed environmental monitoring.

Low-power wide-area (LPWA) technologies, most notably LoRa and Narrowband IoT, have become increasingly attractive because they support long-range communication at low data rates and very low power consumption (Sinha et al., 2017). LoRaWAN operates in unlicensed sub-GHz bands, allowing individual nodes to communicate over distances of several kilometres in rural settings and to operate for months on small batteries. Its use of chirp-spread-spectrum modulation provides robustness to interference, and its adaptive data-rate mechanism helps to balance range, throughput and energy use. These characteristics make LoRaWAN particularly suitable for environmental applications in which nodes are distributed over large areas and mains power is unavailable.

A common architecture places sensing nodes in a star-of-stars topology, in which nodes transmit to gateways or concentrators that forward data to a cloud backend over a broadband uplink such as 4G or Ethernet (Al-Fuqaha et al., 2015). The cloud layer provides elastic storage, remote monitoring, automated alerting and integration with external services. This three-tier arrangement separates the concerns of sensing, transport and analytics, allowing each layer to be upgraded independently. The literature indicates that such architectures scale well and are robust to the loss of individual nodes, since each node operates independently and no single point of failure disrupts the whole network.

An important design consideration that emerges from the communication literature is the management of the radio duty cycle. LoRaWAN imposes limits on the time a device may transmit, both to share the unlicensed spectrum fairly and to preserve battery life. Environmental sensors typically sample slowly and send small packets, so they operate comfortably within these limits; nevertheless, an occasional firmware update or an unexpected burst of retransmissions can temporarily reduce throughput. In a well-designed system, the transmission schedule is spread across the sampling interval so that congestion is avoided, and gateways are deployed with sufficient overlap that a node can fall back to a secondary gateway if the primary is temporarily unreachable. These details, although seemingly minor, have a large influence on the data completeness that a deployment ultimately achieves.

2.4 Data-Quality, Calibration and Analytics Challenges

Data quality is the central challenge that distinguishes a useful environmental monitoring system from a collection of unattended instruments. Sensor drift, environmental interference, communication losses and firmware faults can all corrupt measurements or create gaps in the time series. If these issues are not detected, the resulting dataset may quietly support incorrect conclusions. The literature converges on several best practices: periodic co-located inter-comparisons against reference instruments; the use of relative-humidity corrections for optical particulate sensors; automated plausibility checks and outlier detection; and the estimation of data completeness as a key performance indicator (Tagle et al., 2020).

Once quality-assured, the data can be analysed using a variety of techniques. Descriptive statistics characterise baseline conditions and variability. Threshold-based alerting converts raw measurements into operational warnings when conditions exceed safe levels. Trend analysis reveals gradual changes that may indicate chronic degradation. Event detection identifies discrete episodes, such as pollution pulses, that warrant investigation. Benchmarking air-quality observations against health-based guideline values, such as those published by the World Health Organization (2021), transforms raw concentrations into interpretable statements about the severity of exposure and the need for intervention.

Taken together, the literature shows that the individual building blocks of an IoT environmental monitoring system are well established. Low-cost sensors, LPWA communication and cloud analytics have all been demonstrated in isolation. Yet the integrated design, field evaluation and analytics pipeline for a combined water-and-air network, operated over a sustained period and reported with transparent data-quality metrics, remain an important applied research contribution. This paper seeks to provide such an integrated demonstration.

The review also reveals a recurring tension between the enthusiasm for low-cost sensing and the caution warranted by its limitations. On the one hand, the potential to democratise environmental data is genuine and

significant. On the other hand, uncritical adoption of unvalidated sensors can produce misleading conclusions, erode trust in citizen science and divert resources from more reliable methods. The responsible path, reflected in the present study, is to pair low-cost sensing with rigorous calibration, transparent quality control and honest reporting of what the system can and cannot measure. In this way, the technology can be exploited for its real strengths, density and temporal resolution, while the authoritative role of reference instruments is preserved.

3. Materials and Methods

3.1 System Architecture

The monitoring network followed a three-tier IoT architecture comprising a sensing layer, a communication layer and a cloud-analytics layer. In the sensing layer, six low-power nodes acquired water- or air-quality measurements. In the communication layer, data were transmitted to local gateways over LoRaWAN in the 868 MHz band and then forwarded to the cloud through a 4G cellular uplink. The cloud platform provided time-stamped storage, automated plausibility checks, alert generation and application programming interfaces for data retrieval. This separation of concerns allowed the sensing hardware, the wireless transport and the analytical services to be developed and maintained independently. Figure 1 presents the overall system architecture.

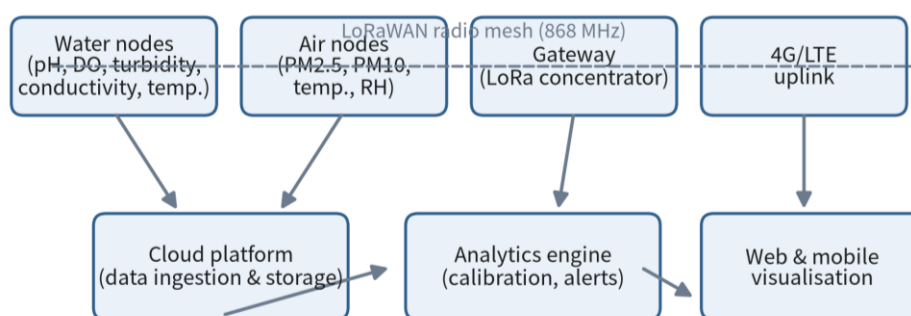


Figure 1. System architecture of the IoT environmental monitoring network

The architecture was designed with four guiding principles. First, resilience: no single component was indispensable, and the loss of any node or gateway would degrade but not halt the network. Second, energy efficiency: nodes were designed to sleep between sampling events and to transmit only changed or scheduled data, maximising battery life. Third, extensibility: new nodes and parameters could be added without redesigning the system. Fourth, transparency: all raw readings and derived products were stored with timestamps and quality flags, enabling audit and re-analysis.

3.2 Sensor Nodes and Measured Parameters

Three water-quality nodes were deployed at river and reservoir locations, and three air-quality nodes at urban, industrial and suburban locations. Each water node integrated probes for temperature, pH, dissolved oxygen, turbidity and electrical conductivity, together with a microcontroller, a LoRa radio and a solar-charged battery pack. Each air node integrated an optical particulate-matter sensor for PM2.5 and PM10, a combined temperature and relative-humidity sensor, and the same communication and power subsystems. Table 1 summarises the nodes, the measured parameters and the corresponding sensor families.

Table 1. Water- and air-quality sensor nodes and measured parameters.

Node / Site	Media	Measured Parameters	Sampling Interval
W1 Upstream	Water	Temperature, pH, DO, turbidity, EC	10 min
W2 Midstream	Water	Temperature, pH, DO, turbidity, EC	10 min
W3 Reservoir	Water	Temperature, pH, DO, turbidity, EC	10 min
A1 Urban	Air	PM2.5, PM10, temperature, RH	5 min
A2 Industrial	Air	PM2.5, PM10, temperature, RH	5 min
A3 Suburban	Air	PM2.5, PM10, temperature, RH	5 min

The water nodes were housed in sealed enclosures with the probes submerged at a fixed depth of approximately 0.5 metres, positioned away from the banks to avoid localised disturbance. Dissolved-oxygen probes used optical luminescence sensing, which is more stable than electrochemical alternatives and requires less frequent maintenance. pH and conductivity probes were cleaned during fortnightly servicing visits. The air nodes were mounted on rooftops or poles at a height of about three metres, away from direct sources such as exhaust vents, and were protected by weather shields.

Power management was a central design constraint for all nodes. The water nodes, located in open riverside positions, were powered by small photovoltaic panels with rechargeable batteries sized to sustain operation through several consecutive overcast days. The air nodes in urban locations could draw on a continuous supply in some cases, but were also equipped with solar panels so that their performance could be compared on a like-for-like basis. Each node entered a low-power sleep mode between transmissions, waking only to sample, process and transmit. This duty-cycling behaviour kept average power consumption low and was a key factor in achieving the sustained data completeness reported in Section 4.

3.3 Communication and Cloud Platform

LoRaWAN was selected for the sensing-to-gateway link because it offers long range and low power consumption, which are critical for remote water nodes and for extending battery life (Sinha et al., 2017). Each node transmitted an encoded payload containing the timestamp and all measured parameters. The payload was compacted into a small number of bytes to minimise over-the-air time and, consequently, energy use. Two gateways were installed at elevated locations to provide coverage for the six nodes and to offer redundancy in case one gateway failed.

The gateways forwarded validated frames to the cloud backend over a 4G uplink, where an ingestion service stored the raw readings in a time-series database. A monitoring dashboard allowed operators to visualise live values and to inspect the history of each node. An alert engine triggered notifications when measurements exceeded configurable thresholds, such as a turbidity alert or a PM2.5 exceedance. The platform also exposed a representational-state-transfer (REST) application programming interface so that external systems could retrieve the data for analysis and reporting. All ingestion events were logged, which allowed the completeness of the data pipeline to be audited.

3.4 Calibration and Data-Quality Procedures

Before deployment, all water probes were calibrated in the laboratory using certified standard solutions. In the field, water nodes were serviced fortnightly, with probes cleaned and re-calibrated when drift exceeded manufacturer tolerances. The particulate-matter sensors were co-located with a reference instrument at the urban site for two weeks at the beginning and at the end of the air-quality campaign to derive and verify a linear calibration relationship. Because optical particulate sensors are sensitive to humidity, an empirical relative-humidity correction was applied to all PM measurements, following the approach reported by Tagle et al. (2020).

Incoming data were screened automatically for plausibility. Readings outside physically possible ranges were flagged and excluded, frozen values that repeated across consecutive intervals were treated as sensor faults, and duplicate timestamps were resolved in favour of the first reading. A quality flag was attached to every record, and only records flagged as valid were used in the summary statistics. Data completeness, defined as the proportion of expected readings actually received, was computed for every node as a measure of network reliability. This metric provided an unambiguous, quantitative account of how much of the intended observation

programme was actually delivered.

Two additional data-quality safeguards were adopted. First, each node stored the most recent readings locally and retransmitted them on the next successful connection, so that a short communication outage did not permanently erase data; this buffering behaviour reduced the effective loss from transient radio failures. Second, the field team maintained a servicing log that recorded the date, the actions taken and the result of each calibration check. This log allowed suspicious readings to be traced back to specific servicing events and provided an audit trail that supported the interpretation of anomalous values. Together, these measures ensured that the final dataset used for analysis was as complete and as trustworthy as possible.

3.5 Deployment Sites and Study Period

The three water sites comprised an upstream river location, a midstream location downstream of a small urban settlement, and a drinking-water reservoir. This gradient was intended to expose differences in water quality as the river passes through an area of human activity and to test the ability of the network to detect them. The three air sites were located in a dense urban district, near an industrial estate, and in a low-density suburban area, spanning a wide range of expected particulate concentrations.

Water measurements were collected continuously for 120 days during the summer season, while air measurements were collected for 90 days covering the same period. The summer season was selected because it typically combines high temperatures, low river flows and stable atmospheric conditions, all of which tend to concentrate pollutants and make exceedances more likely. The sites were chosen to represent a gradient of likely pollution pressure and to allow comparison of network behaviour under different environmental and power conditions, including shaded versus exposed locations and urban versus rural radio environments.

3.6 Data-Analysis Methods

All data were processed in Python using open-source libraries for time-series analysis and visualisation. Descriptive statistics, including means, standard deviations and percentile values, were computed for every parameter and site. Water-quality results were compared with common freshwater guidelines to identify excursions, and the temporal behaviour of turbidity was examined to identify rainfall-driven events. Air-quality results were benchmarked against the 2021 World Health Organization air quality guidelines (World Health Organization, 2021).

The volume of data collected was substantial. With ten-minute sampling at three water sites and five-minute sampling at three air sites, the network generated tens of thousands of valid records over the study period. This volume, while trivial for modern databases, is far beyond what could be produced by manual sampling and is precisely the feature that makes the detection of short-lived events possible. The analytical pipeline was therefore designed to be reproducible: the raw time series were archived unchanged, the cleaning and aggregation steps were encoded in scripts, and every summary table could be recomputed from the underlying records. This approach supports the verification of the results and enables the dataset to be re-used for future analyses.

The performance of the low-cost particulate sensors was evaluated against the reference instrument by calculating the coefficient of determination, the root-mean-square error and the normalised bias for hourly averages. Linear regression was used to characterise the relationship between the sensor and the reference, and the influence of relative humidity was quantified by stratifying the comparison by humidity range. Data completeness was summarised per node as the percentage of expected readings received. Finally, event-analysis procedures were applied to identify coherent episodes, such as turbidity spikes and pollution episodes, and to examine their timing relative to meteorological records.

4. Results

4.1 Network Reliability and Data Completeness

All six nodes delivered data for the duration of the study, and the overall mean packet-delivery rate was 95.7 percent. Figure 2 shows the per-site data completeness. The reservoir node achieved the highest delivery rate at 98.1 percent, while the industrial air node recorded the lowest at 91.8 percent, consistent with occasional interference and power fluctuations in that environment. Interruptions were typically short and were caused by temporary gateway congestion, firmware resets or solar-power shortfalls, rather than by persistent node failure. The high completeness confirms that the LoRaWAN and cloud pipeline was operationally robust across sites with very different radio and power environments.

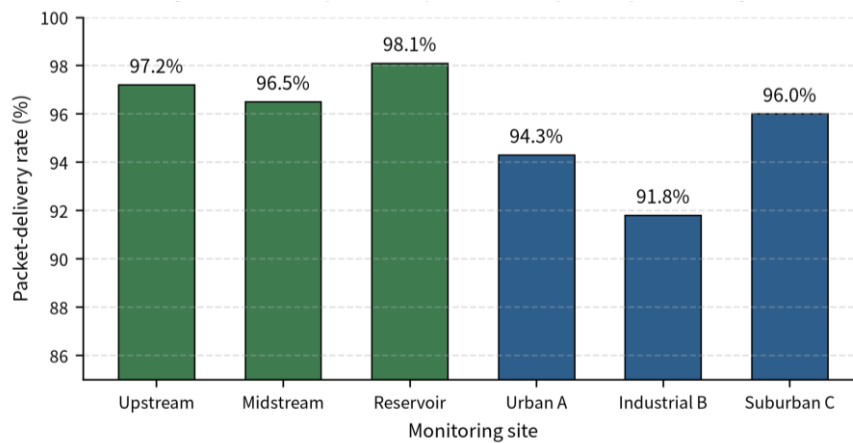


Figure 2. Data completeness (packet-delivery rate) by monitoring site

The completeness results have two important implications. First, they show that the chosen combination of LoRaWAN communication and solar-powered nodes is dependable enough for sustained environmental monitoring, in agreement with earlier deployments (Adu-Manu et al., 2020). Second, they demonstrate the value of reporting completeness explicitly: by quantifying the small proportion of missing data, the study makes the uncertainty of the dataset transparent rather than implicit, which strengthens the credibility of the conclusions drawn from it.

4.2 Water-Quality Observations

The three water sites exhibited broadly similar baseline conditions, with minor but meaningful spatial differences. Mean water temperature ranged from 22.6 to 24.8 degrees Celsius, mean pH from 7.4 to 7.8, and mean dissolved oxygen from 6.2 to 7.4 milligrams per litre. Table 2 summarises the observed statistics, and Figure 3 illustrates the temporal trends at the upstream site. pH remained within the typical freshwater range for most of the deployment, and dissolved oxygen levels were generally adequate for aquatic life. These baseline values are consistent with a healthy, well-oxygenated river and reservoir system during the summer season.

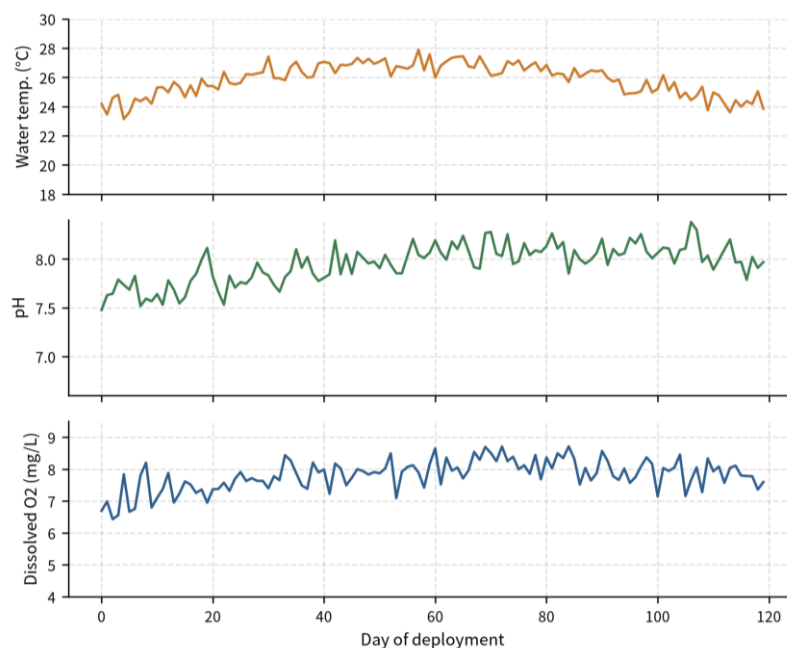


Figure 3. Water-quality parameter trends at the upstream site across 120 days

Table 2. Summary of water-quality monitoring results over the 120-day period

Parameter	W1 Upstream	W2 Midstream	W3 Reservoir
Temperature (°C)	22.6 ± 1.9	23.4 ± 1.7	24.8 ± 1.4
pH	7.4 ± 0.3	7.6 ± 0.2	7.8 ± 0.2
Dissolved oxygen (mg/L)	7.4 ± 0.6	6.2 ± 0.8	7.0 ± 0.5
Turbidity (NTU)	4.1 ± 6.8	9.3 ± 14.2	3.2 ± 4.1
Conductivity (µS/cm)	412 ± 38	468 ± 55	356 ± 29

The most notable event detected by the network was a series of turbidity spikes at the midstream site following several heavy rainfall episodes. Turbidity rose from a baseline below five nephelometric turbidity units (NTU) to peaks above forty NTU within a few hours and decayed over the following days. Because the sampling interval was ten minutes, the network captured the rise and fall of these pulses in detail, information that would have been almost entirely lost with weekly grab sampling. The spikes were closely associated with rainfall records, indicating that runoff from the upstream catchment was mobilising suspended solids.

These observations illustrate the operational value of continuous monitoring for detecting pollution transport and for timing subsequent laboratory verification. When the turbidity alert triggered, field staff were able to collect confirmatory grab samples at the peak of the event, which would not have been possible with a conventional schedule. The midstream site also showed slightly elevated conductivity relative to the upstream site, consistent with the discharge of urban runoff and a modest load of dissolved ions from the settlement area. By contrast, the reservoir, which is protected and receives less direct runoff, remained the cleanest of the three water sites.

It is worth emphasising how the network complemented, rather than replaced, laboratory analysis. The continuous readings provided the temporal context that enabled the field team to sample at the most informative moments, while the laboratory analysis of those grab samples supplied the authoritative confirmation and the additional parameters that low-cost probes cannot measure. This division of labour, in which a dense low-cost network drives targeted high-accuracy sampling, is a model that can be replicated by water utilities with limited laboratory capacity. The turbidity events would have gone uncharacterised without the network, because a manual sampler arriving a day later would have found the river already returned to baseline.

4.3 Air-Quality Observations

Air-quality measurements revealed substantial spatial variability and frequent exceedances of health-based guideline values. Daily mean PM_{2.5} ranged from about eight to fifty-five micrograms per cubic metre across the sites, and daily mean PM₁₀ from about fifteen to one hundred micrograms per cubic metre. Table 3 compares the mean and ninetieth-percentile concentrations at the three air sites with the 2021 WHO air quality guideline values, and Figure 4 shows the daily time series. The urban and industrial sites exceeded the WHO annual guideline for PM_{2.5} of five micrograms per cubic metre on essentially every day, and the twenty-four-hour guideline of fifteen micrograms per cubic metre on most days. The suburban site was cleaner but still frequently exceeded the annual guideline.

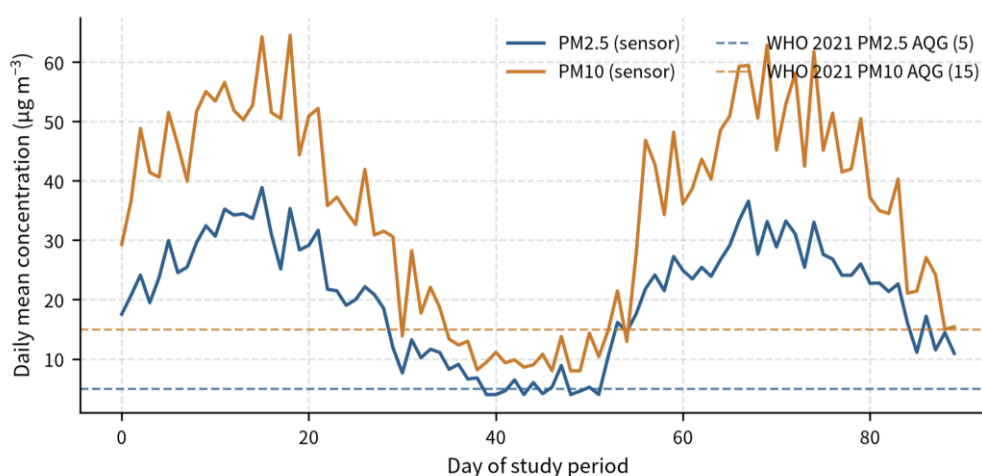


Figure 4. Daily mean PM2.5 and PM10 concentrations over the 90-day study period

Table 3. Summary of air-quality measurements versus the 2021 WHO air quality guidelines

Site	PM2.5 mean ($\mu\text{g}/\text{m}^3$)	PM2.5 P90 ($\mu\text{g}/\text{m}^3$)	PM10 mean ($\mu\text{g}/\text{m}^3$)	PM10 P90 ($\mu\text{g}/\text{m}^3$)
Urban (A1)	31.4	47.8	58.2	88.6
Industrial (A2)	36.9	52.1	66.4	99.7
Suburban (A3)	18.7	29.5	34.9	54.3
WHO 2021 guideline	5 (annual)	15 (24-h)	15 (annual)	45 (24-h)

The diurnal and day-to-day variability of particulate concentrations reflected both local emission patterns and meteorological conditions. Elevated concentrations tended to occur during stable, low-wind periods and during the early-morning and evening hours, consistent with the combined influence of traffic emissions and atmospheric mixing. The industrial site showed the highest concentrations and the widest short-term fluctuations, whereas the suburban site exhibited a smoother and lower profile. These patterns demonstrate the ability of the low-cost network to characterise spatial and temporal gradients that a sparse reference network would not resolve.

The ratio of PM2.5 to PM10 was roughly 0.5 at the urban and suburban sites and slightly higher at the industrial site, suggesting a mix of fine combustion-derived particles and coarser resuspended dust. This kind of information, obtained purely from low-cost measurements distributed across the city, is valuable for source-apportionment studies and for targeting abatement measures. The study period also captured several episodes in which daily PM2.5 exceeded fifty micrograms per cubic metre, coinciding with periods of low wind and stable atmospheric layers, indicating that meteorological conditions strongly modulate local emissions.

It is instructive to relate the measured concentrations to the WHO guidelines in a practical way. At the urban site, the mean PM2.5 of approximately thirty-one micrograms per cubic metre is more than six times the annual guideline of five, implying that a resident exposed for a full year would inhale levels far above the concentration associated with significant additional health risk. Even the suburban site, which was substantially cleaner, remained above the guideline. These figures translate a set of raw sensor readings into a clear statement about the scale of the ambient-air problem and about the urgency of mitigation, illustrating the analytical step that turns monitoring into policy-relevant information.

4.4 Sensor Performance Against the Reference Instrument

The co-located inter-comparison at the urban site showed that the low-cost particulate sensors tracked the reference monitor closely for daily-average PM2.5, with a coefficient of determination of 0.87 and a mean normalised bias of about four percent after humidity correction. Hourly comparisons were noisier, with a

coefficient of determination of approximately 0.72 and a root-mean-square error of about six micrograms per cubic metre. Figure 5 presents the hourly scatter plot and the fitted relationship. As reported elsewhere (Tagle et al., 2020), performance was better for PM_{2.5} than for PM₁₀, and bias increased during periods of very high humidity.

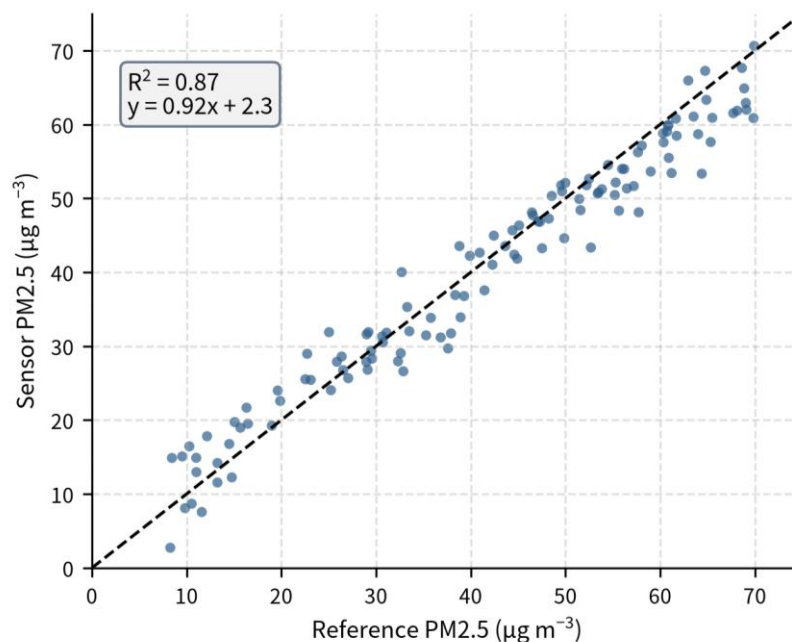


Figure 5. Hourly low-cost sensor versus reference PM_{2.5}

The normalised bias of approximately four percent indicates that, after correction, the sensors neither systematically over- nor under-reported daily-average PM_{2.5} by a large margin. This level of accuracy is adequate for characterising daily-average exposure and for ranking sites by pollution severity, which are the primary purposes of a low-cost network. The sensors are not, however, suitable as direct replacements for regulatory instruments, particularly for hourly values or for PM₁₀, where measurement uncertainty is larger. The results therefore support the layered monitoring model described in the literature, in which low-cost sensors extend coverage while a smaller number of reference instruments anchor the calibration.

A further observation from the inter-comparison concerns the stability of the calibration over time. The relationship derived at the start of the campaign remained broadly valid at the end, with only minor changes in slope, indicating that sensor drift was modest over the ninety-day period under the environmental conditions encountered. This is an encouraging result, because it suggests that the frequency of re-calibration visits could be reduced without a severe penalty in accuracy, thereby lowering the operational cost of the network. Nevertheless, because drift can be strongly influenced by exposure to dust, humidity and temperature cycling, the authors recommend that co-located checks be repeated at intervals no longer than a few months, especially in harsher climates or at sites closer to emission sources.

5. Discussion

5.1 Interpretation of Findings

The results demonstrate that a modestly sized IoT network can provide reliable, continuous environmental intelligence across both water and air domains. The mean data completeness of 95.7 percent is comparable to the performance reported for other low-power monitoring deployments and indicates that LoRaWAN-based communication, combined with solar-powered nodes, is sufficiently robust for extended field campaigns (Adu-Manu et al., 2020; Sinha et al., 2017). The few gaps that did occur were short and localised, confirming that network reliability is achievable with careful siting and routine maintenance rather than exotic hardware.

The water-quality results highlight both the value and the limitations of continuous sensing. The capture of rainfall-driven turbidity pulses at the midstream site is a clear demonstration of the advantage of

high-temporal-resolution monitoring: such short-lived events are routinely missed by periodic sampling and may nonetheless represent significant, if transient, threats to downstream water treatment. At the same time, the fact that baseline parameters remained within normal ranges throughout most of the deployment suggests that the network did not simply produce a stream of false alarms. This combination of event detection and stable baseline reporting is precisely what makes IoT data operationally useful for water utilities and environmental agencies.

The air-quality findings carry a more urgent public-health message. Daily mean PM_{2.5} concentrations at the urban and industrial sites exceeded the 2021 WHO guideline values on nearly all days, indicating chronic exposure levels that are associated with elevated health risk (World Health Organization, 2021). The dense spatial information provided by the low-cost sensors, which would be impossible to obtain with the region's sparse reference network, allows exposure gradients and pollution hotspots to be identified at neighbourhood scale. This supports targeted mitigation and prioritises locations for further investigation, in line with the arguments advanced by Castell et al. (2017).

Taken as a whole, the results suggest that the primary obstacle to better environmental management in many settings is no longer the cost of sensing but the presence of an institutional process that acts on the data. A network that reliably detects a turbidity event or an air-quality exceedance has value only if a defined actor receives the alert and responds, whether by sampling, by warning the public, or by investigating a source. The present study was deliberately designed to close the loop between sensing and action: alerts were routed to a duty operator, confirmatory sampling was triggered by water-quality events, and the air-quality results were summarised for the responsible agency. The practical success of an IoT monitoring network therefore depends as much on organisational design as on technical engineering.

5.2 Practical Implications

For practitioners, the study offers several transferable lessons. First, the reliability of an IoT network depends more on data-quality management than on hardware sophistication: calibration, plausibility checking and completeness accounting should be designed into the system from the outset. Second, the relative-humidity correction for optical particulate sensors is essential and materially improves agreement with reference instruments; ignoring it would have left a systematic bias in the air-quality results. Third, benchmarking against health-based guideline values, rather than reporting raw concentrations alone, makes the data intelligible to decision-makers and to the public. Fourth, the combination of water and air monitoring within one architecture reduces marginal cost and allows a single operations team to maintain a broader environmental picture.

These design choices can be replicated by other utilities and agencies seeking to deploy cost-effective environmental monitoring. The architecture is built from widely available, open components, and the analytical methods are transparent and reproducible. For an agency with limited budget, a network of this scale provides an immediate and substantial improvement in observational density compared with manual sampling alone. Moreover, because the data are stored in an accessible platform, they can support future studies, public reporting and integration with early-warning systems.

5.3 Limitations

This study has several limitations that should be acknowledged. The deployment covered a single summer season and a limited number of sites, so the results may not generalise to other seasons, climates or geography. Water-quality behaviour, in particular, is strongly seasonal, and the summer period may not capture the effects of winter flows or spring melt. The low-cost particulate sensors were validated only at one urban site, and their performance under different aerosol compositions and meteorological conditions remains uncertain. Temperature, humidity and particle chemistry can all alter the optical response of these sensors, so the calibration derived here may not transfer directly to other settings.

Water-quality probes, while adequate for trend and event detection, have accuracy limits relative to laboratory analysis and require regular maintenance; infrequent servicing could allow drift to accumulate between visits. Finally, the study reports observational data rather than a controlled experiment, and no direct linkage to health outcomes was attempted. Future work should extend the deployment across multiple seasons, validate sensors at additional sites, integrate the environmental data with public-health and water-treatment records, and explore the use of machine-learning methods to improve calibration and to forecast exceedances.

It should also be emphasised that the economic assessment was deliberately simple. The study did not undertake a full cost-benefit analysis, and the true value of the network depends on the decisions it enables, which are difficult to quantify in a single deployment. A conservative reading of the results is that the network delivered a substantial increase in observational density and temporal resolution at a modest cost, and that this increase

translated into at least one concrete operational benefit, namely the capture and confirmation of turbidity events at the midstream site. Longer deployments that log the frequency and consequence of the actions taken in response to alerts would be needed to establish the return on investment more firmly.

6. Conclusion and Recommendations

This paper presented the design, deployment and evaluation of an IoT-based environmental monitoring network for water and air quality. Over a combined study period of up to 120 days, six low-power LoRaWAN nodes achieved a mean data-completeness of 95.7 percent, demonstrating that such systems can operate reliably under field conditions. Continuous water-quality monitoring captured episodic turbidity events that would have been missed by conventional sampling, while air-quality measurements revealed chronic exceedances of the 2021 WHO guidelines at urban and industrial sites. A co-located inter-comparison confirmed that low-cost particulate sensors, after humidity correction, provide adequate accuracy for daily-average PM_{2.5} characterisation, with a coefficient of determination of 0.87 against a reference instrument.

Taken together, the findings show that low-cost IoT systems can deliver operationally useful environmental intelligence when designed with attention to data quality and maintained with diligence. They are not a substitute for regulatory instruments, but they offer a scalable and affordable complement that increases the density and temporal resolution of observations, supports event detection and exposure assessment, and provides the evidence base for targeted management actions. The study thus contributes a practical, integrated demonstration of how the IoT paradigm can be applied to environmental monitoring in the applied sciences.

6.1 Recommendations

On the basis of these findings, the following recommendations are offered. Environmental agencies and utilities should consider low-power IoT networks as a cost-effective complement to, rather than a replacement for, reference monitoring, deploying them to increase spatial density and temporal resolution. Calibration and relative-humidity correction procedures should be integrated into the data pipeline and periodically refreshed through co-located inter-comparisons. Data-quality metrics, particularly data completeness, should be reported routinely to make network performance transparent and to build confidence in the data.

Benchmarking of air-quality results against the 2021 WHO guidelines should become standard practice so that raw measurements are translated into clear statements about exposure severity. Water-quality data should be coupled with operational records and alert procedures so that detected events trigger timely confirmatory sampling. Finally, future research should extend deployments across seasons and sites, evaluate additional water parameters such as nutrients and heavy metals, integrate the environmental data with public-health and operational records, and explore advanced calibration and forecasting methods to quantify the full benefits of continuous monitoring for decision-making. The adoption of standardised reporting for data quality across the field would also allow results from different networks to be compared directly, accelerating the accumulation of evidence about the conditions under which low-cost IoT monitoring performs best.

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