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SISTEM PEMANTAUAN KUALITAS AIR IOT BERBIAYA RENDAH: TINJAUAN TERSTRUKTUR SENSOR, ARSITEKTUR, KINERJA, DAN TANTANGAN

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Abstrak

Pemantauan kualitas air IoT berbiaya rendah menjanjikan pengukuran terdistribusi, tetapi harga murah belum menjamin akurasi atau kesiapan lapangan. Tinjauan terstruktur ini mengevaluasi 16 studi primer 2017–2026 dengan kerangka Cost–Performance–Deployability (CPD) melalui pencarian multi-sumber dan penelusuran sitasi. Enam studi mencapai bukti biaya C3, tujuh validasi rujukan P4, satu validasi jangka panjang P5, lima deployment D4, dan satu D5; dua memenuhi kriteria kesiapan tinggi. Sistem low-cost yang kredibel memerlukan transparansi biaya, validasi metrologi, keandalan komunikasi, pemeliharaan, dan ketahanan lapangan.

Kata kunci: Internet of Things, Pemantauan Kualitas Air, Sensor Berbiaya Rendah, Validasi Lapangan, LoRaWAN.

LOW-COST IOT-BASED WATER QUALITY MONITORING SYSTEMS: A STRUCTURED REVIEW OF SENSORS, ARCHITECTURES, PERFORMANCE, AND CHALLENGES

Abstract

Low-cost IoT water-quality monitoring promises distributed measurement, but inexpensive hardware does not guarantee accuracy or field readiness. This structured review evaluated 16 primary studies from 2017–2026 using a Cost–Performance–Deployability (CPD) framework through multi-source searching and citation chasing. Six studies reached C3 cost evidence, seven P4 reference validation, one P5 long-term validation, five D4 deployments, and one D5 deployment; two met the high-readiness criterion. Credible low-cost monitoring requires cost transparency, metrological validation, communication reliability, maintenance evidence, and field robustness.

Keywords: *Internet of Things, Water Quality Monitoring, Low-cost Sensors, Field Validation, LoRaWAN.*

INTRODUCTION

Water-quality monitoring supports drinking-water safety, aquatic ecosystem management, aquaculture productivity, pollution detection, and decentralized water-resource governance. Conventional monitoring based on manual sampling and centralized laboratory analysis can provide high analytical quality, but it is frequently constrained by sampling frequency, logistics, skilled personnel, instrument cost, and the time required before results become available. These limitations have motivated the development of connected sensing platforms that combine low-cost sensors, embedded electronics, wireless communication, and real-time visualization.

The Internet of Things (IoT) provides a technical foundation for such monitoring by linking physical sensors to processing, communication, storage, and visualization layers. Across the included literature, architectures range from Raspberry Pi and Arduino prototypes to ESP8266/ESP32 nodes, NB-IoT buoys, LoRaWAN gateways, smartphone-connected systems, and custom sensor electronics. Recent systems increasingly combine wireless communication with solar power, local storage, mobile dashboards, cloud services, or automated control. Examples include a large-area wireless sensor network using pH, dissolved oxygen, and temperature probes [2], a rural Arduino/Bluetooth system [8], an NB-IoT water-resource monitoring buoy [9], and solar-assisted LoRaWAN monitoring [10].

Yet the phrase "low-cost" does not have a consistent operational meaning. Some studies provide only a qualitative affordability claim, whereas others publish a complete bill of materials or total system cost. For example, Bogdan et al. reported a component total of approximately EUR 120.2 [8], Agade and Bean reported a GatorByte buoy hardware cost of about USD 950 plus cellular service [9], Jabbar et al. reported a system cost of approximately USD 240 [10], and Subowo and Pradita reported approximately IDR 950,000 for an aquaculture implementation [14]. These systems cannot be compared meaningfully on purchase price alone because their sensing scope, power system, communication range, enclosure, storage, and deployment conditions differ.

Previous reviews have synthesized low-cost water-quality sensors and IoT monitoring technologies. De Camargo et al. systematically reviewed sensor models, manufacturers, costs, and measurement performance and emphasized that relatively few low-cost sensors had been rigorously compared with reference instruments [18]. That review established an important sensor-level evidence base, but practical monitoring readiness also depends on the embedded platform, communication architecture, power supply, calibration strategy, maintenance burden, and duration of field deployment. Recent long-term work has further demonstrated that drift, temperature compensation, cleaning frequency, and network range can become decisive once low-cost probes are operated continuously [20].

This review therefore proposes a Cost–Performance–Deployability (CPD) evidence framework to assess complete monitoring systems rather than sensors alone. Cost evidence evaluates whether the low-cost claim is quantitatively substantiated; performance evidence evaluates calibration and validation against credible references, including long-term drift behavior; and deployability evidence evaluates the duration and realism of actual use. The framework is intended to distinguish inexpensive prototypes from systems supported by balanced evidence of affordability, measurement credibility, and field maturity.

The objectives of this review are to identify the water-quality parameters most frequently monitored, describe the dominant sensor technologies and embedded platforms, compare communication and data-management architectures, evaluate cost transparency and measurement validation, assess field-deployment maturity, and synthesize the technical challenges that continue to limit low-cost IoT water-quality monitoring. The CPD framework is then used to map evidence maturity and formulate priorities for future applied-physics and instrumentation research.

METHODS

2.1 Review Design and Search Strategy

A structured literature review was conducted in August 2026 using transparent screening and data-extraction procedures informed by the reporting principles of PRISMA 2020 [16] and PRISMA-S [17]. The review covered publications from January 2015 through August 2026. Searches were performed iteratively across scholarly publisher and index platforms that provide peer-reviewed engineering and environmental literature, including IEEE-related bibliographic records, ScienceDirect, SpringerLink, MDPI, PubMed/PMC, PLOS, and institutional repositories. Search concepts combined "water quality" with "Internet of Things" or IoT or "wireless sensor network" and "low-cost", "low cost", affordable, or "cost-effective". A technology-sensitive variant also used Arduino, ESP32, ESP8266, Raspberry Pi, LoRa, LoRaWAN, and NB-IoT. Backward and forward citation chasing from relevant reviews and highly pertinent primary studies was used to identify additional evidence.

2.2 Eligibility and Study Selection

Eligible papers were peer-reviewed primary studies written in English that described a physical water-quality sensing system, incorporated networked or remote data transmission, explicitly positioned the system or sensors as low-cost/affordable or provided quantitative cost evidence, and reported enough technical detail to characterize the sensing and communication architecture. Studies were eligible across drinking water, rivers and streams, lakes and reservoirs, aquaculture, wastewater, groundwater, coastal or marine environments, irrigation water, and related environmental applications. Reviews, editorials, non-English papers, pure simulations, water-level-only systems, and papers without sufficient low-cost or technical evidence were excluded.

After DOI/title deduplication and targeted eligibility assessment, 24 candidate records were evaluated and 16 primary studies were retained for the comparative synthesis. Eight records were excluded because they were reviews, non-English publications, lacked sufficient low-cost evidence, or did not provide enough verifiable technical information for the planned cross-study analysis. The final evidence set spans 2017–2026 and includes laboratory prototypes, controlled-water experiments, short field pilots, multi-day or multi-week deployments, and one study with long-term stability evaluation.

2.3 Cost–Performance–Deployability Framework

Each included study was coded in three evidence dimensions. Cost evidence was classified as C1 when low cost was claimed without complete quantitative reporting, C2 when selected component prices were available, and C3 when a full or near-full bill of materials or total system cost was reported. Performance evidence ranged from P0 (no independent validation) and P1 (calibration or functional testing only) to P2 (limited reference comparison), P3 (repeated reference validation), P4 (field or strong laboratory validation against credible reference instruments/methods), and P5 (long-term validation that explicitly assessed drift, stability, cleaning, or recalibration). Deployability ranged from D1 (bench/laboratory prototype), D2 (controlled-water experiment), D3 (short-term field deployment), D4 (multi-day or multi-week field deployment), to D5 (long-term or operational field deployment). A high-readiness profile was defined as C3 combined with P4/P5 and D4/D5.

2.4 Data Extraction and Synthesis

For each study, data were extracted on publication year, application context, water-quality parameters, sensor models, embedded platform, communication technology, cloud or dashboard platform, power source, sampling interval, cost, calibration procedure, reference instrument, performance metrics, deployment duration, and operational challenges. Because the reviewed studies used heterogeneous sensors, environments, validation procedures, and performance metrics, a statistical meta-analysis was not appropriate. Descriptive frequencies and comparative evidence mapping were therefore used, with emphasis on engineering trade-offs and the maturity of cost, performance, and deployment evidence.

RESULTS AND DISCUSSION

3.1 Study Characteristics and Publication Trends

The reviewed evidence set contains 16 studies published between 2017 and 2026. The largest annual contribution occurred in 2024 (5/16 studies), while 2019, 2021, 2023, and 2026 each contributed two studies. Application contexts comprised drinking water (5/16), rivers or streams (4/16), lakes or reservoirs (3/16), aquaculture (3/16), and one portable or mixed monitoring context. The distribution indicates a transition from basic connected prototypes toward field systems intended for surface-water, urban-river, rural, and aquaculture applications.

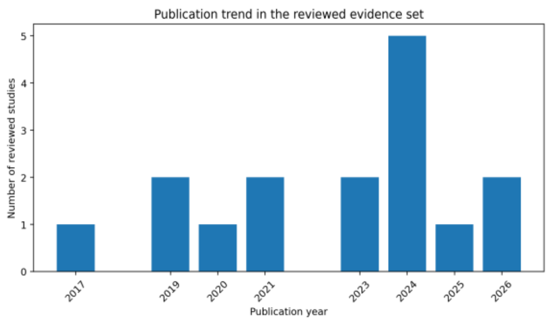

Figure 1. Publication trend among the 16 studies included in the review.

3.2 Water-Quality Parameters and Sensor Technologies

pH and temperature appeared in all 16 reviewed systems, making them the core variables of low-cost IoT water-quality monitoring. Turbidity was included in 10/16 studies, dissolved oxygen in 7/16, total dissolved solids in 5/16, and electrical conductivity in 3/16. Salinity and ammonia were each represented in one system. This concentration on pH, temperature, turbidity, dissolved oxygen, TDS, and conductivity reflects both their environmental relevance and the availability of relatively accessible sensors and interface electronics.

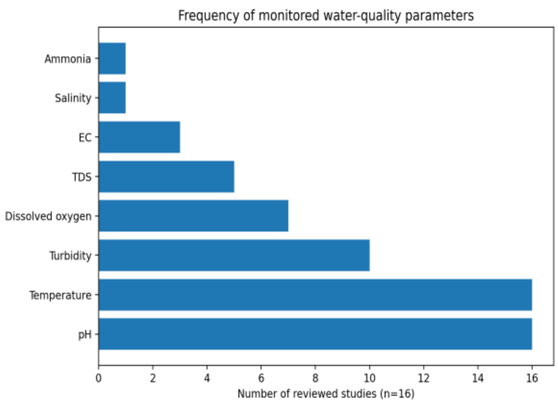

Figure 2. Frequency of water-quality parameters monitored in the reviewed evidence set.

Implementation examples show a broad range of sensing technologies. Bogdan et al. used the DS18B20 temperature sensor, SEN0161 pH sensor, SEN0244 TDS sensor, and SEN0189 turbidity sensor [8]. Mohd Jais et al. combined DS18B20, a DFRobot pH probe, dissolved-oxygen and electrical-conductivity sensors, and an MQ137 ammonia sensor in aquaculture [12]. Alam et al. developed low-cost electrochemical sensing for pH, free chlorine, temperature, and bisphenol A using custom readout electronics [5], while Akhter et al. demonstrated an IoT-enabled low-cost phosphate-sensing approach for smart agriculture [7]. Hagh et al. extended low-cost monitoring to optical parameters, including turbidity, phycocyanin, and chlorophyll-a [13]. Naloufi et al. evaluated a six-sensor DFRobot-based multiprobe incorporating temperature, two pH probes, conductivity, turbidity, and dissolved oxygen [20]. These studies show that low-cost monitoring is no longer restricted to a single sensor type, but integration complexity and calibration burden increase with parameter diversity.

3.3 Embedded Platforms and IoT Architecture

The included systems show a clear shift from generic embedded prototypes toward application-specific architectures. Early designs used Raspberry Pi, Arduino, or MCU/PC combinations [1,4], whereas later systems increasingly used ESP8266/ESP32, specialized IoT boards, or microcontrollers integrated with LoRaWAN and NB-IoT. This transition is important because controller selection affects analog-interface quality, sleep modes, energy consumption, communication options, and maintainability.

Two broad architectural patterns were evident. The first uses a relatively simple node that reads sensors and sends measurements directly over Wi-Fi or Bluetooth to a nearby smartphone, server, or cloud service. The second separates the sensing node from a gateway or wide-area communication layer, as in LoRaWAN, ZigBee-to-GSM, and NB-IoT systems. The latter architecture is more suitable for remote sites or multiple distributed nodes, but it also introduces gateway, coverage, power, and maintenance considerations that must be included in a meaningful assessment of affordability.

3.4 Communication Technologies and Data Management

Communication technologies were highly heterogeneous. Bluetooth was used for short-range mobile interaction in portable and rural systems [6,8]. Wi-Fi was common in local or aquaculture deployments [11,12,14,19]. LoRaWAN or LoRa-based links supported longer-range, low-power environmental monitoring [10,13,15,20], while GatorByte used NB-IoT for real-time reporting and retained Bluetooth for local diagnostics [9]. Demetillo et al. used ZigBee within the sensing network and GSM for longer-distance transfer [2]. The long-term urban-river study also showed that nominal long-range radio capability must be verified under actual site conditions: the tested LoRa gateways did not exceed approximately 200 m in that deployment [20]. No single communication technology is therefore optimal for all settings; selection depends on coverage, energy consumption, range, infrastructure, maintenance, and recurring service cost.

Data services ranged from mobile applications and local dashboards to ThingSpeak, The Things Network, custom web portals, and cloud servers. ThingSpeak appears in several systems because of its simplicity for rapid prototyping and real-time visualization [4,10,12]. Local storage is nevertheless valuable even in connected systems: micro-SD cards and local servers can preserve records during network interruptions and reduce dependence on continuous internet connectivity. This is particularly important in remote regions, where a nominally inexpensive cloud architecture may become unreliable or costly if cellular access is intermittent.

3.5 Cost Evidence and the Meaning of "Low-Cost"

The CPD analysis classified eight studies as C1, two as C2, and six as C3. Thus, 37.5% of the reviewed studies provided full or near-full quantitative system-cost evidence. The C3 studies demonstrate why explicit cost reporting is essential for engineering comparison. A rural Arduino/Bluetooth system was reported at approximately EUR 120.2 [8], the River Nile early-warning prototype at about USD 197 [3], a solar-powered LoRaWAN rural system at about USD 240 [10], the GatorByte buoy at about USD 950 plus cellular service [9], a local-web aquaculture system at approximately IDR 950,000 [14], and the long-term urban-river monitoring units at approximately EUR 285–400, compared with substantially more expensive reference multiprobes [20]. These values span a wide range because sensing scope, enclosure, power system, communication capability, and deployment conditions differ.

Table 1. Studies with C3 Cost Evidence in the Reviewed Dataset

Study	Curr.	Cost	Main scope
Kamal et al. [3]	USD	~197	pH, turbidity, temperature
Bogdan et al. [8]	EUR	120.2	pH, TDS, turbidity, temperature
Agade & Bean [9]	USD	~950	pH, DO, EC, temperature, GPS
Jabbar et al. [10]	USD	~240	pH, TDS, turbidity, temperature
Subowo & Pradita [14]	IDR	950,000	pH, TDS, temperature
Naloufi et al. [20]	EUR	285–400	temperature, pH, EC, turbidity, DO

This variation supports a central conclusion of the review: "low-cost" should be treated as an evidence claim rather than a device category. A system that costs USD 950 may include a field-ready enclosure, multiple research-grade probes, location tracking, local storage, cloud services, and cellular telemetry, whereas a much cheaper prototype may monitor only two or three parameters over local Wi-Fi. Future publications should therefore report not only sensor price, but also the controller, ADC, communication module, enclosure, power system, calibration materials, server or connectivity expenses, maintenance, and expected probe-replacement cost.

3.6 Performance Validation and Measurement Quality

Performance evidence was stronger than cost evidence in several recent studies. Seven of the 16 reviewed studies reached P4, indicating field or strong laboratory comparison against credible reference instruments or methods, and one additional study reached P5 by explicitly evaluating long-term stability, drift, cleaning, and recalibration. Demetillo et al. reported coefficients of determination of approximately 0.97–0.98 for dissolved oxygen, pH, and temperature when evaluated alongside reference measurements [2]. Mohd Jais et al. conducted three months of validation against a YSI Professional Pro device and reported accuracies ranging from 76% to 98% across temperature, pH, ammonia, dissolved oxygen, and salinity-related measurements [12]. Basino et al. compared an ESP32/ADS1115 system with calibrated commercial handheld instruments over 14 days and reported R^2 values of 0.9928 for temperature, 0.8906 for pH, 0.9962 for dissolved oxygen, and 0.7656 for TDS [19]. Naloufi et al. extended validation to temperature effects and temporal stability, showing that conductivity and dissolved-oxygen measurements required temperature compensation and that regular cleaning/calibration was necessary to control drift [20].

At the other end of the evidence spectrum, four studies remained at P1 and one at P0, indicating that part of the low-cost IoT literature still emphasizes calibration or basic functionality rather than independent measurement performance. This concern is consistent with the previous systematic review of low-cost sensors [18]. In practical monitoring, calibration at deployment is not equivalent to evidence of sustained accuracy. Sensor drift, biofouling, electrode ageing, temperature effects, salinity, contamination, analog-to-digital converter limitations, enclosure moisture, and maintenance intervals can alter performance over time. The presence of only one P5 study [20] shows that long-term metrological evidence remains rare rather than absent.

3.7 Field Deployment Readiness

Deployability was distributed across D1 (3 studies), D2 (3), D3 (4), D4 (5), and D5 (1). The single D5 study assessed sensor stability from short laboratory tests through multi-month monitoring and explicitly linked performance to maintenance and recalibration requirements [20]. This gradient is scientifically important because field deployment introduces challenges that cannot be reproduced completely in controlled water, including weather, sediment load, temperature cycling, biofouling, power interruptions, signal blockage, pump failure, and maintenance access.

Several studies demonstrate meaningful progress toward sustained field use. Demetillo et al. operated a solar-assisted system in two creeks for approximately two weeks [2]. Lal et al. collected data from three water bodies over more than three weeks and reported that some low-cost probes were unsuitable for continuous immersion, leading to the use of a pumped sampling chamber [11]. Mohd Jais et al. conducted a three-month aquaculture validation [12], while Subowo and Pradita reported a seven-day biofloc-pond deployment with 99% data-delivery reliability [14]. Naloufi et al. evaluated long-term stability for up to three months and showed that weekly or periodic calibration and cleaning can be required depending on the sensor [20]. By contrast, Gómez-Henk et al. described a multiparameter LoRaWAN platform as a laboratory-scale engineering proof-of-concept for which metrological validation and long-term field testing remain future work [15]. These studies show why innovation readiness should not be equated automatically with operational readiness.

3.8 Cost–Performance–Deployability Synthesis

Table 2. Distribution of CPD Evidence Levels

Dimension	Level	n
Cost	C1	8
Cost	C2	2
Cost	C3	6
Performance	P0	1
Performance	P1	4
Performance	P2	1
Performance	P3	2
Performance	P4	7
Performance	P5	1
Deployability	D1	3
Deployability	D2	3
Deployability	D3	4
Deployability	D4	5
Deployability	D5	1

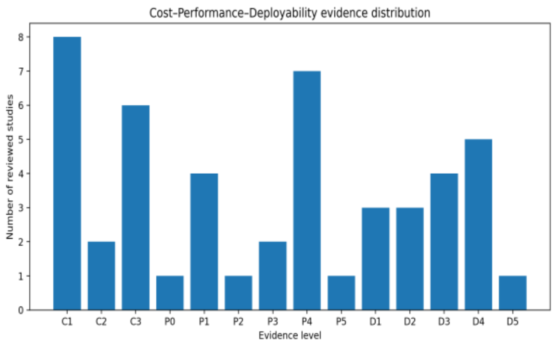

Figure 3. Distribution of Cost, Performance, and Deployability evidence levels.

When cost, performance, and deployability are considered jointly, two studies meet the predefined high-readiness criterion. Subowo and Pradita combine complete cost reporting, reference comparison, and a seven-day field deployment (C3–P4–D4) [14], while Naloufi et al. provide complete system-cost evidence, long-term stability and drift assessment, and multi-month deployment evidence (C3–P5–D5) [20]. Most other systems remain asymmetric: some have strong cost transparency and reference validation but only short field exposure [3,9,10], whereas others have longer deployment and validation but incomplete total-cost reporting [2,12,19]. The central gap is therefore not the complete absence of mature examples, but their rarity and the lack of standardized evidence across affordability, metrological credibility, and operational maturity.

3.9 Challenges and Future Directions

First, cost reporting needs standardization. Future studies should publish a complete bill of materials and distinguish one-time hardware cost from recurring expenses such as cellular service, cloud hosting, calibration standards, replacement probes, enclosure maintenance, and batteries. Without these data, cross-study affordability comparisons remain weak.

Second, validation should move from one-time calibration toward long-term metrological assessment. Comparative studies should report error, bias, RMSE or MAE, repeatability, drift, recalibration interval, temperature compensation, and reference-instrument uncertainty. Where feasible, raw paired reference and sensor data should be made openly available.

Third, continuous immersion and biofouling remain important design constraints. The pumped-sampling strategy used by Lal et al. [11] and the intermittent hydraulic chamber proposed by Gómez-Henk et al. [15] illustrate alternative architectures when low-cost probes are not suited to permanent submersion. Naloufi et al. further showed that cleaning and recalibration schedules are integral to maintaining data quality during longer deployments [20]. Future systems should compare in-situ immersion, flow-through cells, intermittent sampling, automatic cleaning, and anti-fouling approaches under comparable field conditions.

Fourth, communication choices should be benchmarked as part of system performance rather than listed only as implementation details. LoRaWAN, NB-IoT, Wi-Fi, Bluetooth, and hybrid networks should be evaluated using communication range, power consumption, packet-delivery rate, latency, coverage dependence, gateway cost, and recurring service cost. The optimal architecture for a fish pond with local Wi-Fi differs fundamentally from one intended for remote rivers or distributed lake stations.

Fifth, energy autonomy requires stronger evidence. Solar power is increasingly used, but many studies report the presence of a solar panel without a detailed energy budget. Future work should report average and peak current, duty cycle, battery capacity, charging conditions, expected autonomy under poor weather, and the energy consequences of sensor warm-up, pumps, wireless transmission, and cloud communication.

Sixth, reproducibility should become a defining property of low-cost monitoring. Open firmware, schematics, PCB files, enclosure designs, calibration procedures, datasets, and bills of materials can transform a prototype into a reusable platform. GatorByte provides a strong example of open hardware and software assets [9], while Naloufi et al. also provide code resources for their multiparameter platform [20]. Edge intelligence and machine learning may support anomaly detection, drift compensation, predictive maintenance, and water-quality forecasting, but such algorithms should be built on validated and traceable sensor measurements.

REVIEW LIMITATIONS

This review was designed as a structured engineering evidence synthesis rather than an exhaustive bibliometric census of every IoT water-quality publication. The multi-source search and citation-chasing strategy prioritized peer-reviewed studies with sufficient technical information for cross-study comparison, but some relevant records may remain outside the reviewed set. Cost comparisons are also affected by publication year, currency, local procurement conditions, taxes, import costs, and differences in sensing scope. In addition, performance metrics were too heterogeneous for formal meta-analysis, and deployment duration alone cannot capture every aspect of operational maturity. The CPD framework should therefore be interpreted as a transparent comparative tool rather than a universal technology-readiness standard.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The reviewed evidence shows that low-cost IoT water-quality monitoring has evolved from simple connected prototypes toward increasingly sophisticated systems incorporating long-range communication, cloud or local dashboards, solar power, multi-parameter sensing, local storage, and field validation. Six of the 16 studies provide full or near-full cost evidence, seven reach P4 reference-validation level, one reaches P5 long-term performance validation, five reach D4 multi-day or multi-week deployment, and one reaches D5 long-term deployment. Two studies satisfy the predefined combined high-readiness criterion. These findings support the CPD framework as a practical way to distinguish inexpensive prototypes from systems supported by balanced evidence of affordability, measurement credibility, and field maturity.

Recommendations

Future research should adopt complete bill-of-materials cost reporting, long-duration validation against credible reference instruments, explicit assessment of drift and recalibration needs, communication-reliability and energy-autonomy testing, and operational deployments that document uptime, failures, maintenance, and sensor-replacement costs. For resource-limited or remote settings, promising architectures combine multi-parameter sensing with low-power microcontrollers, LoRaWAN or NB-IoT communication where appropriate, solar-assisted power, local data backup, robust waterproof or intermittent-sampling designs, and transparent calibration procedures. Open firmware, hardware documentation, and datasets should be encouraged to improve reproducibility and practical transfer.

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