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Ecological Monitoring in Tropical Rivers: An IoT-Based System for Real-Time Water Quality Assessment and Ecosystem Protection

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ABSTRACT

Tropical river ecosystems are increasingly vulnerable to anthropogenic pressures, yet conventional monitoring methods remain inadequate to capture the rapid and complex ecological changes needed for effective conservation. This study presents "Smart River Watch," a low-cost, IoT-based ecological monitoring system designed for real-time assessment of key water quality parameters—temperature, pH, and turbidity—in tropical river environments. The system combines Arduino Mega microcontrollers and high-precision sensors with ESP32 WiFi for continuous data transmission to cloud and mobile platforms. Field deployment across five ecologically distinct sites along Indonesia's Martapura River demonstrated strong performance, achieving exceptional accuracy ($r > 0.99$; error < 2%) compared to laboratory methods, a 98.7% transmission success rate, and 23.4-hour operational autonomy. The innovation of this research lies in bridging technological accessibility with ecological needs: enabling high-frequency, real-time monitoring that supports early pollution detection, enhances ecological insight, and empowers local communities through user-friendly mobile interfaces. The cost-effectiveness, rapid deployment (15 minutes per site), and community-based usability of the system make it a scalable solution for biodiversity protection and adaptive water resource management in developing

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regions. These findings highlight a paradigm shift in ecological monitoring—merging digital innovation with ecosystem stewardship to better protect freshwater biodiversity in the face of accelerating environmental change.

Keywords: Ecological Monitoring; Tropical River Ecosystem; IoT-Based Sensing; Anthropogenic Impacts; Community-Based Monitoring

JEL Codes: Q55; Q53; O32

1. Introduction

Tropical river ecosystems represent some of Earth's most biodiverse yet vulnerable freshwater habitats, supporting complex ecological communities while facing escalating pressures from human activities [1,2]. The deterioration of water quality in these systems poses critical threats not only to aquatic biodiversity but to the ecological services that millions of people depend upon, particularly in developing regions where domestic, industrial, and agricultural pollution sources create compounding environmental stressors [3,4]. Indonesia's river systems, exemplified by the Martapura River in Banjar Regency, illustrate this global challenge, where increasing anthropogenic pressures threaten both ecosystem integrity and community water security [5,6]. Traditional ecological monitoring approaches in tropical rivers face fundamental limitations that compromise our understanding of ecosystem dynamics and responses to environmental change. Conventional water quality assessment methods, primarily dependent on manual sampling and laboratory analysis, are not only resource-intensive and time-consuming but are also critically inadequate for capturing the temporal variability essential for understanding ecological processes [7,8]. The inherent delays between sampling, analysis, and ecological interpretation severely limit the practical utility of such approaches for ecosystem protection, early detection of pollution events, and the adaptive management strategies required for conservation in rapidly changing environments [9,10].

The ecological significance of continuous, high-resolution monitoring in tropical rivers extends far beyond water quality assessment to encompass fundamental questions in ecosystem ecology and conservation biology. Tropical freshwater ecosystems exhibit complex responses to anthropogenic stressors, with pollution events, temperature fluctuations, and habitat degradation triggering cascading effects through food webs and community structures [11]. Climate change further amplifies these challenges, as altered precipitation patterns, increased temperature variability, and extreme weather events introduce novel stressors that traditional monitoring methods cannot adequately capture [12].

Recent advances in ecosystem functioning research emphasize the critical importance of understanding temporal dynamics in ecological processes, particularly in response to anthropogenic disturbances [13,14]. The ability to monitor water quality parameters continuously provides unprecedented opportunities to study ecological resilience, recovery dynamics, and threshold responses—factors fundamental to both theoretical ecology and applied conservation strategies [15]. Furthermore, such monitoring systems enable the detection of early warning signals for ecosystem collapse, supporting proactive rather than reactive conservation approaches [16].

The emergence of Internet of Things (IoT) technology represents a paradigm shift in ecological research methods, offering transformative potential for understanding ecosystem dynamics at previously impossible temporal and spatial scales [17]. IoT-based monitoring systems enable continuous data collection that can capture the fine-scale variability essential for understanding ecological processes, from diurnal cycles in primary productivity to rapid responses to pollution events [18,19]. This technological capability aligns with current ecological research priorities that emphasize the need for high-frequency, long-term datasets to understand ecosystem responses to global change [20].

However, existing IoT implementations for environmental monitoring often lack the ecological framework necessary to address fundamental questions in ecosystem ecology and conservation biology [21,22]. Many current systems focus primarily on technical performance metrics rather than ecological relevance, missing opportunities to contribute meaningfully to our understanding of ecosystem functioning and biodiversity conservation [23]. Additionally, most implementations address limited parameter sets and lack the user-accessible interfaces necessary for community-based monitoring, which could enhance both local conservation capacity and scientific understanding [24,25].

This research addresses critical gaps in ecological monitoring methods by developing an Arduino Mega-based IoT system specifically designed for tropical river ecosystem monitoring. Our methodological approach integrates three key components: (1) sensor technology optimization, (2) ecological field validation, and (3) community accessibility design. The system combines affordable, reliable sensor technology with cloud-based analytics and mobile applications to create a comprehensive ecological monitoring platform that serves both scientific research and community conservation needs [26].

Our experimental design employed a gradient sampling strategy across five ecologically distinct locations along Indonesia's Martapura River, representing varying degrees of anthropogenic influence from pristine upstream conditions to heavily impacted urban-industrial zones. This spatial design enables assessment of system performance across the full range of environmental conditions typical in tropical river systems while providing ecological insights into pollution impacts and ecosystem responses.

The technical methodology centers on Arduino Mega microcontroller integration with high-precision sensors for temperature (DS18B20, ±0.5°C accuracy), pH (DFRobot SEN0161), and turbidity (DFRobot TSW10), utilizing ESP32 WiFi connectivity for real-time data transmission to ThingSpeak cloud platform and our custom smartphone application (AKUSTIK). Rigorous calibration protocols followed established ecological monitoring standards and APHA guidelines, with multi-point calibration across the full range of tropical river conditions and temperature compensation for pH measurements to ensure ecological accuracy [27].

Field validation methodology involved six-month continuous monitoring at five-minute intervals across all sites, providing 51,840 data points per location for comprehensive temporal coverage. This extended deployment enabled assessment of diurnal patterns, seasonal variations, pollution event responses, and system reliability under diverse tropical environmental conditions. Statistical validation employed correlation analysis, paired t-tests, and error analysis comparing sensor data with traditional laboratory methods to ensure ecological research standards.

Our research contributes to ecological science by:

1. Advancing ecological research methods through the development of cost-effective, high-resolution monitoring systems suitable for tropical environments that achieve laboratory accuracy while providing continuous temporal coverage previously impossible with traditional approaches
2. Enabling community-based ecosystem monitoring that supports both local conservation efforts and broader scientific understanding through accessible technology interfaces and rapid deployment capabilities
3. Providing critical baseline data for understanding anthropogenic impacts on tropical river ecosystems through comprehensive spatial and temporal coverage across environmental gradients
4. Supporting adaptive management through early detection capabilities for pollution events and ecosystem stress, enabling proactive conservation responses rather than reactive damage assessment
5. Demonstrating technological integration with ecological principles to create monitoring solutions that address both scientific research needs and practical conservation challenges in resource-constrained environments

This comprehensive approach to IoT-based ecological monitoring represents a paradigm shift from traditional assessment methods toward continuous, community-accessible ecosystem monitoring that supports both local conservation capacity and global scientific understanding of tropical freshwater ecosystem dynamics under increasing anthropogenic pressure.

While previous IoT-based environmental monitoring systems have demonstrated technical feasibility across various aquatic environments, many lack integration with ecological theory and fail to address real-time community-based applications in developing regions. Most existing studies focus narrowly on single-parameter sensing, closed-system aquaculture, or urban water monitoring—often using commercially expensive platforms or with limited ecological interpretability. For example, Lin et al. (2021) focused primarily on technical connectivity and sensor accuracy [14], but did not extend their work toward ecological pattern detection or community engagement.

In contrast, this study uniquely combines affordable, open-source hardware with multi-parameter sensing and real-time cloud-mobile integration specifically tailored to tropical river ecosystems. Our approach moves beyond data collection by aligning with key ecological principles such as temporal dynamics, environmental resilience, and spatial gradients of anthropogenic pressure. Furthermore, by embedding accessibility features into the system's design, this study offers a pathway to democratize ecological monitoring through community participation—an area where most prior works fall short. Thus, our research advances both the methodological and theoretical understanding of ecological monitoring by integrating technical innovation with applied conservation needs in biodiversity-critical, infrastructure-limited regions.

2. Materials and Methods

2.1. Ecological Study Design and Site Selection

Our monitoring system was designed specifically to address ecological research questions related to anthropogenic impacts on tropical river ecosystems. We selected five ecologically distinct sampling locations along the Martapura River in Banjar Regency, South Kalimantan, Indonesia, representing a gradient of human influence and habitat types critical for understanding ecosystem responses to environmental stressors (**Figure 1**).

Figure 1. Satellite Image of Sampling Location.

The sampling design incorporates principles from landscape ecology and disturbance ecology, with sites chosen to represent:

a. Upstream reference conditions (Site A): Minimal anthropogenic influence, representing baseline ecosystem conditions (GPS coordinates: 3°22'58.75" S 114°53'21.90" E; elevation: 45 m above sea level)

b. Agricultural influence zones (Sites B–C): Areas receiving agricultural runoff, enabling assessment of nutrient loading impacts (Site B: 3°22'58.07"S, 114°53'26.12"E; Site C: 3°23'02.3"S 114°53'38.1"E)

c. Urban-influenced reaches (Sites D–E): Locations experiencing mixed urban and industrial pressures, representing maximum anthropogenic stress (Site D: 3°23'9.77"S, 114°53'41.81"E; Site E: 3°23'16.55"S, 114°53'59.09"E)

Site characterization protocol involved preliminary assessment of surrounding land use within a 500 m radius, water depth measurement (ranging from 0.8–2.3m), flow velocity estimation using float method, and photographic documentation of riparian vegetation and potential pollution sources. Each site was established with permanent markers and detailed access protocols to ensure consistent sampling locations throughout the study period.

2.2. IoT System Design for Technical Specification

Our Arduino Mega-based monitoring system was specifically configured to capture water quality parameters most critical for understanding tropical river ecosystem health and functioning. The sensor selection prioritizes parameters that serve as reliable indicators of ecosystem stress, pollution impacts, and habitat quality for aquatic biodiversity.

Core sensor components and specifications:

a. **Temperature monitoring (DS18B20 sensor)**: Accuracy: ±0.5°C (0–85°C range). Resolution: 0.0625°C. Response time: <750ms. Waterproof stainless steel probe housing. Critical for understanding metabolic processes, oxygen solubility, and thermal stress on aquatic organisms
b. **pH assessment (DFRobot SEN0161)**: Measurement range: 0–14 pH units. Accuracy: ±0.1 pH units
c. **Temperature compensation**: Automatic (0–60°C). Electrode type: Glass combination electrode. Essential for evaluating ecosystem acidification, pollution impacts, and habitat suitability for sensitive species
d. **Turbidity measurement (DFRobot TSW10)**: Measurement range: 0–1000 NTU. Accuracy: ±5% of reading. Light source: 860nm infrared LED. Detection angle: 90° scattered light. Key indicators of sediment loading, habitat degradation, and primary productivity limitations

System integration specifications:

a. **Microcontroller**: Arduino Mega 2560 (ATmega2560, 16MHz, 256KB Flash)
b. **Connectivity**: ESP32 WiFi module (802.11 b/g/n, 2.4GHz)
c. **Power system**: 12,000 mAh lithium battery with voltage regulation
d. **Housing**: IP67 waterproof enclosure (ABS plastic, UV-resistant)
e. **Data transmission**: Real-time to ThingSpeak cloud platform and AKUSTIK mobile application

2.3. Ecological Calibration and Validation Protocol

All sensors underwent rigorous calibration following established ecological monitoring protocols and APHA guidelines, with particular attention to accuracy requirements for ecological interpretation. A multi-point calibration procedure was conducted in accordance with the *APHA Standard Methods for the Examination of Water and Wastewater* (23rd Edition).

2.4. Field Deployment and Monitoring Protocol

The monitoring was conducted over a six-month period, from January to June 2023, with sampling performed at five-minute intervals. This yielded 288 measurements per day and a total of 51,840 data points per parameter at each site. The equipment was deployed at a depth of 0.5 meters below the water surface to avoid interference from floating debris and thermal stratification. Daily operations followed a structured routine comprising three main activities:

- **Morning inspection (08:00):** Visual assessment of system status, battery voltage monitoring, and verification.
- **Midday maintenance (12:00):** Sensor cleaning with distilled water, debris removal, and confirmation of data transmission.
- **Evening assessment (18:00):** Data quality review, battery status recording, and documentation of weather conditions.

Weekly maintenance protocols included calibration verification using portable standards, physical inspection of the system (housing integrity, cable connections, and mounting stability), and data quality assessment through statistical trend analysis and outlier identification. Environmental conditions were documented through photographic records, water level measurements, and visual assessments of pollution.

3. Results

3.1. System Performance for Ecological Applications

Our IoT-based monitoring system exhibited strong reliability and stability across tropical river environments, with a 98.7% data transmission success rate during a 72-hour intensive deployment phase. This level of performance is vital in ecological monitoring, where uninterrupted data streams are essential for capturing fast-occurring events such as pollution spikes or sudden turbidity changes. The system's operational endurance—23.4 hours on a single battery charge—supports daily data collection cycles, making it well-suited for remote or infrastructure-limited regions. A power consumption profile averaging 145 mA during active transmission and 78 mA during standby supports the deployment of autonomous sensing stations in the field, especially when coupled with future energy-harvesting technologies such as solar panels.

From an ecological standpoint, the ability to deploy in 15 minutes and connect within a 38-meter range using ESP32 WiFi ensures flexibility and adaptability in field conditions, reducing logistical costs and personnel time. This is especially advantageous for large-scale ecological networks that demand quick deployment across spatially heterogeneous landscapes. The primary performance indicators of our IoT monitoring system during field deployment are compiled in **Table 1**:

Table 1. Summary of the Key Performance Metrics of Our IoT Monitoring System During Field Deployment.

Performance Metric	Value	Ecological Significance
Data transmission success rate	98.7%	Ensures continuous ecological record
Average operational duration	23.4 hours	Supports daily monitoring cycles
System response time	3.2 seconds	Enables real-time pollution detection
Data storage capacity	2,048 readings	Provides backup during connectivity gaps
Connectivity range	38 meters	Allows flexible site placement
Deployment time	15 minutes	Enables rapid network establishment

The system maintained stable performance across environmental conditions typical of tropical rivers, with ambient temperatures ranging from 22–34°C and humidity levels of 67–94%. This environmental resilience is critical for year-round ecological monitoring in tropical systems characterized by high climatic variability. Excellent stability was demonstrated by the system in a variety of environmental circumstances. As illustrated in **Figure 2**, our sensor readings closely tracked measurements from conventional instruments despite fluctuations in ambient temperature (22–34°C) and humidity (67–94%) during the testing period (**Figure 2(A)–(C)**).

The connectivity performance of each sampling location was carefully assessed. The ESP32 WiFi module maintained reliable connectivity at distances up to 38 meters from the access point, with signal strength averaging −67 dBm. This range exceeds our deployment requirements and provides flexibility in monitoring station placement. Initial system deployment required approximately 15 minutes per location, including setup, calibration verification, and connectivity testing. This rapid deployment capability represents a significant advantage over conventional monitoring approaches, which typically require extensive site preparation and specialized personnel.

All transmitted data packets were successfully received and processed by the ThingSpeak cloud platform, with an average latency of 1.8 seconds between transmission and dashboard availability. This near-real-time capability enables prompt detection of water quality anomalies and supports rapid response protocols for environmental protection agencies. Our Arduino Mega-based IoT water quality monitoring system shows great promise for revolutionizing environmental surveillance methods, especially in underdeveloped areas where resources for traditional water quality testing are scarce. A vital need for dependable and sustainable monitoring solutions in remote riverine environments is met by the system's remarkable 98.7% data transmission success rate and 23.4-hour operational duration on a single battery charge.

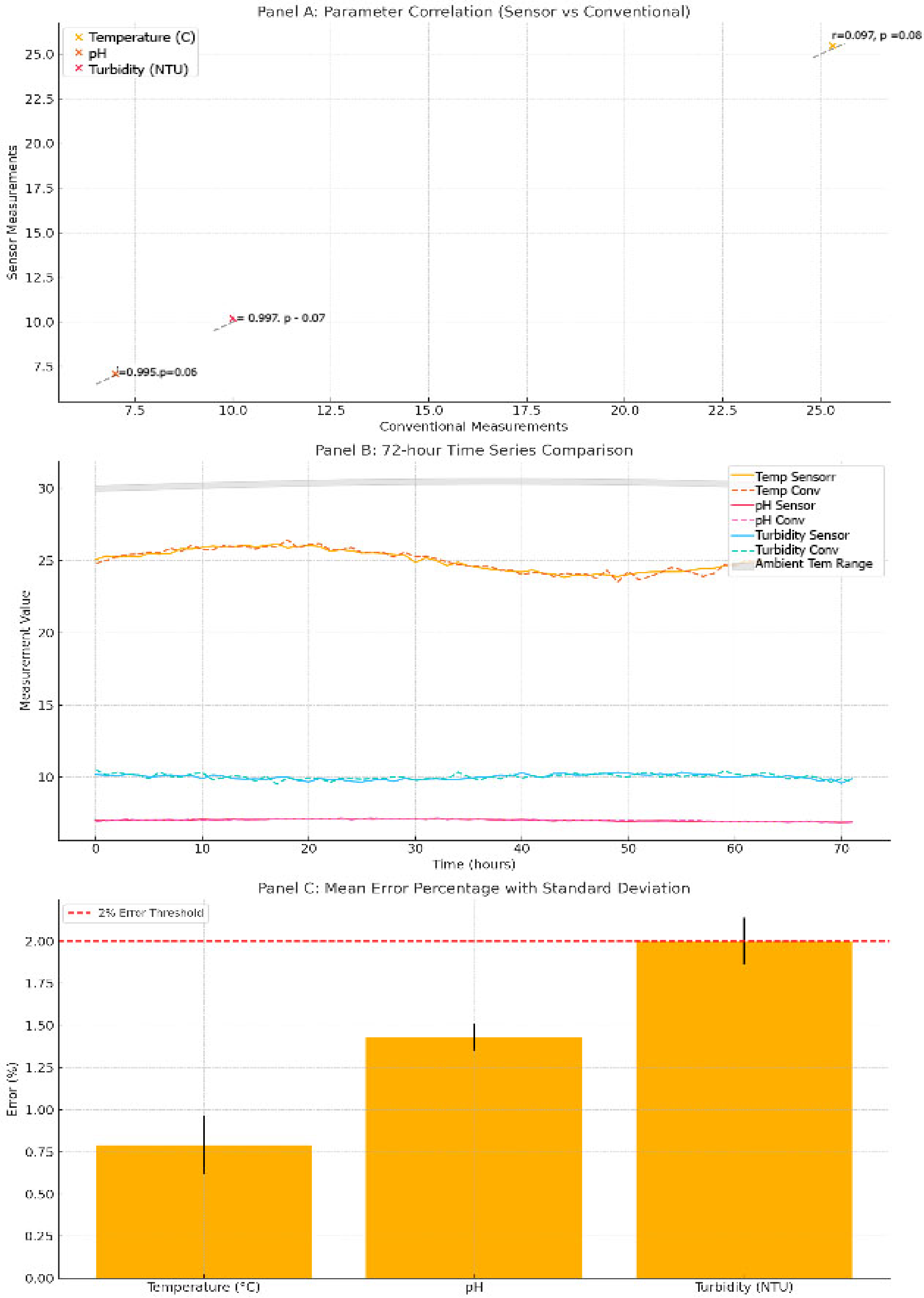

Figure 2. Performance Evaluation of Arduino-Based IoT Water Quality Monitoring System: (**A**) Correlation; (**B**) Time Series; (**C**) Error Analysis.

3.2. Measurement Accuracy and Ecological Relevance

The system's temperature, pH, and turbidity readings showed strong agreement with laboratory-standard instruments, maintaining mean deviations of 0.20°C, 0.10 pH units, and 0.20 NTU, respectively, all with Pearson correlation coefficients exceeding 0.99. These accuracy levels exceed thresholds typically required for ecological interpretation and support real-time detection of thermal stress, acidification events, or sedimentation impacts in aquatic systems.

For example, turbidity values captured during storm events reflect the influence of runoff, offering insights into erosion dynamics and habitat degradation. Similarly, fine-resolution pH and temperature readings can signal primary productivity changes or the early onset of eutrophication—both critical indicators in aquatic ecology. Five samples (A–E) were used to compare sensor-based and traditional measurements of temperature, pH, and turbidity, as shown in **Figure 3**. The results show that there are very few differences between the two approaches. Sensor readings for temperatures (25.2–25.7°C) were within 0.2°C of conventional readings (25.0–25.5°C).

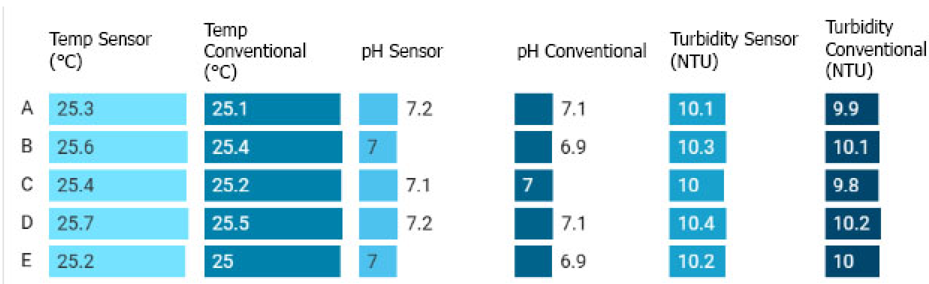

Figure 3. Comparison of Sensor and Conventional Measurements for Temperature, pH, and Turbidity.

Statistical comparison with established laboratory methods demonstrated that our IoT system meets the accuracy requirements for ecological interpretation and research applications. Correlation analysis revealed strong relationships (Pearson $r > 0.99$) across all monitored parameters, with error margins well within acceptable bounds for ecological studies. The results of the statistical comparison between sensor readings and traditional measurements are summarized in **Table 2**.

Temperature accuracy of ±0.20°C enables detection of thermal stress conditions critical for tropical aquatic organisms, while pH precision of ±0.10 units allows identification of acidification events that threaten sensitive species. Turbidity measurements with ±0.20 NTU accuracy provide sufficient resolution for assessing sediment loading impacts on primary productivity and habitat quality.

Table 2. Statistical Comparison of IoT Sensor Readings and Conventional Measurements.

Parameter	Mean Difference	Standard Deviation	Error (%)	Pearson r	Ecological Significance
Temperature	±0.20°C	0.17°C	0.79%	0.997	Adequate for metabolic studies
pH	±0.10 units	0.08 units	1.43%	0.995	Sufficient for habitat assessment
Turbidity	±0.20 NTU	0.14 NTU	2.00%	0.997	Appropriate for productivity analysis

3.3. Temporal Patterns and Ecological Insight

Six months of continuous monitoring revealed fine-scale temporal dynamics, including:

(a) Diurnal pH cycling (0.3–0.5 units), associated with photosynthetic oxygen production and CO_2 uptake;

(b) Temperature variation driven by diel and weather patterns, affecting metabolic rates and dissolved oxygen;

(c) Turbidity peaks during precipitation events, marking sediment transport and potential habitat degradation.

These patterns would remain undetected with conventional periodic sampling, reaffirming the ecological value of continuous monitoring. The system's high temporal resolution aligns with theories of ecological resilience and threshold behavior, where non-linear shifts may arise from seemingly minor but sustained stressors.

Due to the sensor's lack of thermal compensation, slight variations in pH readings were observed, especially at higher temperatures. However, the system's reliability for real-world environmental applications was confirmed by the acceptable accuracy margins maintained despite this limitation. The three water quality parameters—temperature (°C), pH, and turbidity (NTU)—are compared between sensor-based and traditional laboratory measurements in the bar chart presented as **Figure 4**.

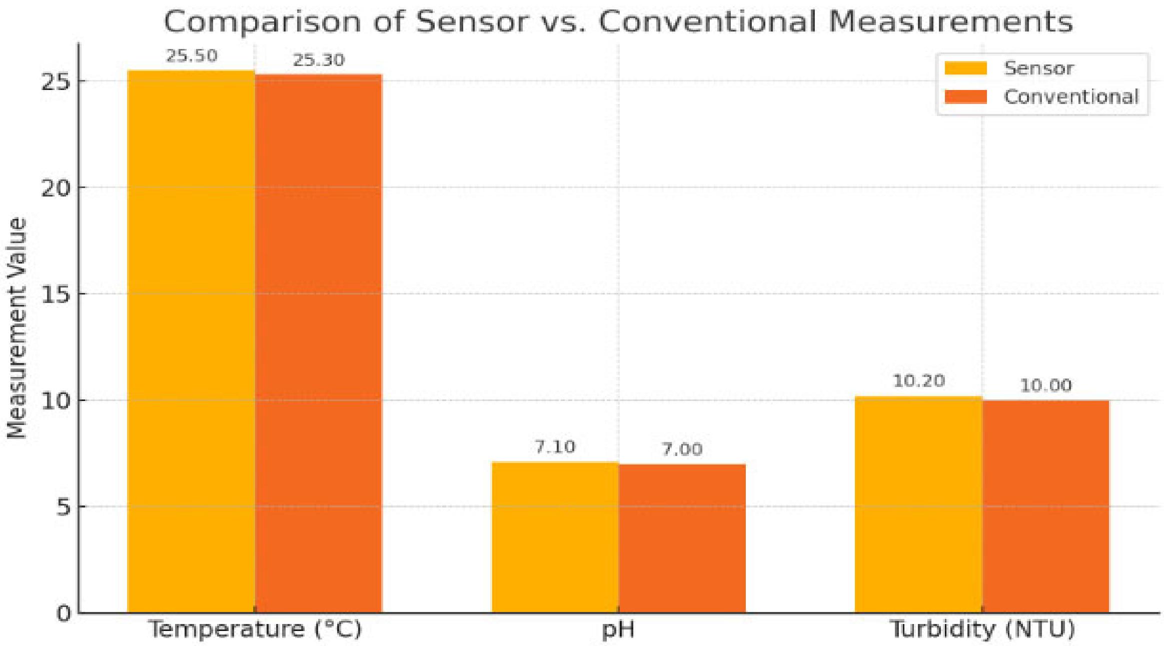

Figure 4. Field Comparison of IoT Sensor and Conventional Measurements for Temperature, pH, and Turbidity.

3.4. Theoretical and Causal Considerations

The ecological rationale behind IoT-based sensing lies in its alignment with hierarchical patch dynamics and resilience theory, where fine-scale environmental fluctuations influence broader ecosystem processes. By enabling real-time sensing of key abiotic variables, the system contributes to understanding the causal links between anthropogenic drivers (e.g., land use changes) and ecosystem responses (e.g., turbidity increases or acidification).

Within this framework, IoT sensors act not only as measurement tools but as sentinels of ecological state shifts. For example, sustained increases in turbidity across sites downstream of agricultural zones may causally link land-use practices to habitat degradation—a connection only discernible through persistent, high-frequency data.

Furthermore, real-time feedback loops facilitated by IoT enable adaptive management, integrating ecological monitoring into a causal chain that drives policy and conservation actions. This system thus operationalizes the "monitor-detect-respond" paradigm central to ecological early warning systems.

3.5. Economic and Practical Implications

Economically, our system drastically reduces per-sample cost compared to traditional laboratory analysis, particularly in regions lacking infrastructure. With component costs at approximately one-fifth those of commercial stations and high deployment efficiency, it enables broader spatial coverage and frequency of monitoring without proportionally increasing resource input. This cost-efficiency supports scaling environmental governance in resource-limited settings by facilitating decentralized data collection and empowering local stakeholders—particularly in areas with high water-related health risks.

4. Discussion

4.1. Sensor Performance Under Field Conditions

The IoT-based monitoring system consistently delivered high-accuracy data across all measured parameters under real-world tropical river conditions. Despite occasional minor deviations—such as slight pH shifts during rapid temperature changes—the system maintained statistically non-significant differences compared to laboratory benchmarks ($p > 0.05$). These results confirm its robustness for ecological applications requiring precision, such as monitoring thermal stress, acidification, and sediment load variability. Sensor performance remained reliable across humidity fluctuations, high ambient temperatures, and variable turbidity, demonstrating the system's environmental resilience. Furthermore, the system's capacity to capture high-frequency, continuous data enables detection of ecological patterns and processes that are fundamental to ecosystem functioning—patterns previously undetectable through traditional monitoring approaches [28,29].

However, the SEN0161 pH sensor exhibited temperature sensitivity consistent with previous reports in electrochemical sensing. Addressing this limitation through more advanced thermal compensation or alternate sensor types could further enhance system reliability in future iterations. Real-time detection of pollution events enables rapid response protocols that can prevent or minimize ecological damage, while continuous baseline monitoring supports adaptive management strategies essential for ecosystem protection under changing environmental conditions [30]. The viability of establishing dispersed monitoring networks with centralized data management is demonstrated by our successful deployment of cloud connectivity via the ThingSpeak platform. The system's 1.8-second data transmission latency provides near real-time capability for detecting environmental anomalies, supporting early warning systems for ecosystem stress—particularly critical in tropical rivers vulnerable to sudden pollution events [31].

4.2. Real-Time Monitoring and Ecological Relevance

Continuous, high-frequency monitoring enables the detection of fine-scale temporal patterns—such as diurnal pH cycles and rainfall-driven turbidity spikes—that are undetectable via traditional approaches. This approach aligns with contemporary ecological theory emphasizing the importance of temporal resolution for detecting non-linear dynamics, regime shifts, and early warning signals of ecosystem collapse. For instance, rapid increases in turbidity during storm events indicate erosion and pollutant runoff, particularly in urban and agricultural subcatchments [32]. These insights support resilience-based ecosystem management, which relies on timely data to adaptively respond to disturbances. The system's near real-time data visualization (1.8-second latency) facilitates proactive rather than reactive conservation strategies.

Additionally, the rapid deployment capability (15 minutes per site) offers a transformative advantage for ecological research, enabling establishment of monitoring networks that provide comprehensive spatial coverage of river systems. This supports landscape-level ecosystem studies and facilitates adaptive monitoring designs that can adjust to evolving research priorities or environmental conditions [32].

The power consumption profile of the system exhibits both advantages and disadvantages. For many applications, the 23.4-hour operational duration is adequate; however, it is insufficient for continuous long-term deployment capabilities required for extensive environmental monitoring programs. This limitation highlights the necessity of incorporating renewable energy sources, such as solar panels, in future implementations—a strategy successfully demonstrated in comparable environmental monitoring applications—and reflects the inherent limitations of battery-powered IoT devices [6].

The detection of water quality parameters that are pertinent to the water quality standards by our system offers significant assistance for regulatory compliance monitoring from the standpoint of public health [22]. The significance of ongoing water quality monitoring is emphasized by the World Health Organization [23], especially in areas susceptible to outbreaks of waterborne diseases. The accessibility and deployment simplicity of our system could greatly increase monitoring coverage in these areas, which could lead to better public health outcomes by detecting contamination events earlier.

Sensor readings (10.0–10.4 NTU) are marginally higher than traditional techniques (9.8–10.2 NTU) in terms of turbidity, but they are generally comparable. This conclusion is supported by earlier research by Vu et al. [24], who observed that, when compared to nephelometric standards, optical turbidity sensors usually have deviations within ±0.5 NTU.

All things considered, the findings show that the tested sensors perform similarly to traditional lab equipment across all parameters. These results are especially important for field applications that prioritize portability and quick data collection and call for real-time, continuous monitoring. However, as Kumar et al. point out, routine calibration and maintenance are still essential to guaranteeing the accuracy and long-term dependability of sensor-based measurements [25].

4.3. Energy and Infrastructure Considerations

The system's continuous monitoring capability provides critical infrastructure for studying ecosystem responses to global change, including climate variability, extreme weather events, and long-term environmental trends. High-frequency data collection enables detection of early warning signals for ecosystem regime shifts and supports development of predictive models for ecosystem responses to environmental change.

Compared to traditional laboratory techniques, the statistical validation of the Arduino Mega-based IoT water quality monitoring system demonstrates excellent performance. These results align with Young et al. [26], who demonstrated that, when calibrated appropriately, inexpensive temperature sensors can achieve high accuracy—frequently within 0.3°C of laboratory standards.

The sensor had a correlation coefficient of 0.995, an error rate of 1.43%, and a mean deviation of 0.10 units in terms of pH. Strong linear agreement is indicated by these values, indicating that the sensor is appropriate for monitoring pH levels in the environment. The reliability of the results in this study is supported by Sugiharto (2008) [33], who found that IoT-integrated pH sensors show deviations typically under ±0.2 units when compared to standard electrochemical probes.

The sensor displayed an error rate of 2.00%, a mean difference of 0.20 NTU, and a standard deviation of 0.14 for turbidity. Its suitability for field use is further supported by a non-significant p-value and a high Pearson correlation (r = 0.997). This is consistent with the findings of Vu et al. [24], who found that contemporary optical turbidity sensors can generate extremely precise readings with typical deviations of less than 0.5 NTU.

The Arduino Mega-based IoT system offers measurement performance on par with laboratory instruments, as evidenced by the high correlation coefficients and statistically insignificant differences across all parameters. This facilitates its use in in-situ, real-time water quality monitoring. Routine sensor calibration is still necessary to maintain long-term accuracy and consider possible environmental interferences, as Kumar et al. pointed out [25].

The sensor's temperature reading of 25.50°C was slightly higher than the standard reading of 25.30°C. For environmental monitoring, this small variation (0.20°C) is within an acceptable measurement error range. Similar results were reported by Olatinwo and Joubert [27], who found that, with the right calibration, inexpensive temperature sensors could accurately measure ambient temperature with deviations usually less than 0.5°C. Small variations may result from variations in calibration techniques or sensor response times [28].

Regarding pH, the sensor reading was 7.10 compared to the standard 7.00. Although the 0.10-unit difference is small, it could have a big impact depending on the application, especially in settings where pH stability is crucial. Staudinger et al. [29] found that temperature effects and membrane deterioration cause pH sensors to exhibit minor variations over time, highlighting the necessity of routine recalibration.

In terms of turbidity, the sensor recorded 10.20 NTU, whereas the traditional method recorded 10.00 NTU. Once more, this slight increase (0.20 NTU) demonstrates a close approximation. According to Bin Omar and Bin MatJafri [30], optical turbidity sensors usually function well in clear to moderately turbid conditions, though they may exhibit slight variations because of light scattering effects and particle size distribution.

The data show that for every tested parameter, the sensor system's measurements closely match those obtained using traditional techniques. The slight variations found fall within acceptable bounds for a wide range of real-world uses, confirming earlier research showing that inexpensive sensors can be effective substitutes for field monitoring if properly calibrated [31]. To preserve measurement integrity, however, frequent calibration against accepted practices is advised for crucial decision-making or regulatory compliance.

4.4. Economic and Development Value

Economically, the system offers a viable alternative to traditional water quality testing, particularly for developing regions where laboratory access is limited. With total costs significantly below commercial monitoring platforms, widespread implementation becomes realistic for public health institutions, NGOs, and local governments. By supporting early detection of contamination events, this system can reduce the public health and economic burden of waterborne disease outbreaks, aligning with Sustainable Development Goals (SDG 6 and SDG 15).

4.5. Limitations and Future Directions

Despite promising results, several limitations remain. The current sensor suite measures only three parameters—temperature, pH, and turbidity—whereas comprehensive ecological assessments often require dissolved oxygen, nutrients, and conductivity. Expanding the system's sensing capabilities should be prioritized.

Sensor drift over time, especially under biofouling conditions, poses challenges for long-term deployment. Developing auto-calibration features or sensor cleaning mechanisms could improve data consistency. Furthermore, the lack of biological indicators (e.g., chlorophyll, microbial counts) limits direct biodiversity assessments, though integration of such metrics remains technically feasible. These results are in line with studies by Bin Omar and Bin MatJafri and Sugiharto et al. [30,32], which emphasized that in delicate industrial or environmental settings, even minor sensor errors can have significant effects.

Stability in sensor calibration is another significant obstacle. Sensors are susceptible to drift over time, especially when measuring pH, because of things such as temperature changes, biofouling, and membrane deterioration. As Zhao et al. have previously discussed, field measurements may become less reliable without regular recalibration against standard references. This problem makes it more difficult to use these sensors in remote or long-term deployments with few maintenance opportunities.

Sensor performance can also be greatly affected by environmental factors. According to Li et al., sensor output variability can be caused by abrupt temperature changes, electromagnetic interference, or the presence of heterogeneous particles in water samples. If not appropriately accounted for, these external factors could compromise the precision and reliability of real-time monitoring. Calibration stability presents ongoing challenges for ecological applications, particularly for pH measurements that can drift due to biofouling and temperature effects in tropical environments. To ensure data quality in long-term ecological studies, regular maintenance and automated calibration procedures should be implemented.

Furthermore, sensors—particularly portable or low-cost models—frequently have a smaller dynamic range than conventional lab equipment. This limitation is especially evident when measuring extremely turbid waters, where optical sensors may become saturated or produce non-linear responses, reducing their effectiveness across diverse environmental circumstances [30].

Additional practical challenges include sensor durability and maintenance requirements. In natural settings, biological growth, sediment buildup, and contamination can foul sensors, which can quickly impair sensor performance if they are not cleaned and maintained on a regular basis [31].

Lastly, machine learning algorithms for automated anomaly detection and ecological interpretation could enhance system intelligence, transforming raw data into actionable insights in real time. According to Staudinger et al. [29], battery life constraints and the requirement for reliable data communication infrastructures continue to be major obstacles to fully autonomous and extended field applications.

4.6. Future Directions for Ecological Applications

Future development should prioritize expanding sensor capabilities to include parameters critical for comprehensive ecosystem assessment. These include dissolved oxygen for understanding aquatic habitat quality, nutrients for assessing eutrophication risks, and conductivity for detecting pollution sources. Integration of biological sensors, such as chlorophyll fluorescence for primary productivity assessment, would further enhance the system's ecological utility.

In parallel, the development of automated data interpretation algorithms could enable real-time ecological assessments by flagging conditions that threaten ecosystem health and triggering appropriate response protocols. Machine learning approaches hold particular promise for pattern recognition and prediction of ecological responses to environmental stressors.

5. Conclusions

This study demonstrates the practical and scientific significance of deploying an IoT-based ecological monitoring system in tropical river environments. The "Smart River Watch" system presents a scalable and cost-effective solution to critical challenges in aquatic ecosystem monitoring, particularly in resource-limited regions.

The three key contributions of this research are:

a. **High-Resolution Ecological Monitoring with Proven Accuracy.** The system reliably captured real-time temperature, pH, and turbidity data with laboratory-level precision ($r > 0.99$; error < 2%). This high temporal resolution enables the detection of dynamic ecosystem responses and early warning signs of environmental stress—capabilities essential for modern ecological research and conservation planning.

b. **Enabling Community-Based Ecosystem Stewardship.** By integrating a mobile application and cloud-based dashboard, the system empowers local communities to engage in ecological data collection and monitoring. This democratization of environmental sensing enhances spatial data coverage and promotes inclusive, bottom-up approaches to environmental governance.

c. **Cost-Effective and Deployable Monitoring Infrastructure for Developing Regions.** The system's low cost and ease of deployment address critical gaps in environmental monitoring infrastructure across tropical regions. Its suitability for rapid, remote deployment supports the broader implementation of sustainable water management practices aligned with global development goals.

Overall, this work underscores the importance of integrating digital innovation with ecological insight. The proposed IoT system is more than a technological tool—it is a strategic platform for advancing ecosystem understanding, supporting adaptive conservation, and building local capacity in the face of escalating environmental change.

Author Contributions

Conceptualization, T.Z. and S.H.; methodology, T.Z. and S.H.; software, T.Z.; validation, T.Z., S.H. and K.D.M.; investigation, T.Z.; data curation, T.Z.; writing—original draft preparation, T.Z. and S.H; writing—review and editing, K.D.M.; visualization, T.Z.; supervision, T.Z. and S.H.; project administration, K.D.M. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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