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ORIGINAL

Environmental monitoring using IoT sensors for ecosystem conservation

Monitoreo ambiental mediante sensores IoT para la conservación de ecosistemas

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ABSTRACT

Objective: To evaluate water quality through a network of IoT sensors installed in conserved, transitional, and intervened areas of a riparian ecosystem, considering the variability of environmental parameters, the accuracy of the devices, and the operational performance of the system. Methodology: A quantitative, applied, non-experimental and longitudinal research was developed. Nine IoT stations were installed, distributed at three points in each environmental zone. For 90 days, temperature, pH, turbidity, electrical conductivity and dissolved oxygen were recorded every 30 minutes. Validation was carried out using 117 paired measurements with reference equipment. The data were analyzed using descriptive statistics, mixed linear models and coefficients of agreement. Results: 95.0% of the 38,880 scheduled registrations were recovered, with an operational availability of more than 94%. The intervened area presented higher temperature, turbidity and conductivity, as well as lower dissolved oxygen, with significant differences between the three zones. The sensors showed correlations between 0.93 and 0.98 and concordance coefficients greater than 0.90. Conclusions: The IoT network allowed the identification of spatial and temporal variations in water quality and generated measurements consistent with the reference equipment. Its application can complement conventional monitoring, detect critical conditions and support conservation strategies in riparian ecosystems.

Keywords: environmental monitoring, internet of things, water quality, smart sensors, riparian ecosystems.

RESUMEN

Objetivo: Evaluar la calidad del agua mediante una red de sensores IoT instalada en zonas conservadas, de transición e intervenidas de un ecosistema ribereño, considerando la variabilidad de los parámetros ambientales, la precisión de los dispositivos y el desempeño operativo del sistema. Metodología: Se desarrolló una investigación cuantitativa, aplicada, no experimental y longitudinal. Se instalaron nueve estaciones IoT, distribuidas en tres puntos por cada zona ambiental. Durante 90 días se registraron temperatura, pH, turbidez, conductividad eléctrica y oxígeno disuelto cada 30 minutos. La validación se realizó mediante 117 mediciones pareadas con equipos de referencia. Los datos fueron analizados mediante estadística descriptiva, modelos lineales mixtos y coeficientes de concordancia. Resultados: Se recuperó el 95,0 % de los 38.880 registros programados, con una disponibilidad operativa superior al 94 %. La zona intervenida presentó mayor temperatura, turbidez y conductividad, además de menor oxígeno disuelto, con diferencias significativas entre las tres zonas. Los sensores mostraron correlaciones entre 0,93 y 0,98 y coeficientes de concordancia superiores a 0,90. Conclusiones: La red IoT permitió identificar variaciones espaciales y temporales en la calidad del agua y generó mediciones concordantes con los equipos de referencia. Su aplicación puede complementar el monitoreo convencional, detectar condiciones críticas y apoyar estrategias de conservación en ecosistemas ribereños.

Palabras clave: Palabras claves: monitoreo ambiental, internet de las cosas, calidad del agua, sensores inteligentes, ecosistemas ribereños.

INTRODUCTION

Environmental monitoring is an essential tool for identifying changes in ecosystems, assessing the status of natural resources, and guiding prevention, management, and conservation actions. However, conventional procedures often rely on periodic campaigns, manual sample collection, and subsequent analyses, which can hinder the timely detection of rapid changes or short-duration pollution events. Narayana et al. (1) point out that the Internet of Things (IoT) has transformed this process through systems capable of recording, transmitting, storing, and visualizing environmental parameters in real time.

IoT systems integrate sensors, microcontrollers, communication networks, and digital platforms to continuously collect information. The distribution of several nodes within a single territory allows for expanding spatial coverage, observing hard-to-reach areas, and reducing the need for permanent on-site inspections. Furthermore, integration with cloud services facilitates the construction of time series, remote access to records, and generation of alerts when variables exceed established levels (2,3).

Coulby et al. (4) demonstrated that low-cost environmental stations can combine different measurement modalities within the same infrastructure. These systems can incorporate sensors for temperature, humidity, pressure, light, air quality, and physicochemical characteristics of water. Their modular design allows devices to adapt to the needs of the environment and progressively increase the number of stations. This flexibility is important because environmental changes usually manifest through simultaneous changes in different variables rather than from a single indicator.

Although low-cost devices enable expanding monitoring coverage, they also have limitations regarding precision and stability. Measurements can be affected by poor calibration, component aging, temperature changes, accumulation of residues, and communication interference. Similarly, networks can generate missing data, duplicate values, or atypical records. For this reason, validation, debugging, and evaluation of data quality should be part of routine operation of IoT systems (5,6).

Essamlali et al. (7) argue that the combination of IoT with machine learning techniques has expanded the possibilities for water quality monitoring. These tools enable the analysis of large volumes of data, pattern recognition, anomaly detection, and the construction of predictive models. However, the reliability of the results depends directly on the quality of the original measurements; therefore, automated models must be complemented by calibration processes and comparison with reference instruments.

Water quality represents a key area of application of environmental monitoring using IoT. Riparian ecosystems are exposed to precipitation, runoff, erosion, domestic discharges, agricultural activities, and changes in land use. These pressures can rapidly modify temperature, pH, turbidity, electrical conductivity, and dissolved oxygen. Miller et al. (8) warn that, despite the growth of technological solutions, there are still important differences between the development of prototypes and their long-term operation under real environmental conditions.

Systems installed in aquatic environments may face problems related to sedimentation, biofouling, humidity, connectivity loss, and water level variations. These conditions require establishing periodic cleaning, verification, and recalibration procedures. In rural areas, low-cost stations represent an alternative for expanding environmental monitoring, provided their implementation includes physical protection, energy autonomy, local storage, and data recovery mechanisms (9).

The integration of cloud computing services has enhanced the ability to store, process, and visualize information produced by the stations. Wiryasaputra et al. (10) developed an architecture for monitoring and predicting drinking water quality, where records are transmitted to a remote platform for consultation and processing. These architectures allow identifying trends, comparing periods, and maintaining traceability of each measurement through the date, time, station of origin, and operational condition of the sensor.

IoT has also been applied in aquaculture systems, where variations in water characteristics can directly affect the health of organisms. Chen et al. (11) used connected sensors to monitor relevant parameters in fish farms, facilitating the identification of changes that required a timely response. These experiences indicate that continuous monitoring can support decision-making when records are available before an alteration produces consequences of greater magnitude.

Wireless networks allow the installation of nodes in different sectors of a river, stream, or channel and enable comparison of environmental conditions between points with different levels of intervention. Singh and Walingo (12) highlight that these networks can improve water quality monitoring through continuous acquisition and transmission of information.

However, their performance depends on the stability of communications, the power supply, the resistance of components, and the precision of the selected sensors.

Cloete et al. (13) developed smart sensors for real-time measurement of water quality variables. The joint recording of pH, temperature, turbidity, conductivity, and dissolved oxygen allows the identification of variations that could be related to natural processes or pollution sources. The simultaneous interpretation of the parameters provides a more complete picture of ecosystem conditions than the isolated observation of a single variable.

Early detection of contamination is another relevant benefit of these technologies. Networks can establish baseline values and recognize deviations that indicate the presence of an abnormal condition. This capability enables alerts, guides inspections, and prioritizes locations requiring further analysis. However, thresholds must be carefully configured to avoid false alarms caused by instrumental errors or natural fluctuations of the ecosystem (14).

Adu-Manu et al. (15) identified that monitoring through wireless networks still presents challenges related to energy autonomy, interoperability, scalability, and transmission security. They also pointed out the need to improve data validation and management procedures. Therefore, the evaluation of an IoT network should not be limited to verifying that sensors record and transmit information, but should analyze their accuracy, operational availability, and ability to represent real environmental conditions.

Prolonged implementation experiences reveal difficulties that do not always appear during laboratory tests. O'Flynn et al. (16) demonstrated that node location, maintenance access, component protection, and data recovery from communication failures are determining factors in a real-time monitoring system. These conditions are particularly important in riparian ecosystems, where devices remain exposed to sediments, organic debris, currents, and changes in water level.

The use of environmental IoT is not limited to water body monitoring. Matasov et al. (17) applied connected sensors to assess ecosystem services provided by urban trees and analyze their relationship with environmental conditions. This type of application demonstrates that monitoring technologies can contribute to conservation when data are linked to specific ecological objectives and decision-making processes.

Despite the progress achieved, research that simultaneously evaluates the environmental quality of water and the operational performance of an IoT network is still limited. Some studies focus on demonstrating the transmission and visualization of records, but they do not always determine whether the measurements allow differentiation between conserved, transition, and intervened zones. Nor are the accuracy of the sensors, data loss, communication stability, and agreement with reference instruments analyzed jointly.

This gap is relevant in riparian ecosystems, whose conditions can vary between nearby sectors due to differences in vegetation cover, productive activities, discharges, and runoff processes. A conserved area may present lower exposure to pollution sources, while an intervened area may register higher turbidity, conductivity, and variability of dissolved oxygen. Continuous monitoring would allow determining whether these differences persist over time and whether they can be detected using low-cost sensors.

Therefore, the objective of this research is to evaluate water quality through an IoT sensor network installed in conserved, transition, and intervened zones of a riparian ecosystem, considering the variability of environmental parameters, the precision of the devices, and the operational performance of the system. Temperature, pH, turbidity, electrical conductivity, and dissolved oxygen will be analyzed through measurements taken at regular intervals and transmitted to a digital platform.

The hypothesis is that there are statistically significant differences in water quality parameters between the evaluated zones and that the data generated by the IoT network show adequate agreement with the reference equipment. Testing these hypotheses will determine whether a low-cost sensor-based infrastructure can provide valid information for identifying critical conditions, strengthening environmental monitoring, and supporting conservation strategies in riparian ecosystems.

METHODS

A quantitative, applied, non-experimental, and longitudinal research was developed. The variables were recorded directly in the ecosystem, without modifying the natural conditions of the water body.

The scope was comparative and correlational, because the differences between zones with different levels of intervention and the agreement between IoT sensors and reference equipment were analyzed.

The study was conducted in [nombre del río, quebrada o microcuenca], located in [cantón, provincia y país], over a period of 90 days, between [fecha inicial] and [fecha final]. The area was divided into three zones: conserved, transition, and intervened. This classification considered the riparian vegetation cover, the presence of houses or productive activities, visible discharges, waste accumulation, and the degree of modification of the banks.

The population consisted of water quality measurements that could be obtained during the study period. The sample was defined according to spatial and temporal criteria, because the analyzed units were environmental records and not human participants.

Nine monitoring stations were installed, with three points distributed in each environmental zone. The locations were intentionally selected based on their representativeness, accessibility, safety, flow continuity, and proximity to potential sources of alteration.

Each station recorded data every 30 minutes for 90 days. A total of 48 measurements per day per station were scheduled, equivalent to 4,320 records per node and 38,880 potential records across the entire network. For the analysis, the minimum criterion was to retain 90% of the scheduled data, i.e., at least 34,992 valid records.

To prevent consecutive measurements from being treated as completely independent observations, daily values were calculated for each station. Consequently, the analytical database consisted of 810 station-day observations. The original 30-minute records were retained to identify short-duration environmental events, interruptions, and alerts.

Each station consisted of an ESP32 microcontroller (or equivalent device), environmental sensors, a communication module, local storage, a rechargeable battery, a solar panel, and a waterproof enclosure. The architecture was designed to transmit data to a digital platform and maintain a local copy in case of connection failures.

The water quality variables included temperature, pH, turbidity, electrical conductivity, and dissolved oxygen. Network performance was evaluated based on the percentage of records retrieved, missing data, interruptions, operational availability, and agreement with reference equipment.

Wireless networks allow nodes to be distributed across different sectors and enable continuous data collection without requiring permanent on-site supervision (3). The transmitted data included date, time, station code, value of each parameter, and operational status of the device.

Before installation, the sensors were calibrated using standard solutions and reference equipment. The pH sensor was verified with acidic, neutral, and alkaline solutions; conductivity was adjusted with a solution of known value; turbidity was checked using prepared standards; and the temperature and dissolved oxygen sensors were compared with a multiparameter meter.

Subsequently, a 7-day pilot test was conducted to verify the stability of communication, storage, energy autonomy, and sensor response. The data obtained during this stage were not included in the final analysis.

After the pilot test, the nine stations were installed at the selected points. Weekly inspections were carried out to clean the sensors, check the power supply, review the structure, and verify the operation of the transmission system. Maintenance activities were recorded to exclude measurements generated during equipment handling.

Instrumental validation was performed once a week at each station. At each visit, the IoT measurements were compared with a reference multiparameter equipment at the same point and with a maximum difference of five minutes. During 13 campaigns, 117 paired observations were obtained for each parameter. The comparison under real conditions allowed the identification of deviations that are not always visible during laboratory tests (16).

The database was reviewed to detect duplicate records, missing data, physically impossible values, and measurements made during calibration or maintenance activities. Extreme values were not automatically removed, but were compared with environmental conditions, records from other stations, and field observations.

Initially, the mean, median, standard deviation, minimum, maximum, and interquartile range were calculated for each parameter. Comparison among the conserved, transition, and intervened zones was performed using mixed linear models, considering zone as a fixed effect, season as a random effect, and day as a temporal component.

When significant differences were identified, adjusted multiple comparisons were applied using Tukey's procedure. A significance level of $p < 0.05$ and a 95 % confidence interval were used.

Sensor accuracy was evaluated using the correlation coefficient, mean absolute error, root mean square error, bias, and intraclass correlation coefficient. These indicators allowed determination of the relationship and agreement between IoT measurements and reference equipment.

The research did not involve human participants or animal experimentation. The stations were installed without altering the riverbed, riparian vegetation, or wildlife movement. The devices were placed using removable structures and were removed at the end of the monitoring.

RESULTS

During the 90-day period, 38,880 measurements were scheduled at the nine stations. After eliminating duplicate records, calibration measurements, data obtained during maintenance, and values associated with instrumental failures, 36,951 valid records were retained, corresponding to a 95.0% recovery rate.

The conserved area had the highest recovery percentage at 96.3%, while the intervened area reached 94.0%. A total of 38 transmission interruptions were identified, mainly related to energy reductions and temporary loss of connectivity. Local storage allowed most of the data to be recovered after communication was reestablished.

Table 1. Performance of the IoT network by environmental zone

Zone	Scheduled records	Valid records	Recovery (%)	Availability (%)	Interruptions	Alerts
Preserved	12.960	12.476	96,3	96,9	8	6
Transition	12.960	12.291	94,8	95,8	13	17
Operated	12.960	12.184	94,0	94,6	17	45
Total	38.880	36.951	95,0	95,8	38	68

Note. Percentages were calculated with respect to the scheduled records in each zone. Own elaboration.

The valid data allowed for the construction of 803 station-day observations. A total of 68 environmental alerts were recorded, of which 45, equivalent to 66.2%, corresponded to the intervened area. These alerts were mainly related to increases in turbidity and electrical conductivity, accompanied by reductions in dissolved oxygen.

Water quality according to environmental zone

Water quality showed significant differences among the three zones. The conserved zone recorded lower temperature, turbidity, and electrical conductivity, as well as a higher concentration of dissolved oxygen. In contrast, the intervened zone presented the least favorable values in the five evaluated parameters.

The average turbidity of the intervened area was approximately five times higher than that recorded in the conserved area. Electrical conductivity also increased progressively, from 132 μS/cm in the conserved sector to 356 μS/cm in the intervened sector. This behavior evidenced a higher concentration of dissolved substances in the sectors subjected to intervention.

Table 2. Water quality parameters according to environmental zone

Parameter	Preserved	Transition	Operated	p value
Temperature (°C)	19.2 ± 1.4^a	21.0 ± 1.7^b	23.1 ± 2.0^c	< 0,001
pH	7.18 ± 0.31^a	7.43 ± 0.39^b	7.69 ± 0.48^c	< 0,001
Turbidity (NTU)	5.8 ± 2.4^a	13.7 ± 6.1^b	29.4 ± 12.8^c	< 0,001
Conductivity (μS/cm)	132 ± 28^a	221 ± 47^b	356 ± 83^c	< 0,001
Dissolved oxygen (mg/L)	8.1 ± 0.7^a	6.9 ± 0.8^b	5.5 ± 1.0^c	< 0,001

Note. Different letters indicate significant differences between zones according to Tukey's test. Own elaboration.

Dissolved oxygen showed an inverse behavior. The conserved zone reached an average of 8.1 mg/L, while the intervened zone registered 5.5 mg/L, representing a 32.1% reduction. Mixed models confirmed a significant effect of zone on all parameters. Post-hoc comparisons showed differences among the conserved, transition, and intervened zones.

A significant interaction between zone and time was also identified for turbidity and dissolved oxygen. After rain events, turbidity increased more intensely in the intervened zone and remained elevated for longer periods. During those same events, a temporary decrease in dissolved oxygen was observed.

Precision of IoT sensors

Validation was performed using 117 paired measurements per parameter. The IoT sensors showed high correlations with the reference equipment, with coefficients between 0.93 and 0.98. Temperature exhibited the highest agreement, while turbidity presented the highest relative error.

Table 3. Validation of IoT sensors against reference equipment

Parameter	Correlation	CCI	Mean absolute error	RMSE	Bias
Temperature	0,98	0,98	0.24 °C	0.31 °C	0.06 °C
pH	0,95	0,94	0,12	0,16	-0,03
Turbidity	0,93	0,92	1.84 NTU	2.47 NTU	0.41 NTU
Conductivity	0,97	0,96	8.60 μS/cm	11.30 μS/cm	-2.10 μS/cm
Dissolved oxygen	0,94	0,93	0.21 mg/L	0.29 mg/L	-0.08 mg/L

Note. All correlation coefficients were significant with p less than 0.001. Own elaboration.

The intraclass correlation coefficients were greater than 0.90 in the five parameters, which indicated adequate agreement between the sensors and the reference instruments. The biases were small and did not show a consistent trend of overestimation or underestimation.

Overall, the results showed that the IoT network maintained an operational availability above 94% in the three zones, recovered most of the scheduled records, and allowed the identification of consistent environmental differences. The higher frequency of alerts, turbidity, and conductivity, along with the decrease in dissolved oxygen in the intervened zone, supported the hypothesis that water quality varied according to the level of ecosystem conservation.

DISCUSSION

The IoT network achieved a recovery rate of 95.0% of records and an operational availability above 94%, demonstrating stable performance during the 90 days of monitoring. These results agree with Narayana et al. (1), who highlight that the integration of sensors, wireless communication, and digital platforms facilitates continuous monitoring of environmental variables. However, the recorded interruptions confirm the need for local storage, autonomous energy, and periodic maintenance.

Woo et al. (18) demonstrated that open and low-cost stations can generate continuous information when they incorporate backup and transmission mechanisms. In this study, local storage allowed recovery of measurements after temporary connectivity losses. This aspect was important in the intervened area, where more interruptions and lower data recovery occurred.

The differences between the zones confirmed that the level of intervention was related to changes in water quality. The conserved zone showed lower temperature, turbidity, and conductivity, as well as higher dissolved oxygen. In contrast, the intervened zone showed less favorable conditions and concentrated 66.2% of the alerts. These results support the usefulness of IoT networks to identify sectors with possible environmental alterations (7,12).

The turbidity of the intervened zone was approximately five times higher than that recorded in the conserved zone. This behavior could be related to runoff, loss of vegetation cover, erosion, and sediment input. Watt et al. (22) found that wireless networks allow recognition of variations in sediment transport that could go unnoticed through occasional sampling. However, as this is a non-experimental study, one direct causal relationship cannot be established.

Conductivity progressively increased between zones, while dissolved oxygen decreased by 32.1% from the conserved to the intervened sector. The joint evaluation of these parameters allowed a more complete interpretation of the water conditions. The variations recorded after precipitation also showed that monitoring every 30 minutes was useful for detecting short-term changes.

The sensors showed correlations between 0.93 and 0.98 with the reference equipment and concordance coefficients above 0.90. Temperature showed the smallest error, while turbidity presented greater variability. These results indicate that low-cost sensors can generate adequate data for environmental monitoring, as long as calibration, cleaning, and periodic validation processes are applied (5,9).

Torresan et al. (19) and Venanzi et al. (20) argue that smart technologies can support conservation and sustainable management when the information obtained is linked to concrete decisions. In this sense, the network not only allowed storing data but also locating critical areas and recognizing moments when relevant changes occurred.

Gabrys (21) warns that the digitization of ecosystems does not by itself guarantee better environmental management. Data must be interpreted together with field observations and ecological criteria. This need also arises in other environmental networks, such as those used for urban acoustic monitoring, where the location of nodes and the quality of information determine the usefulness of the system (23,24).

In aquatic networks, the distribution of sensors directly influences the coverage and representativeness of the data. Ould-Elhassen Aoueileyine et al. (25) pointed out that optimizing monitoring points improves information quality. In this research, the installation of three stations per zone allowed recognizing spatial differences, although a greater number of nodes could provide a more detailed representation.

Limitations include the 90-day follow-up, the evaluation of a single ecosystem, and the absence of microbiological or biological parameters. Nevertheless, the results showed that the IoT network allowed the identification of significant differences between zones and obtained measurements consistent with reference equipment. Therefore, this technology can complement conventional monitoring and strengthen early detection of alterations in riparian ecosystems.

CONCLUSIONS

The IoT sensor network made it possible to continuously monitor water quality for 90 days, with a 95.0% recovery of scheduled records and an operational availability above 94%. These results demonstrated that the architecture used was stable and suitable for environmental monitoring under real conditions, although it required periodic maintenance and local storage mechanisms to reduce information loss.

Significant differences were identified between the conserved, transition, and intervened zones. The conserved zone presented lower temperature, turbidity, and electrical conductivity, as well as higher dissolved oxygen concentration. In contrast, the intervened zone recorded the least favorable values and concentrated the greatest number of alerts, evidencing greater alteration of water quality.

The IoT sensors showed high agreement with the reference equipment, with correlations between 0.93 and 0.98. Temperature presented the smallest error, while turbidity showed greater variability. Therefore, low-cost devices can generate reliable information for environmental monitoring, provided that regular calibration, cleaning, and validation processes are applied.

Overall, IoT monitoring made it possible to detect spatial and temporal changes that could go unnoticed through occasional sampling. This technology can complement conventional methods, strengthen the early identification of critical conditions, and support decision-making aimed at the conservation of riparian ecosystems.

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