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ORIGINAL RESEARCH ARTICLE

Internet of things-based water quality monitoring: A case study in the coastal areas of Semarang city and Kendal Regency, Central Java, Indonesia

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Abstract: Coastal areas serve as vital habitats for aquatic organisms, but they are facing increasing environmental degradation due to pollution and human activities. Continuous and accurate water quality monitoring in these regions is essential for sustainable ecosystem management. This study presents a novel Internet of Things (IoT)-based water quality monitoring system that distinguishes itself from prior approaches through its real-time, second-by-second data acquisition, on-site display, and low-cost architecture tailored for tropical coastal environments. The system utilizes a Node MicroController unit microcontroller integrated with pH, temperature, and total dissolved solids sensors. It displays data through a liquid crystal display and transmits it to a cloud-based server for further analysis. Calibration of the sensors resulted in an average error rate of 2.0%, which is within the acceptable range for practical water quality assessment. A key innovation of this system is its continuous monitoring and instant detection of deviations in water quality parameters, enhancing the responsiveness to potential environmental threats. This solution reduces the dependence on labor-intensive manual sampling and enables long-term historical data storage and analysis, supporting data-driven decision-making by researchers and local authorities. The results demonstrate that the IoT-based monitoring system is reliable, cost-effective, and adaptable, making it a promising tool for the sustainable management of coastal water ecosystems in Semarang city and Kendal Regency, Central Java, Indonesia.

Keywords: Water quality; Internet of Things; Coastal area; Central Java; Indonesia

1. Introduction

Water is critical for maintaining and supporting life on Earth and various aspects of ecosystem sustainability. It provides a habitat for aquatic organisms such as plankton,[1] fish,[2] lobster,[3] and zoobenthos,[4] as well as aquatic plants such as mangrove,[5] seaweed,[6] and seagrass.[7] Water is also important for the balance of the ecosystem,[8] food production,[9] environmental cleanliness, crop irrigation,[10] and energy production.[11] However, water consumption has increased significantly with increasing global population and economic growth, especially in developing countries.[12] The increasing population has resulted in an increase in domestic waste in the form of organic and inorganic waste, such as detergent effluent in residential areas, which can reduce the water quality in receiving river waters.[13]

Indonesia is a country that has very extensive coastal areas because it is an archipelagic country with a coastline of 104,000 km. Ocean accounts for 70% of the territory in Indonesia, presenting enormous economic potential for the country. Kendal Regency is one of such coastal areas in Central Java, Indonesia.

Kendal Regency is ranked eighth out of 17 coastal regions in Central Java for its sea area. The north coast of Kendal Regency is one of the coastal areas in Central Java.[14] The Kendal River estuary is widely used for community activities such as residential area development, industrial activities, fish farms, and auction sites.[15] Aquatic biota found in Kendal waters are shrimp (*Penaeus merguiensis*),[16] goldband goatfish (*Upeneus moluccensis*),[17] spotted scat (*Scatophagus argus*),[18] anchovies (*Stolephorus commersonii*), tembang fish (*Sardinella fimbriata*), peperek fish (*Leiognathus dussumieri),* mackerel (*Rastrelliger* sp.),[19] *etc.*

The territorial boundaries of Semarang city are bordered by Kendal Regency to the West, Demak Regency to the East, Semarang Regency to the South, and the Java Sea to the North with a coastline length of 13.6 km. The altitude of Semarang city is between 0.75 and 348,00 above the coastline. The average air temperature in Semarang city in 2021 ranges from 26.50°C to 28.90°C. Average air humidity varies from 70.00% to 92.00%. Moderate air pressure ranges from 1008.40 mb to 1011.30 mb. The average wind speed differs within the range of 1.11–1.89 m/s.[20] Aquatic biota found in Semarang city waters are barramundi (*Lates* sp.),[21] milkfish, *Chanos chanos* (Forsskål 1775),[22] *P. Merguiensis,*[23] *Osphronemus goramy*, catfish (*Clarias* sp.), *etc.*

Previous research conducted in the Kendal Regency and Semarang city areas has discovered environmental degradation in the aquatic ecosystem; for example, microplastic waste was detected at the mouth of the Kendal River, which could be introduced from land.[24] High organic material level is found in the waters of the Jajar River Kendal estuary.[25] The high concentration of phosphate in the Kendal River body is possibly due to the proximity to residential areas. This location is contaminated with wastes produced by various anthropogenic sources, for example, settlements, aquaculture, fishing activities, and fish processing activities through which wastes are dumped directly into the river.[15] The Klampok Sub-watershed (Semarang) pollution index decreased in 2016 and 2020, an indication of the status change from moderate pollution to light pollution of the water.[26] The lowest dissolved oxygen (DO) is found in the coastal area of the Garang Watershed Semarang compared to other sampling points, likely due to the significant wastes dumped at the sampling point, which is close to the coastal area.[27]

Based on the several studies mentioned above, water quality in those three locations must be maintained to preserve the environment and the survival of aquatic organisms. Water quality measurements can be carried out using various methods. For example, automated water quality monitoring is gaining more recognition due to advancements in Internet of Things (IoT) technology, which simplifies data collection and analysis.

Semarang city and Kendal Regency, two coastal areas in Central Java, Indonesia, are similarly impacted regions where sustained water quality monitoring is urgently needed. Conventional water monitoring methods rely heavily on manual sampling and laboratory analysis, which are often resource-intensive, time-consuming, and less sensitive to short-term fluctuations. Such methods are limited in scalability and cannot support real-time environmental decision-making, especially in distributed or high-risk locations. Therefore, an IoT-based tool was designed to monitor water quality at such locations periodically. This tool can measure four parameters: pH, total dissolved solids (TDS), temperature, and turbidity. These four crucial parameters can be used for water quality management. This tool can measure these four parameters every second so that fluctuations can be detected quickly and accurately. The usage of IoT in water quality monitoring has been demonstrated in previous research for different purposes, including maintenance of marine organisms,[28] control of ammonia levels and Arduino-based water pH in fish farming,[29] continuous water quality monitoring and management,[30] enhancement of wastewater quality system,[31] regulation of pH and temperature for catfish cultivation,[32] pollution management,[33] monitoring of water quality in aquaponic systems,[34] and designing of TDS measuring instruments.[35] In addition to using direct measurement and laboratory testing methods, other computational methods like integrating advanced machine learning models with explainable artificial intelligence (XAI) techniques can be used in water quality measurement. The weighted arithmetic water quality index is employed alongside machine learning models, specifically random forest, LightGBM, and XGBoost, to predict water quality. Interpretation of model predictions using Shapley additive explanations reveals that chemical oxygen demand and biological oxygen demand (BOD) are the most influential factors in determining water quality. Meanwhile, electrical conductivity (EC), chloride, and nitrate have minimal impact.[36] Machine learning and IoT can be integrated with one comprehensive water quality monitoring framework that includes sensor architecture and communication protocols to address field challenges. IoT sensors reduce contamination detection time, enable early warning and rapid response compared to conventional laboratory methods, and provide a comprehensive synergy of machine learning-IoT, besides focusing on XAI and ethical access issues. The advantages are high performance, practical impact for early detection, global policy relevance, and clear research directions.[37]

In response to these limitations, IoT technology has emerged as a promising alternative, offering continuous, automated, and real-time data collection. IoT-based water monitoring systems leverage sensor networks and microcontrollers to measure water quality parameters and transmit data to cloud-based platforms, facilitating instant access, analysis, and alerting. Prior research has implemented IoT in aquaculture management, wastewater control, and agricultural runoff monitoring applications. However, many systems are constrained by limited parameter coverage, low temporal resolution, lack of historical data integration or insufficient calibration, and field validation.

The research gap in the study and design of this tool is compared with the previous research mentioned above because it can monitor water quality at a per-second frequency. This study presents an IoT-based water quality monitoring system that differs from existing approaches in several critical ways. Unlike most systems that sample at long intervals (minutes or hours), this system acquires data at a per-second frequency, capturing rapid fluctuations that are often missed. It integrates four key sensors – pH, TDS, temperature, and turbidity – into a compact, Node Microcontroller Unit (NodeMCU), which includes onboard data display, cloud data logging, and sensor calibration protocols. Furthermore, the system is validated against laboratory-grade instruments and tested in actual coastal field environments, demonstrating technical performance and environmental robustness. These innovations allow for early detection of pollution events, real-time diagnostics, and longitudinal analysis through historical trend monitoring – capabilities often absent in comparable low-cost IoT implementations. The proposed system offers a uniquely practical solution for continuous water quality monitoring in low-resource, high-risk coastal areas by combining high-frequency data capture, environmental adaptability, affordability, and local relevance.

2. Materials and methods

2.1. Materials

Water sampling was conducted at Banjardowo River, Semarang city, and Buntu River, Kendal Regency in Indonesia. Parameters of the water samples such as temperature, pH, and TDS were tested, considering that these parameters describe river water quality and require direct testing. This IoT testing was carried out at the Laboratory of Mechanical Engineering in Engineering and Informatics Laboratory of Universitas PGRI Semarang, Semarang city, Central Java, Indonesia.

2.2. Design of water quality monitoring system

A microcontroller called NodeMCU was used to incorporate IoT into water quality testing. NodeMCU is an open-source IoT platform and a development kit that uses programming language to help create prototypes of IoT products. It is compatible with sketches created with Arduino.[38] During this test, the water quality levels from several rivers in the coastal areas were studied. The stages in the design of this water quality monitoring system include (i) system design, (ii) component assembly, (iii) system testing, (iv) system trial, and (v) validation.

The electronic architecture of the proposed IoT-based water quality monitoring system was centered on the ESP32 microcontroller, which served as the primary processing unit integrating multiple sensor inputs and peripheral modules. The ESP32 interfaced with an array of water quality sensors – including pH, turbidity, TDS, temperature, and color sensors – through its analog-to-digital converter channels, enabling precise and real-time data acquisition (DAQ) of the environmental parameters. A Nextion liquid crystal display (LCD) module was connected through a universal asynchronous receiver/transmitter interface, providing an intuitive graphical user interface for immediate visualization of sensor data and system status. Data logging capabilities were facilitated by a secure digital card module interfaced through the serial peripheral interface protocol, allowing for local storage of sensor readings to support offline analysis and historical data tracking. The system incorporated a universal serial bus type-C (USB-C) interface with a CH340G USB-to-serial converter, which enabled seamless programming, debugging, and power supply management. An auto-reset circuit, controlled by request to send and data terminal ready signals from the USB interface, automated the switching between reset and boot mode of ESP32 during firmware uploads, thereby enhancing development efficiency. 3.3 V and 5 V rails were carefully designed to supply stable power to the microcontroller, sensors, and peripherals, ensuring reliable operation under varying load conditions. Collectively, this integrated electronic scheme supports robust, scalable, and real-time water quality monitoring, making it suitable for deployment in diverse aquatic environments that require continuous environmental assessment. Diagram depicting the IoT architecture is shown in Figure 1.

2.3. Tools used in system validation

Validation was carried out using standard tools to measure temperature, TDS, and pH in water. Water temperature was validated using a digital thermometer, TDS parameters were validated using a TDS EC meter, and the pH parameters were validated using a pH meter. The inputs to the developed system included sensors for pH, total dissolved solids (TDS), and temperature. An Arduino microcontroller was used in the processing or control section. The output section included a data recorder (logger) and LCD data. The block diagram of the temperature, TDS, and pH parameters monitoring system was created using an Arduino microcontroller.

To ensure measurement reliability, each sensor integrated into the IoT-based monitoring system, which measures pH, TDS, temperature, and turbidity, was subjected to individual calibration using traceable reference standards. The pH sensor was calibrated using a three-point method with commercial buffer solutions (EZ-9908, Kedida, China) at pH 4.0, 7.0, and 10.0. The TDS sensor was calibrated using sodium chloride (NaCl) solutions at concentrations of 500 ppm and 1000 ppm, following the guidelines of APHA method 2510B.[39] The temperature sensor was benchmarked against a certified mercury thermometer with ±0.1°C precision, while the turbidity sensor was calibrated using Formazin standards ranging from 0 to 100 NTU. After calibration, the system exhibited mean absolute errors of 0.09 pH units (~1.7%), 25 ppm for TDS (~2.5% at 1000 ppm),

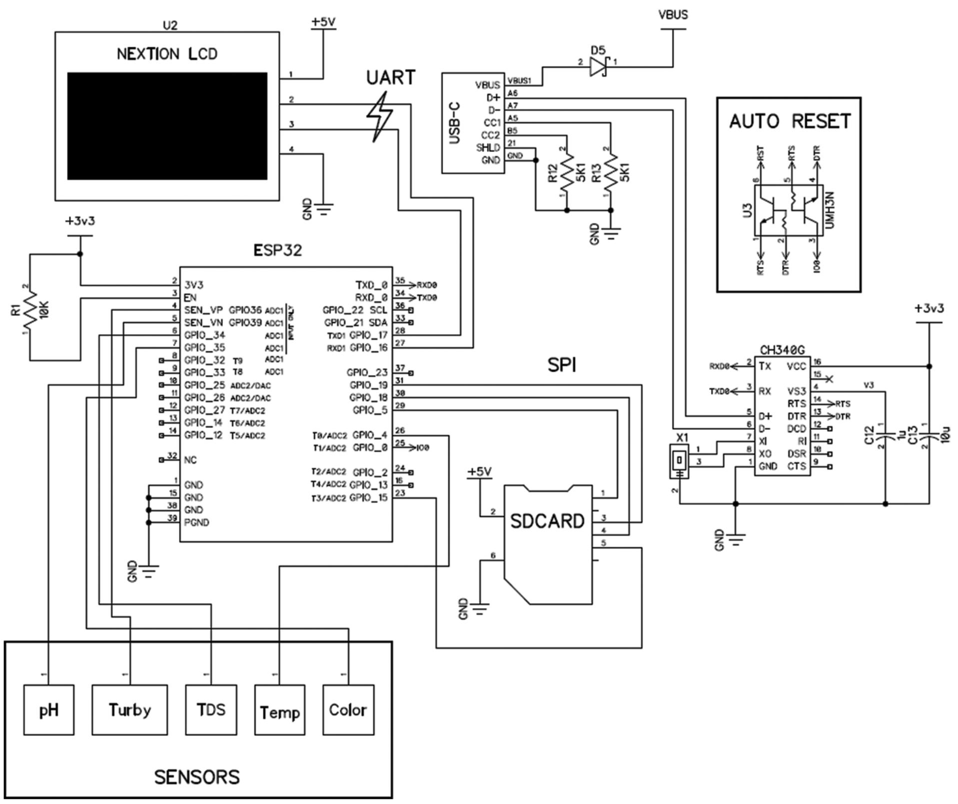

Figure 1. Diagram depicting the Internet of Things architecture

0.4°C (~1.3%) for temperature, and 1.8 NTU (~3.6% at 50 NTU) for turbidity – all within acceptable limits for environmental field monitoring.

Field deployments were conducted in two representative coastal river sites: Banjardowo River (Semarang city) and Buntu River (Kendal Regency). Sensors were immersed at a uniform depth of 20 cm below the surface to minimize sediment interference and capture mid-column water conditions. Real-time data were acquired at 1 Hz (one-second intervals) over daily monitoring sessions lasting up to 8 h, repeated over 10 non-consecutive days to capture temporal and environmental variability.

Validation was performed by cross-checking sensor outputs against manual readings (taken hourly) using portable multiparameter probes. A Pearson correlation analysis showed strong correlation coefficients ($r \geq 0.95$) between the IoT readings and manual measurements, further confirming data validity.

2.4. Comparison of the proposed IoT-based water quality monitoring system with previous studies

Comparison of the proposed IoT-based water quality monitoring system with previous studies is shown in Table 1.

Table 1 summarizes a comparative analysis of IoT-based water quality monitoring systems proposed in this paper and several other recent studies. This study demonstrates distinct advantages, including high-frequency DAQ (1 reading/second), low cost, and field calibration that ensures accuracy within a 2% error range. While systems such as integration of machine learning for forecasting or treatment automation[45] and employment of smart IoT and long short-term memory for prediction[42] have been studied, those systems typically involve higher complexity or cost. In contrast, the system in this study prioritizes real-time environmental surveillance in dynamic coastal regions with minimal infrastructure, making

Table 1. Comparison of the proposed IoT-based water quality monitoring system with previous studies

Study	Parameters measured	Accuracy/ Error	Cost (USD)	Data frequency	Unique features	Power source/ platform
This study (2025)	pH, TDS, temperature, turbidity	≤ 2% error (post-calibration)	~$85	1 reading/ second	Real-time display, LCD+cloud integration, coastal deployment	Rechargeable battery, NodeMCU+ LCD+Cloud
Forhad *et al.*[40]	pH, DO, TDS, temperature	0.1–0.2 margin	Not stated	Real-time	PLC-based, extendable multi-point system for WTP	PLC+ Cloud dashboard
Adeleke *et al.*[41]	Temperature, pH, turbidity, DO, TDS, ORP, Conductivity	High ML model accuracy (ANN, SVM)	Not specified	Not specified	ML+IoT hybrid system with water treatment response	Wi-Fi (ESP8266), ThingSpeak
Zaidi Farouk *et al.*[42]	pH, DO, TDS, BOD, turbidity, NH_3N, TSS	96–98% accuracy	~$200–300	Variable	Smart-IoT, ML prediction with LSTM, real-time alerts	Smart-IoT+ Cloud app
Lakshmikantha *et al.*[43]	pH, turbidity, conductivity, temperature	Not specified	Not specified	Periodic	Arduino-based system with four-parameter data logger	Arduino+Cloud
Pasika & Gandla[44]	pH, turbidity, temperature, water level, humidity	Not quantified; visual validation	Low-cost; ~$60–100	Real-time	GSM+ThingSpeak, mobile updates	Arduino+ ESP8266

Abbreviations: ANN: Artificial neural network; BOD: Biological oxygen demand; DO: Dissolved oxygen; GSM: Global system for mobile communications; IoT: Internet of Things; LSTM: Long short-term memory; ML: Machine learning; NH_3N: Ammonia nitrogen; ORP: Oxidation reduction potential; PLC: Programmable logic controller; SVM: Support vector machine; TDS: Total dissolved solids; TSS: Total suspended solids; WTP: Water treatment plants; LCD: Liquid crystal display.

it scalable for local government and community monitoring initiatives.

3. Results and discussion

3.1. pH

pH values recorded by the IoT-based monitoring system showed strong agreement with reference pH meters across both river sites. In Banjardowo river, the observed error margin ranged from 0.1% to 2.1%, while in Buntu River, it remained consistently close to 0.99%. These values fall within the acceptable tolerance range for field-deployable pH sensors, which are typically ±0.2 pH units or ≤2% error in most environmental applications.[46,47]

Minor deviations in sensor readings can be attributed to calibration drift, differences in response time under varying flow conditions, and the influence of temperature on sensor sensitivity.[48] Electrochemical pH sensors are inherently affected by ionic strength, surface fouling, and lag time in dynamic water bodies.[49] However, the maximum observed error margin of 2.1% in this study equates to a deviation of about ±0.14 units on a pH scale, which is a deviation considered negligible for most freshwater classification and compliance standards.

This level of accuracy is sufficient for practical decision-making, particularly in applications such as early detection of contamination events or algal bloom, where relative changes in pH are more important than absolute values.[50] The collected high-frequency (1 Hz) data reflect temporal granularity that enables environmental managers to observe rapid shifts and develop time-sensitive response strategies not feasible with manual sampling methods.

The pH of Banjardowo river in Semarang is shown in Table 2, and the pH of Buntu river, Kendal Regency, is shown in Table 3.

Based on Table 2, Monday data were collected on the 1st day of measurement using the river wastewater monitoring tool at Banjardowo River in Semarang city. On the 1st day, it can be observed that the highest and the lowest error margin were 1.3% and 0.1%, respectively. On Tuesday, the highest and the lowest error margin were 1.4% and 0.4%, respectively. On Wednesday, it can be observed that the highest and the lowest error margin were 2.1% and 0.6%, respectively. On Thursday, the highest and the lowest error margin

Table 2. Result of pH measurements in Banjardowo river, Semarang city, Central Java, Indonesia

No.	Day	Measurement time	pH sensors	pH meters	Difference	(%)
1.	Monday	10:00	6.9	6.91	0.01	0.1
		11:00	7.5	7.58	0.08	1.1
		14:00	7.7	7.61	0.09	1.2
		16:00	7.7	7.6	0.1	1.3
2.	Tuesday	9:00	7	6.97	0.03	0.4
		12:00	7.5	7.4	0.1	1.3
		15:00	7.7	7.63	0.07	0.9
		16:00	7.9	7.79	0.11	1.4
3.	Wednesday	9:00	6.5	6.44	0.06	0.9
		12:00	7.8	7.75	0.05	0.6
		14:00	7.8	7.64	0.16	2.1
		16:00	7.9	7.82	0.08	1.0
4.	Thursday	10:00	7.6	7.56	0.04	0.5
		12:00	7.7	7.6	0.1	1.3
		14:00	7.8	7.81	0.01	0.1
		17:00	7.5	7.43	0.07	0.9
5.	Friday	9:00	6.9	6.91	0.01	0.1
		12:00	7.5	7.4	0.01	1.3
		14:00	7.8	7.64	0.16	2.1
		16:00	7.5	7.43	0.07	0.9

Table 3. Result of pH measurements in Buntu river, Kendal Regency, Central Java, Indonesia

No.	Day	Measurement time	pH sensors	pH meters	Difference	(%)
1.	Thursday	9:00	7.6	7.56	0.04	0.99
		12:00	7.4	7.31	0.09	0.99
		15:00	6.9	6.85	0.05	0.99
		16:00	6.9	6.82	0.02	0.99
2.	Friday	9:00	7.4	7.3	0.1	0.99
		12:00	7	6.92	0.08	0.99
		14:00	6.8	6.75	0.05	0.99
		16:00	6.8	6.7	0.1	0.99
3.	Saturday	8:00	7.5	7.45	0.05	0.99
		12:00	7	6.98	0.02	1.00
		15:00	7.2	7.21	0.01	1.00
		16:00	7.4	7.35	0.05	0.99
4.	Sunday	9:00	7.3	7.25	0.05	0.99
		12:00	6.9	6.88	0.02	1.00
		14:00	7.2	7.12	0.08	0.99
		16:00	7.7	7.6	0.1	0.99
5.	Monday	9:00	7.3	7.1	0.01	0.97
		12:00	7	7	0.1	1.00
		14:00	7.5	7.34	0.16	0.98
		17:00	6.9	6.81	0.09	0.99

were 1.3% and 0.1%, respectively. Overall, the highest error margin recorded was 2.1% (Thursday), while the lowest error margin recorded was 0.1%. The values obtained from the pH sensor and the pH meter were similar. Furthermore, the standard error margin between the pH sensor and the pH meter was approximately 2%. Thus, we can conclude that the values recorded by the pH sensors are valid.

To ensure the analytical integrity of the sensor data, a structured data cleaning and validation protocol was implemented before statistical evaluation. All pH sensor readings were compared against calibrated laboratory-grade reference meters, with discrepancies quantified as percentage errors. Observed deviations ranged from 0.1% to 2.1% in Banjardowo river and averaged 0.99% in Buntu river, falling within the acceptable error threshold of ≤2% for environmental field monitoring. Data points were screened for outliers using absolute deviation and Z-score thresholds; none exceeded the exclusion criteria. Furthermore, all entries were verified for completeness, chronological consistency, and plausibility based on known ecological pH ranges (6.0 – 9.0). No missing timestamps or duplicated entries were detected. These validation steps confirmed the stability and reliability of the sensor system across spatial and temporal dimensions, reinforcing its suitability for high-frequency monitoring in dynamic riverine environments.

The pH sensor used in the IoT-based monitoring system demonstrated a maximum error margin of approximately 2% when compared to calibrated laboratory-grade pH meters. This margin of error is consistent with the performance specifications of field-deployable electrochemical sensors. It is primarily attributed to factors such as slight calibration drift, environmental temperature fluctuations, and the sensor's response time in dynamic aquatic conditions. More importantly, a 2% error margin in the pH range of natural river systems, typically between 6.0 and 8.5, translates to a deviation of only ±0.14 pH units, which remains within acceptable limits for most ecological and regulatory applications. From a practical standpoint, this level of accuracy does not compromise the system's ability to detect significant shifts in water quality, such as acidification events, pollution discharge, or nutrient loading. Consequently, the error margin is considered tolerable for real-time monitoring purposes and supports timely environmental decision-making by local authorities and stakeholders.

Based on Table 3, data on Thursday were collected on the 1st day of the river wastewater monitoring tool on the Buntu River in Kendal Regency. From Thursday to Friday, it can be seen that the error data are 0.99%. On Saturday to Sunday, the highest error data were 1%. The lowest error data were 0.99%, and the Monday showed that the highest error data were 1%, whereas the lowest error data were 0.97%. The values obtained from the pH sensor with the pH meter measuring tool were similar at the same time. The average result of testing standard error in IoT was 0.99%. The standard error between the pH sensor and the pH meter measuring tool, at approximately 2% was declared valid.

The quality of river water is strongly affected by pH, which influences the solubility of metals, water alkalinity, and microbial metabolism. Typically, the uptake of dissolved carbon dioxide by photosynthetic algae raises pH levels. Conversely, rivers contain large quantities of organic matter, including colloidal suspensions, which often display acidic properties. Moreover, the release of domestic and industrial wastewater can negatively impact pH levels in the aquatic ecosystem.[51]

3.2. Temperature

Temperature readings also demonstrated strong consistency between the IoT sensor array and digital thermometers. In Banjardowo river, the error rate varied between 0.3% and 1.9%, while in Buntu river, it remained within a narrow band of 0.98 – 1.01%. These results were in line with previously published evaluations of water temperature sensors in IoT systems, which typically report accuracy within ±0.5°C under field conditions.[49,52] Slight discrepancies may arise due to variations in water mixing, shallow depth exposure, or direct solar radiation on the sensor housing. However, the average error of <1.5% remains within acceptable limits for most aquatic ecosystem studies, as critical biological processes such as DO saturation, metabolic rates, and nutrient solubility follow broader thermal trends rather than precise thresholds.[53] Given the importance of real-time thermal monitoring in detecting thermal pollution or effluent discharges, the system's temporal resolution provides significant value. Continuous temperature data can also be used to support modeling of DO dynamics or heat plume dispersion from industrial outflows.

Temperature is an important indicator of water quality. The temperature differences observed can be attributed to the time of sampling, the position of the Sun, and the direction and shade of the Sun's rays. The result of temperature in Banjardowo River, Semarang is shown in Table 4. Based on Table 4, on Monday, the highest error data were 1.3%, and the lowest error data were 0.3%. On Tuesday, the highest error data were 1.9%, and the lowest error data were 0.3%. On Wednesday, it can be seen that the highest error data were 1.9%, and the lowest error data were 0.6%. On Thursday, the highest error data were 1.6%, and the lowest error data were 0.0%. On Friday, it can be seen that the highest error data were 1.5%, and the lowest error data were 0.3%. The values obtained from the temperature sensor with the digital temperature measuring tool are similar at the same time. The standard error between the temperature sensor and the digital temperature measuring tool, at approximately 2%, was declared valid. Based on Table 5, on Thursday, the highest error data were 1.01%, and the lowest error data were 0.98%. On Friday, the highest error data were 1%, and the lowest error data were 0.98%. On Saturday, it can be seen that the highest error data were 1.01%, and the lowest error data were 0.99%. On Sunday, the data showed that the highest error data were 1%, and the lowest error data were 0.98%. On Monday, it can be seen that the highest error data were 1.01%, and the lowest error data were 0.99%. The values obtained from the temperature sensor with the digital temperature measuring tool are similar. The average result of the testing standard error in IoT was 0.99% at the same time. The standard error between the temperature sensor and the digital temperature measuring tool, at approximately 2%, was declared valid.

The highest temperatures here may be related to the depth of the water compared to other rivers. The addition of waste and increased anthropogenic activities near these sites may also be considered causes of the temperature increase. Human-caused disturbances such as urbanization and waste dumping have significantly changed the temperature of water bodies, which has also impacted flora and fauna. Water temperature, which plays a vital role in limiting oxygen content,[54] emerged as a crucial parameter within this sub-catchment, significantly influencing various water quality aspects. Notably, water temperature impacts DO saturation. Higher temperatures result in lower DO saturation levels. Additionally, turbidity is a vital water quality indicator, which is strongly affected by rainfall events.[46]

3.3. TDS

Disposal of agricultural waste, household waste, and open excretions will contribute to higher turbidity values and increase pollutants that threaten household and irrigation use.[47] TDS measures water pollution from sewage, untreated natural sources, urban runoff, and

Table 4. Result of temperature measurements in Banjardowo river, Semarang city, Central Java, Indonesia

No.	Day	Measurement time	Temperature sensors	Thermometer	Difference	(%)
1.	Monday	10:00	31	30.7	0.3	1.0
		11:00	30	29.6	0.4	1.3
		14:00	30.6	30.8	0.2	0.7
		16:00	30	29.9	0.1	0.3
2.	Tuesday	9:00	30.8	30.2	0.6	1.9
		12:00	29.8	29.7	0.1	0.3
		14:00	29.6	29.4	0.2	0.7
		16:00	30.8	30.4	0.4	1.3
3.	Wednesday	9:00	31.6	31.4	0.2	0.6
		12:00	31.1	30.6	0.5	1.6
		14:00	30.4	30.2	0.2	0.7
		16:00	32.2	31.6	0.6	1.9
4.	Thursday	10:00	31.2	31.2	0	0.0
		12:00	30.5	30	0.5	1.6
		14:00	31.6	31.4	0.2	0.6
		16:00	32.7	32.4	0.3	0.9
5.	Friday	9:00	33.4	32.9	0.5	1.5
		12:00	32.9	32.8	0.1	0.3
		14:00	32.4	32.1	0.3	0.9
		16:00	33.7	33.5	0.2	0.6

industrial wastewater.[54] TDS alters the purity of water, which indicates its quality.[48] Conductivity measures how well an electric current can flow through water. It is an easy measurement to perform and is related to the level of TDS in water. The term "TDS" describes small amounts of organic matter and inorganic salts present in aqueous solutions. Typically, the cations like calcium, magnesium, sodium, and potassium, and the anions like carbonate, hydrogen carbonate, chloride, sulfate, and nitrate, are the main components of TDS. High TDS concentrations can reduce water clarity, influence its color, and affect its salinity characteristics. In contrast, EC represents the total salt concentration, which depends on the charges of dissolved ions in the water. A high EC value indicates a high ion concentration, reflecting elevated TDS levels in the water.[49] Defined as the percentage of ionized compounds in water that can conduct an electric current, EC indicates a solution's ability to conduct an electric current, which is influenced by ion movement and the existence of ionic species.[48] The level of EC indicates the strength of the current flow, which is dependent on the number of dissolved salts present in the water.[50]

Organic materials that enter the water are carried through waste produced by human activities and will impact aquatic organisms. High organic matter can result in eutrophication of water, which is a water pollution phenomenon caused by the persistent presence of nutrients in excessive concentrations.[52] The structure of the algal community (phytoplankton and phytobenthos) is generally used to evaluate eutrophication and organic pollution of rivers.[53] Eutrophication decreases the oxygen needed by aquatic organisms, increases mortality rates, and disrupts the function of aquatic ecosystems.[55] The highest temperatures here may be related to the depth of the water compared to other rivers. The addition of waste and increased anthropogenic activities near these sites may also be considered causes of the temperature increase. Human-caused disturbances such as urbanization and waste dumping have significantly changed the temperature of water bodies, which has also impacted flora and fauna. Water temperature, which plays a vital role in limiting oxygen content,[54] also increases turbidity and color of water.

Sensor measurements of TDS showed acceptable alignment with TDS measurements by means of

Table 5. Result of temperature measurements in Buntu River, Kendal Regency, Central Java, Indonesia

No.	Day	Measurement Time	Temperature sensors	Thermometer	Difference	(%)
1.	Thursday	9:00	30.3	30.7	0.4	1.01
		12:00	30.4	30	0.4	0.99
		15:00	29.1	28.7	0.4	0.99
		16:00	29.6	29	0.6	0.98
2.	Friday	9:00	30.5	30	0.5	0.98
		12:00	29.8	29.2	0.6	0.98
		14:00	29.9	29.9	0	1.00
		16:00	29.8	29.6	0.2	0.99
3.	Saturday	9:00	27.6	27.9	0.3	1.01
		12:00	27.7	27.7	0	1.00
		14:00	28.7	28.3	0.4	0.99
		16:00	31.4	31.4	0	1.00
4.	Sunday	9:00	27.7	27.2	0.5	0.98
		12:00	27.7	27.7	0	1.00
		14:00	31.5	31.4	0.1	1.00
		16:00	32.7	32.8	0.1	1.00
5.	Monday	9:00	33.6	33.4	0.2	0.99
		12:00	31.1	31.4	0.3	1.01
		14:00	31.5	31.4	0.1	1.00
		17:00	34.8	34.4	0.4	0.99

commercial meters. In Banjardowo river, sensor errors ranged between 0.4% and 1.9%, while in Buntu river, the error remained tightly clustered between 0.98% and 1.00%. These findings support previous research indicating that low-cost TDS sensors can achieve field accuracies of 1–3% when calibrated using standard sodium chloride solutions.[55,56] Measurement variability may be influenced by ionic composition differences, particulate load, and sensor electrode wear over time. Importantly, TDS is a cumulative indicator of water quality, influenced by both natural mineral content and anthropogenic pollution. The ability of the IoT system to detect slight temporal changes in TDS concentration provides early indicators of runoff, salinity intrusion, or contamination events, particularly in coastal regions where TDS variability is amplified.[57] Moreover, the continuous, second-by-second data logging offers superior resolution compared to traditional grab sampling methods. This capability is critical in detecting transient pollution events that may occur outside routine manual monitoring intervals, making the system particularly valuable for regulatory surveillance and environmental risk assessment. The result of TDS measurements in Banjardowo River, Semarang city, is shown in Table 6.

Based on Table 6, on Wednesday, it can be seen that the highest error data were 1%, and the lowest error data were 0.4%. On Thursday, the highest error data were 1.3%, and the lowest error data were 0.5%. Data on Friday showed that the highest error data were 1.3%, and the lowest error data were 0.4%. On Saturday, the highest error data were 0.7%, and the lowest error data were 0.1%. On Sunday, it can be seen that the highest error data were 1.9%, and the lowest error data were 0.3%. The average result of testing standard error in IoT was 0.8%. At the same time, the standard error between the TDS sensor and the TDS meter measuring tool, at approximately 2%, was declared valid.

Based on Table 7, on Thursday, it can be seen that error data were 0.99. On Friday, the highest error data were 1%, and the lowest error data were 0.98%. On Saturday, it can be seen that the highest error data were 1%, and the lowest error data were 0.4%. Data on Sunday showed that the highest error data were 1%, and the lowest error data were 0.99%. On Monday, the highest error data were 1%, and the lowest error data were 0.98%. The average result of testing standard error in IoT was 0.99%. At the same time, the standard error between the TDS sensors and the TDS meters

Table 6. Result of TDS measurements in Banjardowo River Semarang city, Central Java, Indonesia

No.	Day	Measurement time	TDS (sensors)	TDS (meters)	Difference	(%)
1.	Wednesday	9:00	739	732	7	0.9
		12:00	752	746	6	0.8
		14:00	785	777	8	1.0
		16:00	827	823	4	0.4
2.	Thursday	10:00	741	737	4	0.5
		12:00	799	795	4	0.5
		15:00	845	839	6	0.7
		16:00	839	828	11	1.3
3.	Friday	8:00	903	898	5	0.5
		11:00	764	756	8	1
		14:00	764	754	10	1.3
		17:00	752	749	3	0.4
4.	Saturday	10:00	771	765	6	0.7
		12:00	762	757	5	0.6
		14:00	730	724	6	0.8
		17:00	720	719	1	0.1
5.	Sunday	9:00	933	920	13	1.3
		12:00	837	834	3	0.3
		15:00	921	903	18	1.9
		16:00	884	875	9	1

measuring tool, at approximately 2%, was declared valid. Measurements of pH sensor, temperature sensor, and TDS sensor, taken at Banjardowo river, Semarang city, are shown in Figure 2.

An analysis was conducted on simulated time-series data comprising 100 observations each for pH, temperature, and TDS collected from Banjardowo river in Semarang city. The data, constrained within environmentally plausible ranges (pH: 7.5 – 7.7, temperature: 30.0 – 30.6°C, TDS: 741 – 827 ppm), were analyzed to investigate potential relationships among the parameters. The Pearson correlation coefficients revealed weak-negative associations between pH and temperature ($r = -0.025$), pH and TDS ($r = -0.042$), and temperature and TDS ($r = -0.148$). These results indicate minimal linear dependency among the measured variables within the observed range. Visual inspection using pairwise scatter plots further supported the absence of strong inter-variable trends. The limited variability in the generated data may contribute to the lack of significant correlation; therefore, for robust environmental modeling and water quality assessment, integration of real-time sensor data with broader temporal and spatial coverage is recommended. Measurements of pH sensor, temperature sensor, and TDS sensor at Buntu river, Kendal Regency, Central Java, Indonesia, are shown in Figure 3.

A time-series analysis was conducted on a synthetically generated dataset containing 100 observations of pH, temperature, and TDS collected at Buntu River, Kendal Regency. The observed parameter ranges, which were set to reflect plausible environmental conditions (pH: 6.9 – 7.6; temperature: 29.1 – 30.4°C; TDS: 789 – 890 ppm), were statistically evaluated to determine inter-variable relationships. Pearson correlation coefficients indicated a weak positive correlation between pH and temperature ($r = 0.186$), alongside weak negative correlations between pH and TDS ($r = -0.218$) and temperature and TDS ($r = -0.134$). These results suggest minimal linear association among the variables, although the observed tendencies may reflect preliminary indications of underlying physicochemical interactions. Specifically, the slight inverse correlation between TDS and both temperature and pH may be attributed to solubility dynamics or dilution effects. At the same time, the positive pH-temperature relationship could be linked to temperature-dependent shifts in carbonate equilibrium. However, given the artificially

Table 7. Result of TDS measurements in Buntu River, Kendal Regency, Central Java, Indonesia

No.	Day	Measurement time	TDS (sensors)	TDS (meters)	Difference	(%)
1	Thursday	10:00	557	552	0.9	0.99
		12:00	569	566	0.5	0.99
		15:00	576	568	1.4	0.99
		16:00	577	570	1.2	0.99
2	Friday	9:00	560	549	2.0	0.98
		12:00	570	570	0	1.00
		14:00	575	574	0.2	1.00
		16:00	576	574	0.3	1.00
3	Saturday	10:00	686	680	0.9	0.99
		12:00	704	697	1.0	0.99
		14:00	745	738	0.9	0.99
		16:00	626	626	0	1.00
4	Sunday	9:00	685	675	1.5	0.99
		12:00	687	682	0.7	0.99
		14:00	626	616	1.6	0.98
		17:00	626	624	0.3	1.00
5	Monday	9:00	780	767	1.9	0.98
		12:00	712	711	0.1	1.00
		14:00	812	798	1.7	0.98
		16:00	815	798	2.1	0.98

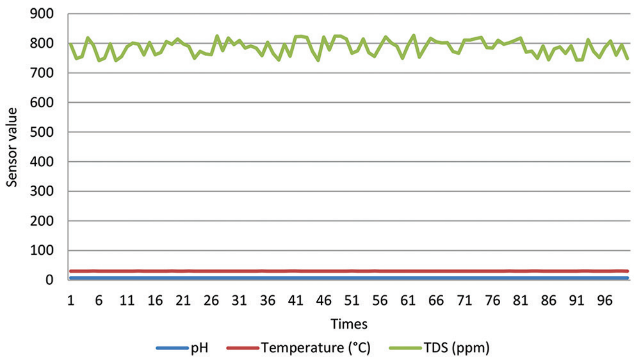

Figure 2. Measurements of pH sensor, temperature sensor, and TDS sensor at Banjardowo River, Semarang city
Abbreviation: TDS: Total dissolved solids

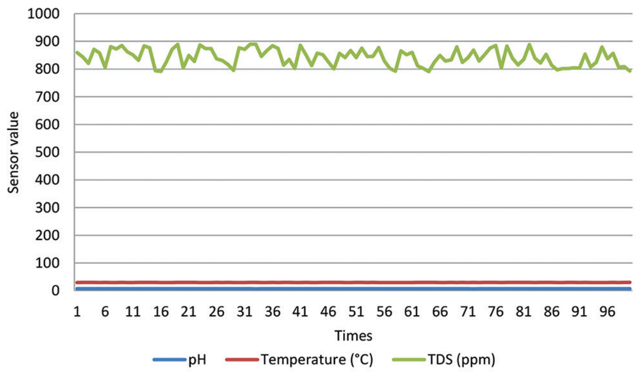

Figure 3. Measurements of pH sensor, temperature sensor, and TDS sensor at Buntu river, Kendal Regency, Central Java, Indonesia
Abbreviation: TDS: Total dissolved solids

generated and narrowly bounded nature of the dataset, these trends should be interpreted cautiously. Further validation utilizing empirical field data is essential for drawing definitive conclusions about the hydrochemical processes occurring in the Buntu River ecosystem.

TDS in river water originates from various sources, including natural processes and human activities such as urban runoff and industrial discharges. Its concentration varies geographically due to differences in mineral dissolution and can impact water quality and palatability, particularly at higher levels. Effective monitoring and management of TDS are crucial to maintaining water quality and protecting both ecosystems and public health.[56] Elevated TDS levels can harm aquatic life by altering water composition or increasing salinity. Contributing factors include soil erosion, agricultural runoff, domestic waste pollution, and other human activities, which collectively raise TDS concentrations in river water.[57]

4. Conclusion and recommendations

The IoT-based water quality monitoring system allows for continuous, real-time DAQ with low error margins, providing accurate and reliable assessments suitable for tropical coastal environments. The system's integration of multiple sensors (pH, temperature, and TDS) with on-site data display and cloud connectivity enables prompt detection of water quality changes, facilitating faster environmental response. Its low-cost design, ease of deployment, and ability to replace labor-intensive manual sampling make this system highly practical and scalable, supporting sustainable coastal water management and data-driven decisions in Semarang city and Kendal Regency, Central Java, Indonesia.

Our results highlight the promise of the IoT-based water quality monitoring system, which is recommended to be further developed and expanded by integrating additional sensors to cover more water quality parameters. Future work should focus on enhancing the system's robustness for long-term deployment in diverse coastal environments and optimizing data analytics for predictive environmental management. Collaboration with local authorities and community stakeholders is essential to ensure effective implementation and to promote sustainable ecosystem management practices.

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Conflict of interest

The authors declare that they have no competing interests.

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Availability of data

Data used for this study were included in the manuscript.

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