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IoT-based real-time monitoring of river water quality: a case study of the Selangor River

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ABSTRACT

Monitoring river water quality is crucial for preserving freshwater ecosystems, ensuring public health, and supporting resource management. Traditional methods, while accurate, lack the scalability and real-time capabilities needed for proactive intervention. This study introduces an IoT-based water quality monitoring system for the Selangor River, integrating sensors for pH, temperature, turbidity, and total dissolved solids (TDS) with a NodeMCU ESP32 microcontroller. To complement the IoT system, a handheld test pen was used to measure salinity and electrical conductivity (EC), offering additional insights into water quality. Field tests at four stations along the river revealed significant spatial variations. Station 1, near the river mouth, showed high salinity, EC, and TDS, indicating saltwater intrusion, with relatively low turbidity. Stations 2 and 3 recorded the highest turbidity levels, suggesting sedimentation and upstream activities, with moderate salinity and EC. Station 4, upstream, demonstrated stable freshwater characteristics, with low salinity, EC, and turbidity levels. The IoT system reliably monitored real-time parameters, and its measurements were validated against those from the handheld test pen. Minor discrepancies in TDS and temperature readings highlighted the importance of calibration.

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1. INTRODUCTION

Monitoring river water quality is of global importance, as rivers serve as essential sources of freshwater, sustain biodiversity, and support various economic and recreational activities. According to the World Health Organization, an estimated 2 billion people globally rely on contaminated water sources, leading to serious public health concerns such as waterborne diseases, which contribute to millions of deaths each year [1], [2]. As rivers are crucial freshwater sources, maintaining their water quality is imperative for ensuring safe drinking water, agricultural irrigation, and industrial usage. Furthermore, rivers play a vital role in sustaining aquatic ecosystems and biodiversity, as changes in water quality can directly affect flora and fauna, disrupting ecological balane and causing loss of biodiversity [3], [4].

In Malaysia, the importance of river water quality monitoring has intensified over recent years due to the country's rapid urbanization and industrial growth. Malaysia's rivers, particularly in states with high population densities and economic activities, face increased pressure from industrial discharges, agricultural runoff, and urban wastewater [5], [6]. These factors have led to incidents of river pollution, such as the 2019 pollution crisis in the Kim Kim River, Johor, which affected thousands of residents and underscored the need for continuous water quality monitoring [7]. The Selangor River, in particular, is a vital water resource in Malaysia, supplying over 60% of the water needs for the populous Klang Valley, including Kuala Lumpur and surrounding areas [8], [9]. With a catchment area of approximately 8,104 square kilometers, the Selangor River provides water for domestic, industrial, and agricultural use, supports local biodiversity, and serves as a recreational site for residents and tourists.

However, the Selangor River faces numerous challenges due to increased urbanization, deforestation, and intensive agricultural practices in the surrounding areas. These activities contribute to pollution through effluents, sedimentation, and nutrient loads, which degrade water quality and threaten the river's ecological health [5], [6], [10]. Rapid urbanization and population growth have led to higher demand for clean water, putting additional pressure on the Selangor River and its water quality [11]. The lack of consistent and comprehensive water quality monitoring has raised concerns about the long-term sustainability of this critical water source. Traditional methods of water quality monitoring, such as manual sampling and laboratory analysis, are accurate but can be time-consuming and labour-intensive, limiting their ability to capture real-time changes in water quality [12].

To address these challenges, leveraging internet of things (IoT) technology for real-time monitoring of water quality offers a promising solution. IoT-based water quality monitoring systems provide continuous, automated data collection and transmission, enabling authorities to respond quickly to pollution events and track trends over time [13], [14]. Numerous research has concentrated on the implementation of IoT-based systems for monitoring water quality, each tackling distinct environmental and technological difficulties. Islam and Asaduzzaman [15] developed an IoT system utilizing pH, temperature, and turbidity sensors in conjunction with an Arduino microcontroller for real-time data acquisition and automatic regulation; however, scaling to larger aquatic environments, such as rivers, presented challenges due to the necessity for multiple installations. Similarly, Munara *et al.* [16] offered an economical system featuring Wi-Fi connectivity for cloud-based data storage and remote access; however, its dependence on stable network connectivity limited its applicability in remote regions with unstable networks.

Varghese *et al.* [17] developed a portable IoT device to monitor parameters like total dissolved solids (TDS), temperature, and conductivity, delivering real-time pollution notifications. Nevertheless, data transfer in remote regions with inadequate GSM coverage limited ongoing monitoring. In Malaysia, Sarnin *et al.* [18] established a GSM-based system in Malaysia for real-time monitoring of turbidity and temperature, demonstrating efficacy in urban regions but encountering challenges in remote river basins due to limited network coverage. Further research underscores the flexibility and obstacles of IoT in various aquatic environments. Arora *et al.* [19] integrated sensors for pH, temperature, turbidity, and water levels into a system that transmits data to a cloud platform for ongoing monitoring. Although effective, it faced dependability challenges in varying environmental circumstances.

Recent studies have further explored IoT-based solutions for water and environmental monitoring. Amin *et al.* [20] developed a real-time water quality monitoring system using Arduino and Wi-Fi modules, allowing data transmission to mobile applications for end-user analysis. While their system effectively tracks pH, turbidity, and temperature, its reliance on Wi-Fi infrastructure limits deployment in remote areas. Similarly, Taha *et al.* [21] implemented LoRa technology for river water quality monitoring, enhancing coverage and energy efficiency compared to Wi-Fi. However, their study identified challenges in non-line-of-sight conditions, where signal attenuation impacted data reliability. These findings indicate the necessity for hybrid communication approaches that combine LoRa and GSM for robust performance.

Beyond water quality, IoT applications have also been extended to flood monitoring. Zain *et al.* [22] designed a wireless flood monitoring system incorporating IoT-based water level sensors and ESP32 microcontrollers to predict flooding events. Their study demonstrated the effectiveness of real-time alerts via the Blynk application, although sensor calibration remained a challenge in fluctuating water conditions. Similarly, Saparudin *et al.* [23] employed LoRaWAN for real-time flood monitoring in the Muar River catchment, integrating mobile IoT gateways for remote data collection. While their study successfully improved flood prediction accuracy, the need for continuous maintenance and network optimization was highlighted as a limitation. Collectively, these studies emphasize the growing role of IoT in environmental monitoring and the need for adaptive solutions that balance connectivity, energy efficiency, and sensor reliability.

Misnan *et al.* [24] employed IoT technology to monitor pH and turbidity in water retention ponds, effectively providing warnings for alterations in quality. Although appropriate for smaller water bodies, this method necessitated optimization for rivers exhibiting spatial variability in water quality parameters. These studies collectively highlight the promise of IoT in water quality monitoring, while stressing the necessity for scalable and dependable network solutions for wider applications. By implementing an IoT-based system in the Selangor River, this project aims to enhance the river's water quality monitoring efforts, contributing to the long-term sustainability and environmental health of one of Malaysia's most important rivers.

2. METHOD

This study employed an IoT-based water quality monitoring system and a handheld digital test pen to assess water quality in the Selangor River. The IoT system was designed to provide real-time data collection and monitoring, integrating sensors for pH, temperature, turbidity, and TDS. To validate and compare data, measurements were also taken with a handheld device that included additional parameters such as salinity and electrical conductivity (EC). Water samples were collected from four distinct stations along the river, allowing for a comprehensive evaluation of water quality variations across different locations. This setup and sampling approach enabled a detailed analysis of water conditions, leveraging both real-time IoT monitoring and direct handheld measurements for cross-verification.

2.1. IoT water quality monitoring

The system architecture, as depicted in Figure 1, integrates multiple sensors, including pH, temperature, turbidity, and TDS, connected to a NodeMCU ESP32 microcontroller. This configuration enables simultaneous monitoring of key water quality parameters. The data collected from the sensors is displayed on a liquid crystal display (LCD) and transmitted via Wi-Fi to a cloud-based storage system, enabling real-time access and remote monitoring. Wi-Fi was chosen for its reliability in areas with network coverage, ensuring seamless data transmission without requiring additional long-range communication modules. The system also features a local LCD display for immediate on-site readings, improving usability for field researchers. The LCD provides real-time feedback to users, allowing them to detect anomalies in sensor readings instantly.

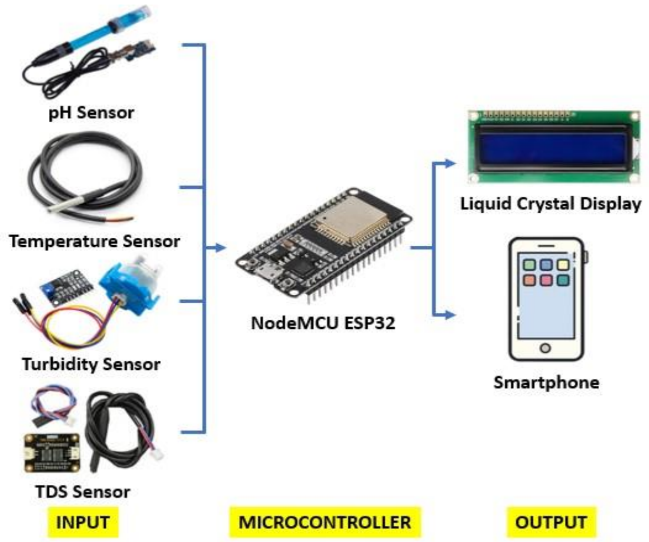


Figure 1. Block diagram of the IoT water quality monitoring

Figure 2 illustrates the internal layout of the IoT water quality monitoring box. Each sensor is connected to the NodeMCU ESP32 microcontroller and linked to the LCD for local data display. The components are securely mounted within a waterproof enclosure to prevent interference from environmental factors. This organized layout ensures minimal noise interference and reliable data collection. The portable and compact design facilitates transportation, allowing the system to be easily deployed at various monitoring points along the river. Additionally, the setup's design allows for straightforward maintenance and calibration, ensuring accuracy in long-term use.

The selection of the ESP32 microcontroller is justified based on its energy efficiency, multi-sensor compatibility, and built-in Wi-Fi and Bluetooth capabilities, which enhance system flexibility [25]. The built-in Wi-Fi functionality reduces dependency on external network modules, simplifying system integration and reducing power consumption. Furthermore, data encryption techniques are employed to secure the transmitted information, preventing potential cybersecurity threats. Cloud storage is equipped with data redundancy mechanisms to prevent loss of critical water quality records, ensuring reliability in long-term monitoring applications [26]. The study's methodology is structured to provide transparency and ensure reproducibility, allowing future researchers to implement and improve upon this water quality monitoring system.

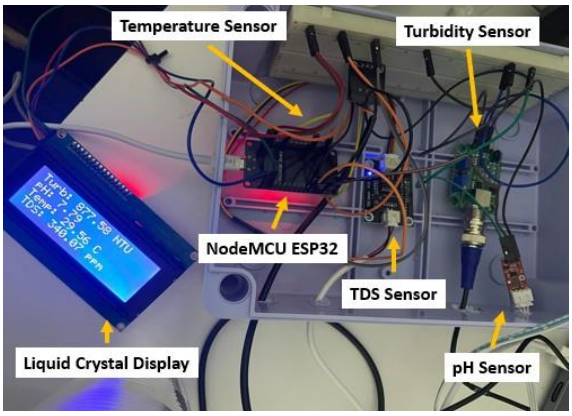
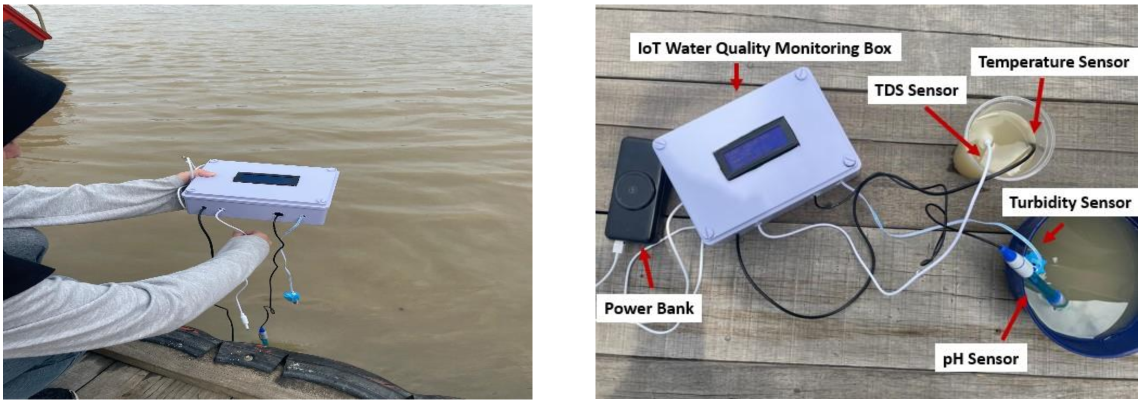


Figure 2. Internal layout of IoT water quality monitoring box

The IoT river water monitoring process is illustrated in Figure 3. Figure 3(a) depicts the field application of the monitoring device at the Selangor River, where the water quality monitoring box was strategically placed near the water surface, with sensors submerged in the river. This configuration minimizes external environmental interference, ensuring precise measurements of parameters such as pH, temperature, turbidity, and TDS. The protective enclosure safeguards the microcontroller and display from water exposure, making the setup reliable for real-time, on-site monitoring. Additionally, the IoT box can be mounted and secured on a bridge for continuous river water monitoring.

Figure 3(b) shows a controlled test conducted with water samples collected in plastic containers, demonstrating the system's capability for both in-situ and ex-situ measurements. This controlled setup was used to validate sensor accuracy under stable conditions prior to full-scale deployment. The system was powered by a portable power bank, emphasizing its energy independence, a critical feature for monitoring in remote areas lacking electricity access. This dual testing approach allows for thorough evaluation of water quality across various sampling points, ensuring the reliability and accuracy of sensor readings before extensive field application.



(a) (b)

Figure 3. IoT water quality monitoring process (a) direct field application and (b) using sample containers

2.2. Data validation and accuracy assessment

In addition to the IoT water quality monitoring box, a handheld digital test pen was utilized, a China brand, to measure key water quality parameters, as shown in Figure 4. This device is capable of measuring five parameters: temperature, pH, TDS, salinity, and EC. However, for comparative analysis with the IoT system, only three parameters were selected, namely temperature, pH, and TDS, as these were the common parameters measured by both devices. The handheld test pen provides a quick and portable solution for field testing, enabling immediate verification of the IoT box readings in real time. Anomalies in sensor readings are flagged using an automated error detection algorithm, reducing the risk of inaccurate data interpretation.

The IoT system is also designed with self-calibration capabilities to improve measurement stability over extended periods of deployment. The calibration process involves periodic reference measurements against standardized solutions, ensuring long-term accuracy.

The use of this digital test pen adds value to the monitoring system by offering direct measurements of salinity and EC in addition to the primary parameters of interest. Meanwhile, the IoT water quality monitoring box provides an additional parameter, turbidity, which the handheld device does not measure. As a result, the combination of both devices allows for a comprehensive assessment of six water quality parameters, although only three are directly comparable between the two systems. This dual device approach enhances the reliability and scope of the water quality assessment by enabling cross verification and expanding the range of monitored parameters.

Figure 4. Handheld digital test pen for measuring water quality parameters (picture credited to Shoppe.com)

2.3. Water quality sampling locations in the Selangor River

Water samples from the Selangor River were collected from four strategically chosen stations to ensure a comprehensive evaluation of water quality across different areas. The selected locations, as shown in Figure 5 and Table 1, include: Station 1 at the Jalan pasir Penambang, Kuala Selangor, Station 2 at Jeti Batu 8 Kg. Asahan, Station 3 at the Jambatan Jalan Raja musa, Bestari Jaya, and Station 4 at the Ampang Pechah (old dam), Kuala Kubu Bharu. Each station represents a distinct segment of the river, allowing for observation of spatial variations in water quality parameters along its course. At each location, both the IoT water quality monitoring box and the handheld digital test pen were deployed to measure key water parameters, providing data for comparative analysis across all sample points. This multi-station approach enhances understanding of water quality conditions in the Selangor River and helps identify localized changes.

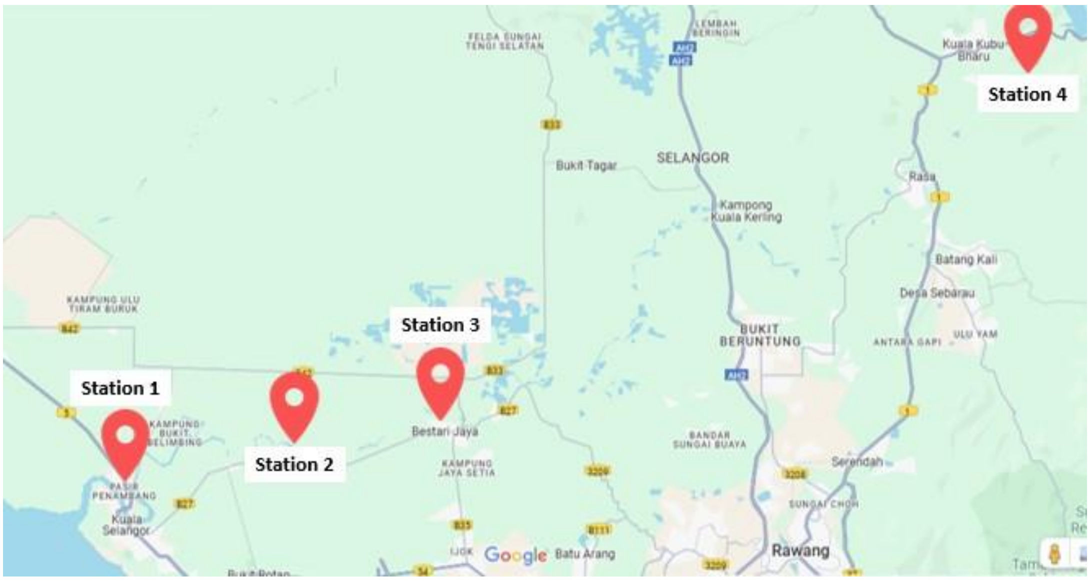


Figure 5. Map of sampling stations along the Selangor River

Table 1. Sampling stations along the Selangor River

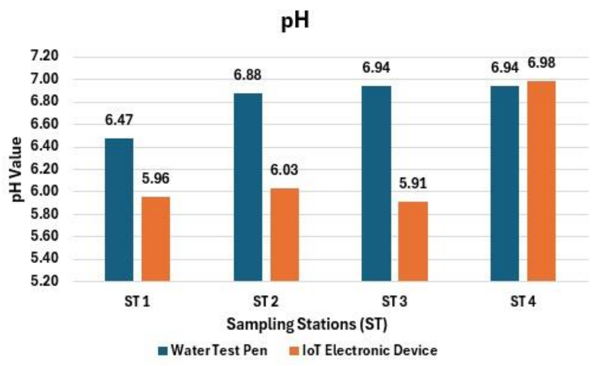
Station (ST)	Location	Coordinate
1	Kuala Selangor	3°20'58.5"N 101°15'03.8"E
2	Jeti Batu 8 Kg. Asahan	3°22'01.9"N 101°20'48.6"E
3	Bestari Jaya	3°23'05.4"N 101°24'33.2"E
4	Kuala Kubu Bharu	3.5439° N, 101.6587° E

3. RESULTS AND ANALYSIS

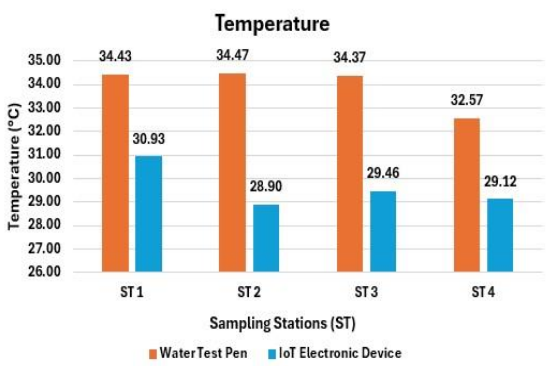
Figure 6 illustrates the comparison of pH and temperature measurements between the IoT device and the handheld test pen across all four sampling stations. As shown in Figure 6(a), the pH measurements reveal some variation between the two devices. The IoT device generally records lower pH values compared to the handheld water test pen. At ST 1, the pH measured by the IoT device is 5.96, while the water test pen records 6.47. This trend of lower IoT readings is consistent across all stations, with the largest discrepancy observed at ST 2, where the IoT device recorded a pH of 6.03 compared to the water test pen's 6.88. These variations may be attributed to calibration differences between the devices or environmental factors affecting sensor sensitivity.

Then, Figure 6(b) presents the temperature measurements across the stations. Here, the IoT device consistently records lower temperatures than the handheld water test pen at each station. For example, at ST 1, the IoT device recorded a temperature of 30.93°C, while the water test pen measured 34.43°C. This pattern is observed across all stations, with similar discrepancies at ST 2, ST 3, and ST 4. These differences could be due to the placement of sensors in the water or the response time of each device to temperature changes, with the IoT device potentially being more responsive to fluctuations. Figure 7 presents the comparison of total dissolved solids (TDS) measurements and the percentage differences in pH, temperature, and TDS between the IoT device and the handheld test pen across all sampling stations. As shown in Figure 7(a), significant differences in TDS values were observed. At ST 1, the IoT device recorded a TDS of 614.6 ppm, while the water test pen measured a higher value of 744.67 ppm. This pattern is observed throughout the stations, with the most significant difference at ST 1 and the smallest difference at ST 2. The differences in TDS measurements between the two devices could be due to calibration or the sensitivity of each device to dissolved particles in the water.

Comparatively, Figure 7(b) displays the percentage differences between the two devices for pH, temperature, and TDS at each station. For pH, the differences are relatively small across all stations, with ST 2 showing the largest variation at 6.66%. Temperature measurements exhibit moderate percentage differences, with ST 3 showing a notable difference of 8.79%. TDS measurements have the highest variation, especially at ST 1, with a significant difference of 58.92%. This trend suggests that while the IoT device and water test pen provide comparable data for pH and temperature, the TDS measurements may require further calibration to ensure accuracy. Therefore, the analysis reveals that the IoT water quality monitoring system is effective in capturing real-time data for pH, temperature, and TDS, although slight discrepancies with the handheld water test pen are evident. These differences highlight the importance of regular calibration and consideration of environmental factors, particularly for TDS, where the variations are most pronounced. The IoT device's capability for remote, continuous monitoring provides a valuable tool for assessing water quality, although complementary use with handheld devices can enhance accuracy and reliability.

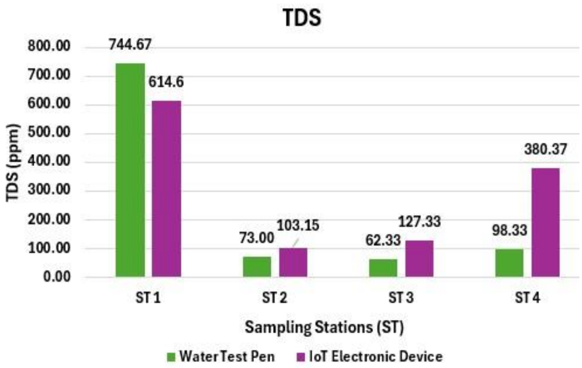


(a)

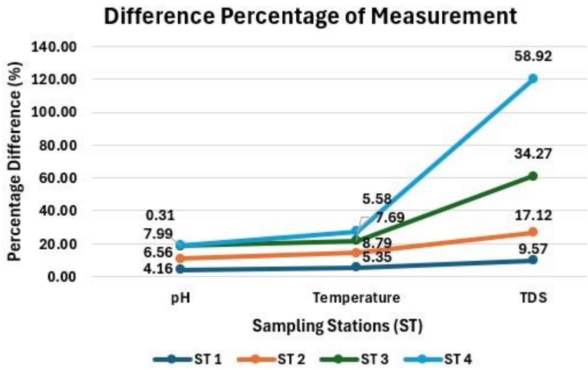


(b)

Figure 6. IoT device vs. handheld pen (a) pH measurements and (b) temperature measurements



(a)



(b)

Figure 7. IoT device vs. handheld pen (a) TDS measurements and (b) percentage differences in pH, temperature, and TDS

The results for turbidity, salinity, and EC measurements were taken three times, named M1, M2, and M3, to ensure accuracy and repeatability of the data. The turbidity measurements are displayed in Figure 8 obtained by the IoT water quality box. Across all stations, there is a noticeable variation in turbidity levels, with ST 2 showing the highest turbidity values, reaching 350.55 NTU in M1. ST 1 records the lowest turbidity values, with the highest measurement at 118.46 NTU in M2. The consistent readings across M1, M2, and M3 at each station demonstrate the reliability of the IoT system. The high turbidity observed at ST 2 and ST 3 could indicate increased suspended particles in these areas, possibly due to upstream activities or natural sediment flow, affecting water clarity.

Figure 9 presents the salinity and electrical conductivity (EC) measurements across all stations, obtained using the handheld digital test pen. As illustrated in Figure 9(a), ST 1 shows significantly higher salinity values compared to the other stations, with values consistently above 740 ppm across M1, M2, and M3. In contrast, ST 3 and ST 4 show much lower salinity levels, around 62 to 101 ppm. This disparity in salinity could be attributed to the proximity of ST 1 to areas where saltwater intrusion might occur, whereas ST 3 and ST 4 are located further upstream, resulting in lower salinity levels. The consistent measurements across M1, M2, and M3 at each station indicate the stability and reliability of the digital test pen for measuring salinity.

Finally, the EC measurements also taken by the digital test pen is shown in Figure 9(b). Similar to salinity, ST 1 exhibits much higher EC levels compared to the other stations, with values around 1451 to 1479 µS/cm. The elevated EC levels at ST 1 may suggest higher ion concentrations due to possible saltwater mixing in this region. The other stations, particularly ST 3 and ST 4, show much lower EC values, ranging from 126 to 203 µS/cm, reflecting the freshwater nature of these areas. The consistency in measurements across M1, M2, and M3 at each station supports the accuracy of the digital test pen for EC measurements.

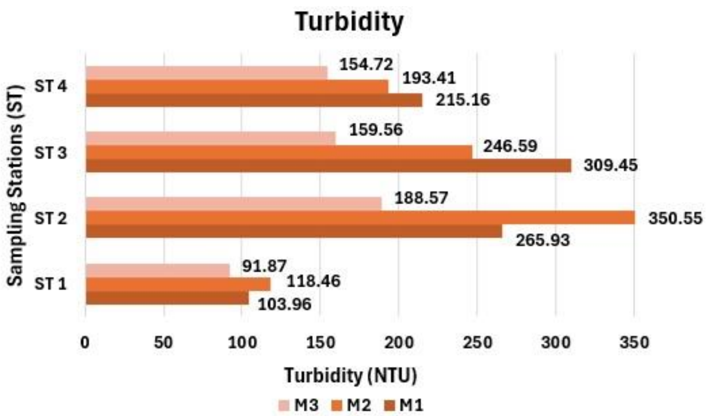
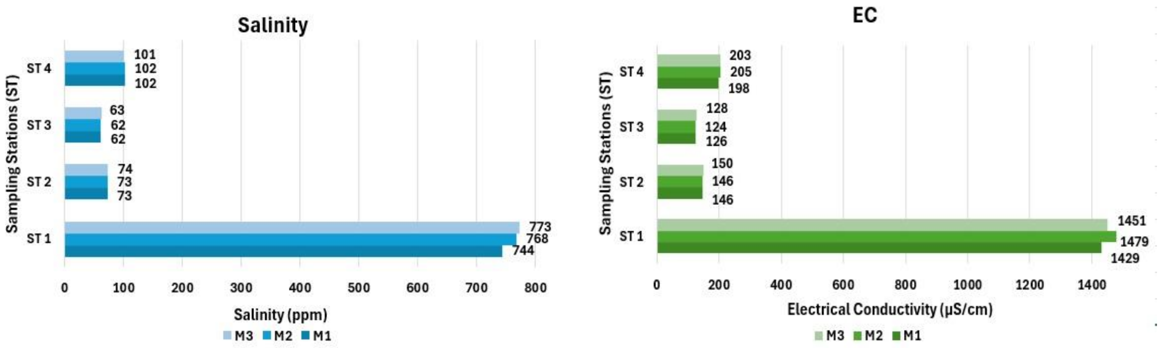


Figure 8. Turbidity measurements by IoT device across stations



(a) (b)

Figure 9. Test pen across stations (a) salinity measurements and (b) EC measurements

4. DISCUSSION

The results obtained from the IoT-based water quality monitoring system and handheld test pen measurements are presented and analyzed in this section. The findings are critically discussed in terms of accuracy, reliability, and implications for future applications.

4.1. Water quality parameter analysis

The findings reveal significant spatial variations in water quality along the Selangor River, with each station presenting distinct characteristics. Station 1 shows high levels of salinity, EC, and TDS, likely due to its proximity to the river mouth, where saltwater intrusion may increase ion concentration. Additionally, turbidity levels at Station 1 are relatively low, indicating minimal suspended particles or sedimentation, possibly because this area experiences more saline water that settles particles. In contrast, Stations 2 and 3 display higher turbidity values, suggesting increased sediment or organic matter, likely from upstream activities or natural sediment flow, which affects water clarity in these areas.

Station 4, located further upstream, reflects typical freshwater characteristics with lower salinity and EC levels. The relatively consistent pH and moderate turbidity at this station suggest less anthropogenic impact, making it a more stable environment. Thus, the IoT water quality monitoring system and the handheld test pen provided valuable, complementary data, demonstrating effective real-time tracking of key parameters and reinforcing the reliability of using both tools together. These findings suggest that while certain parts of the river may face environmental challenges, particularly with salinity intrusion near the river mouth, other sections maintain stable freshwater quality, underscoring the importance of continuous monitoring to address local water quality needs.

The collected data for pH, turbidity, temperature, and TDS across different sampling stations indicate variations influenced by environmental and anthropogenic factors. The pH values remained within an acceptable range for freshwater ecosystems, although slight fluctuations were observed, likely due to rainfall and upstream activities. Turbidity levels varied significantly between stations, with higher values recorded in areas with increased human activity, such as near settlements and agricultural zones. This suggests that land use and erosion contribute to sedimentation, impacting water clarity and aquatic habitats. These findings align with previous studies indicating that human activities, such as deforestation and agricultural runoff, directly influence water quality degradation in river ecosystems.

Temperature and TDS measurements showed consistent trends across locations, with minor deviations attributed to seasonal variations and localized water inflow. The IoT-based system successfully captured real-time fluctuations in these parameters, highlighting its capability for continuous environmental monitoring. However, minor fluctuations in TDS readings suggest possible inconsistencies in sensor response times, reinforcing the importance of cross-validation with traditional laboratory methods. Sensor drift over prolonged deployment periods was noted, emphasizing the need for periodic calibration and maintenance to maintain accuracy. This supports the methodology's inclusion of self-calibration capabilities to mitigate sensor drift and ensure long-term measurement stability.

4.2. Comparison between IoT system and handheld test pen

The dependability of measurements was evaluated by comparing the IoT system's results with those obtained from the handheld test pen. The two systems demonstrated a robust connection in temperature and pH readings, with variations confined to an acceptable error limit. Discrepancies were seen in TDS readings, with the handheld instrument registering somewhat elevated values. This discrepancy may be ascribed to disparities in sensor sensitivity and reaction time. The IoT sensors provide real-time monitoring, whereas the handheld test pen depends on intermittent sampling, potentially resulting in discrepancies due to water movement and sampling depth. These inconsistencies highlight the necessity of sensor calibration and validation against defined laboratory procedures to improve measurement accuracy. The findings indicate that while IoT monitoring provides continuous data collection, regular validation against conventional methods is essential to maintain accuracy.

4.3. Implications of findings and future applications

This study's results indicate that IoT-based monitoring devices can enhance traditional water quality evaluation methods by providing real-time, continuous data collection. This is especially beneficial for the early detection of pollution and the implementation of quick response tactics. Industries and regulatory agencies can employ this approach to enact preemptive measures when water quality declines beyond acceptable thresholds, thereby mitigating environmental harm. The incorporation of automated anomaly detection enhances data trustworthiness by recognizing atypical trends that may signify contamination or environmental disruptions.

Subsequent research may enhance this work by using supplementary water quality metrics, including dissolved oxygen and chemical contaminants, to yield a more thorough evaluation of river health. Furthermore, the application of machine learning algorithms for predictive analysis can augment the system's ability to discern pollution trends over time. Incorporating artificial intelligence could enable the system to deliver predictive notifications for probable contamination occurrences, hence improving water quality management. The results underscore the necessity of enhancing sensor durability and energy economy to facilitate extensive, long-term implementations. Creating energy-efficient and self-sustaining IoT monitoring stations could improve system sustainability, particularly in rural regions with inadequate infrastructure.

5. CONCLUSION

This research effectively created and executed an IoT-based real-time water quality monitoring system for the Selangor River, incorporating pH, turbidity, temperature, and TDS sensors using a NodeMCU ESP32 microcontroller. The findings indicate that the system proficiently detects real-time fluctuations in water quality indicators, offering continuous monitoring capabilities that enhance conventional water sampling techniques. The comparison with portable test pen measurements underscores the system's reliability, with slight variations ascribed to sensor reaction times and external influences. The automated anomaly detection feature improves the precision of the acquired data, hence ensuring the system's efficacy in practical applications. In addition to monitoring, these findings possess significant implications for environmental management and regulatory adherence. The capacity to gather, retain, and remotely access real-time water quality data facilitates proactive decision-making, potentially aiding policymakers, researchers, and local authorities in alleviating pollution problems and enhancing water resource management. Moreover, the system's portable and energy-efficient design renders it appropriate for implementation in rural or underserved regions where ongoing water quality monitoring is frequently difficult. Future research may enhance this study by integrating supplementary water quality metrics, including dissolved oxygen and heavy metal analysis, to yield a more thorough evaluation of river health. The incorporation of machine learning algorithms may augment prediction skills, facilitating early identification of pollution trends and refining response methods. Furthermore, investigating energy-efficient power sources, such as solar charging systems, may improve the system's sustainability for prolonged deployments. This study advances IoT-based environmental monitoring by presenting a scalable, efficient, and adaptive method for real-time water quality testing. These findings may impact future research in intelligent environmental monitoring and assist in creating sustainable strategies for conserving water resources and protecting public health

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This study does not involve human participants or animals; therefore, ethical approval was not required.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, A.M.M., upon reasonable request.

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