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IoT-based real-time monitoring of agricultural wastewater using Raspberry Pi, Node-RED, and Grafana

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ABSTRACT

This study introduces an internet of things-based agricultural wastewater monitoring system (IoT-AWMS) designed to enhance water management through real-time monitoring and advanced sensor integration. The system employs a Raspberry Pi for centralized control, node-RED for automation, InfluxDB for data storage, and Grafana for visualization. A key innovation is the integration of an alternative sensing approach for estimating electrical conductivity (EC), complementing conventional sensors for total dissolved solids (TDS), water temperature (DS18B20), and ambient conditions (DHT11). The system achieves over 85% accuracy in estimating EC across diverse water samples, including drinking water, agricultural runoff, and fertilizer-enriched solutions. Compared with conventional approaches, IoT-AWMS demonstrates superior accuracy, scalability, and cost-effectiveness. Its modular design supports applications in nutrient runoff detection, contamination monitoring, and optimized water resource utilization, with broader potential in precision farming and environmental monitoring. This work contributes a robust, adaptable IoT framework for sustainable agricultural water management.

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1. INTRODUCTION

Agricultural practices, particularly the excessive use of fertilizers, have become a major contributor to global water pollution. Fertilizers, which are rich in nitrogen and phosphorus, often leach into water systems from agricultural fields, causing nutrient pollution that leads to eutrophication, a process that reduces oxygen levels in water bodies, harming aquatic life and reducing biodiversity. This issue is especially common in areas with intensive farming, where fertilizer runoff contaminates groundwater and nearby rivers and lakes, rendering them unsafe for drinking and other uses, and often leading to water cuts due to the presence of pollutants [1], [2]. According to the World Wildlife Fund, agriculture consumes nearly 70% of the world's accessible freshwater, with approximately 60% wasted due to inefficient irrigation and poor water management practices. In recent years, overuse has burdened global water supplies and caused significant contamination of freshwater systems with fertilizers and pesticides, posing risks to human and ecological health [3]. The environmental and health risks posed by fertilizer runoff are further exacerbated in developing countries, where limited access to sustainable agricultural practices and weak regulatory enforcement often result in the unchecked use of chemical inputs [4]. As detailed by recent studies [5], the assessment of the Karasu River revealed notable seasonal fluctuations in parameters such as electrical conductivity (EC) and heavy metal concentrations, highlighting the urgent need for continuous, real-time water quality monitoring. Eutrophication and contamination from both point and non-point sources have been consistently documented, emphasizing the broader environmental impact of agricultural runoff [4].

Internet of things (IoT) technologies have recently emerged as a promising solution for real-time environmental monitoring. For instance, the concept of a smart campus as a digital twin integrates IoT-based wireless sensor networks with cloud computing to enable real-time tracking of environmental parameters, ultimately improving comfort and energy efficiency [6]. Inspired by such developments, the IoT-based agricultural wastewater monitoring system (IoT-AWMS) presented in this project similarly adopts a real-time sensing and cloud-based visualization approach, utilizing Raspberry Pi, Node-RED, InfluxDB, and Grafana to provide actionable insights for sustainable agricultural water management. Furthermore, previous works on IoT-enabled environmental toxicology monitoring for air pollution demonstrate the potential of using cloud servers and advanced analytics, including artificial intelligence (AI), to predict contamination levels [7]-[9]. This suggests future expansions for IoT-AWMS could incorporate predictive models to proactively detect fertilizer runoff risks. Additionally, aligning with green smart city initiatives, the IoT-AWMS contributes to sustainable practices by optimizing water and fertilizer usage, reducing environmental impact, and supporting resource conservation [10]. Prior work has demonstrated the use of Arduino-based systems to monitor industrial wastewater [11], [12], and other implementations have demonstrated the practicality of monitoring parameters such as pH and EC for the detection of water contamination [13], [14]. However, many existing systems lack scalability, offer limited parameter monitoring, or fail to provide advanced data visualization and integration capabilities [15].

To address these limitations, this study proposes an IoT-AWMS, tailored specifically for real-time assessment of agricultural wastewater quality. This system is centered on a Raspberry Pi platform, which collects and processes data from various sensors placed at agricultural runoff sites [16]-[18]. It monitors key water quality indicators, including EC, total dissolved solids (TDS), and water temperature, while also capturing surrounding air temperature and humidity. Notably, the system integrates a custom-developed plastic optical fiber (POF) sensor to measure fertilizer concentration through voltage output, addressing the need for more precise detection of nutrient pollutants.

Data acquisition and processing are automated via Node-RED, with time-series data stored in InfluxDB and visualized through Grafana [19]. InfluxDB, an open-source, time-series database, supports IoT applications by enabling low-latency queries and using Flux for advanced data analysis and query execution [20]. Grafana, also open-source, enhances data monitoring by allowing the creation of custom dashboards to track water quality metrics over time [21]. This integration of IoT technology into agriculture represents a practical and cost-effective solution for real-time water quality monitoring [22]-[24]. This seamless integration supports low-latency analysis and customizable dashboards for real-time monitoring. By equipping farmers and stakeholders with actionable insights, the IoT-AWMS system promotes sustainable farming practices and resource optimization. Furthermore, its modular, scalable architecture enhances its adaptability for broader applications in precision agriculture and environmental management, bridging the gap left by existing solutions.

2. SYSTEM ARCHITECTURE AND ELECTRONIC COMPONENTS

The IoT-AWMS system shown in Figure 1 is designed to continuously monitor agricultural wastewater using a flexible IoT setup. The Raspberry Pi acts as the main controller of the system. It gathers data from several sensors, including TDS sensor for dissolved solids, a water temperature sensor (DS18B20), and DHT11 sensor for ambient conditions. The analog signals from the sensors are converted into digital form using the MCP3008 ADC, allowing the Raspberry Pi to process and analyze the data in real time. After that, the data passes through Node-RED, which organizes and manages how the information flows, and is then saved in InfluxDB, a time-series database optimized for handling large volumes of sensor data. The final step involves utilizing Grafana to generate visually engaging dashboards, enabling the real-time visualization of environmental data. By integrating sensor data with cloud-based monitoring, this flow ensures complete and up-to-date insights into the water quality.

Figures 2 and 3 illustrate the physical implementation and visualization interface of the system, showcasing the integration of the Raspberry Pi with sensor circuitry and the customized Grafana dashboard.

This configuration allows users to remotely monitor water quality metrics in real time, enhancing the system's practical application in precision agriculture. Overall, the IoT-AWMS provides a cost-effective and scalable solution to address water management challenges in agriculture, promoting sustainability and efficiency.

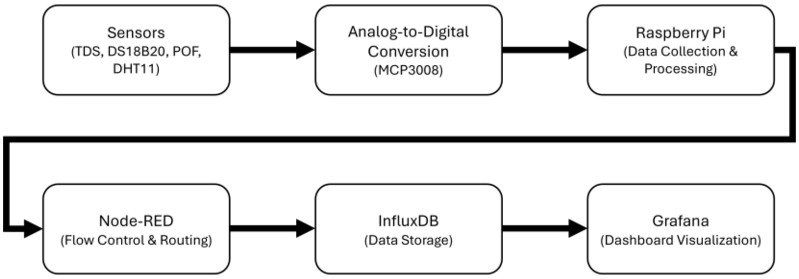


Figure 1. Block diagram

Figure 2. System architecture for IoT water quality monitoring

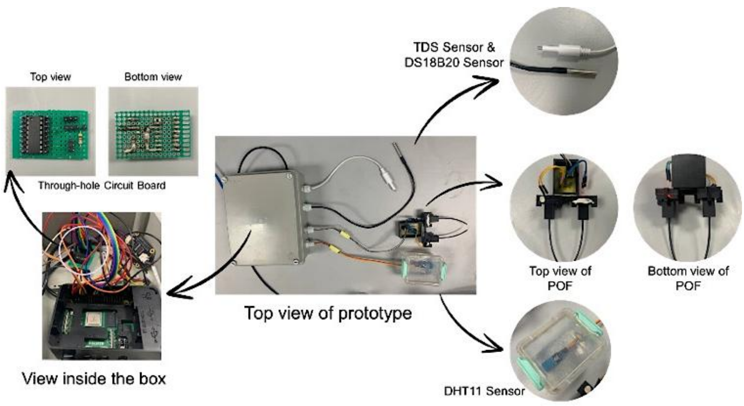


Figure 3. Connection of Raspberry Pi to through-hole circuit board

The integration framework of the Raspberry Pi with Node-RED for sensor communication is illustrated in Figure 4, followed by InfluxDB and Grafana. Figure 4(a) shows that the Raspberry Pi 4 Model B was configured with Raspbian OS and enabled with SSH and VNC for remote access. SPI communication was activated using raspi-config. MCP3008 ADC was interfaced via SPI0. Node-RED was installed using npm install -g --unsafe-perm node-red, and flows were deployed via the default port (1880). Once the interfaces are enabled, the user can use Node-RED to develop the IoT-AWMS framework programming flow as shown in Figure 4(b).

(a) (b)

Figure 4. Integration of Raspberry Pi with Node-RED for sensor communication; (a) configuration of Raspberry Pi communication with Node-RED and (b) programming flow for Raspberry Pi

Figure 5 shows configuration for communication between Node-RED and Grafana can be enabled by enter “influx” in Raspberry Pi terminal so that Node-RED and Grafana can access the database created in InfluxDB v1, and then created the dashboard. Next, go to the "Dashboard" menu in the side tab and create a new dashboard. Click on "Add visualization" and select the data source to display on the dashboard. Finally, add visualizations such as time series or bar charts according to your preferences. There are numerous options for visualizations that can be selected. After selecting the visualization types, configure the dashboard based on the data that stored in the database (InfluxDB).

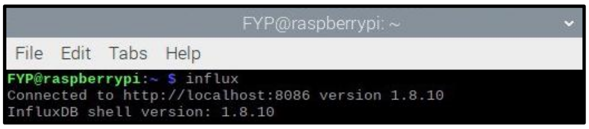


Figure 5. Configuration for Raspberry Pi to communicate with InfluxDB v1

To ensure the stability of IoT-AWMS, system testing will be conducted to analyze its operation and performance for a longer duration. Sensor accuracy has been chosen as the key metric for performance evaluation. Firstly, sensor accuracy is crucial for a water quality monitoring system as it directly reflects the water's condition. TDS value and water temperature data have been collected by the respective sensors to indicate the main framework's environment. If any unusual values are detected in the water, the responsible person can monitor the situation in real-time and have sufficient time to respond to the incident.

All data from sensors is collected in Grafana, and displayed in a dashboard as in Figure 6 (in Appendix), which presents the dashboard displaying data from 9 ml A+B fertilizer stored in InfluxDB. Figure 6(a) display the humidity and temperature readings from the DHT11 sensor, Figure 6(b) shows the temperature data from the DS18B20 sensor, and Figure 6(c) shows the TDS value from the TDS sensor. Multiple solution conditions were evaluated to compare sensor responses. To examine and compare the differences between them, a variety of solutions from various scenarios are used. The entire collection of data is shown on the Grafana dashboard, which is connected to an InfluxDB database for storage. InfluxDB is preferable compared to traditional relational databases such as MySQL. This is due to its superior performance in handling time-series data. Unlike MySQL, InfluxDB provides built-in functions optimized for real-time aggregation for IoT applications with high-frequency sensor inputs.

3. PREPARATION OF SAMPLE: DRINKING WATER, AGRICULTURAL WASTEWATER, AND FERTILIZER WATER

Various samples from drinking water, agricultural wastewater, and fertilizer water are used to test the developed IoT-AWMS. These diverse samples will support the evaluation of the system's accuracy and reliability for measuring various water quality parameters at different conditions. At first, two sources of drinking water (tap water and filtered water) are used as a reference or baseline for comparison to agricultural wastewater and fertilizer water. Figure 7 shows the actual location of collected agricultural wastewater samples at the corn farm at Universiti Teknikal Malaysia Melaka (UTeM). UTeM is in Melaka on the west coast of Peninsular Malaysia, which records peak rainfall every year [25]. Due to heavy rainfall, fertilizers are expected to flow into nearby drainage systems and rivers. Therefore, these samples were collected at three different locations, and labeled as subsurface drainage, agricultural drainage, and water reservoir pond. For the water reservoir pond, the contamination level is expected to be nearly zero, and the water profile is almost identical to drinking water.

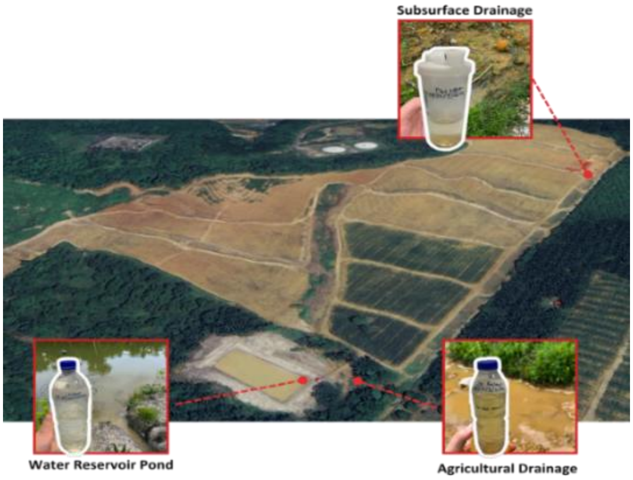


Figure 7. Top-view image of the agricultural wastewater location for three different water samples: subsurface drainage, agricultural drainage, and water reservoir pond

Fertilizer characterization work is important to identify the traces of fertilizer in wastewater. These fertilizers are commercially available, water-soluble formulations designed for cocopeat and hydroponic systems. The fertilizer samples were prepared based on the EC value, which determines the concentration of fertilizer. The unit of EC value is ms/cm, and for each volume concentration (3 ml, 6 ml, and 9 ml) was measured using a commercial sensor, TDS sensor and DS18B20 sensor. The value from TDS sensor and DS18B20 is used to calculate EC values by substituting TDS value (TDS sensor) and the water temperature value (DS18B20 sensor). Next, EC value is also measured by using EC meter from Hanna Instrument for comparing the accuracy of the EC value that is calculated and measured. The typical fertilizer parameters based on farmers' practice will be measured from these prepared samples.

4. SENSOR PERFORMANCE OF IOT-AWMS

Based on farmers' practices in Malaysia, a typical method to identify fertilizer concentration is by using the commercial EC meter. At the start, the EC meter by Hanna Instrument is used to measure EC value for drinking water, agricultural wastewater, and fertilizer water. The measurement has been conducted in the laboratory environment with a room temperature varying from 20 ^{o}C to 25 ^{o}C with 65% to 75% humidity for a day (24 hours). For water security applications, EC value can also be used to measure the excess fertilizer from agricultural sites that drains to the nearby river or water flow. The TDS sensor data reflect the concentration of TDS, and the DS18B20 data indicate the water temperature variations across the samples. The EC value, TDS value, and water temperature are measured simultaneously, then the massive data is uploaded to the cloud database at 1-minute intervals. Data from the meter and sensors were continuously recorded at one-minute intervals over a period exceeding one month. The data in Table 1 from EC meter (measured EC), TDS sensor (TDS value), and DS18B20 sensor (water temperature) are in average values.

Table 1. Average data of EC values, TDS values, and water temperature

Samples		Measured EC ($mS\ cm^{-1}$)	Calculated EC ($mS\ cm^{-1}$)	TDS value (ppm)	Water temperature (^{o}C)
Drinking water	Tap water	0.15	0.17	34.70	24.93
	Filtered water	0.13	0.15	30.70	24.96
Agriculture wastewater	Water reservoir pond	0.07	0.06	13.10	24.69
	Subsurface drainage	0.37	0.30	95.20	23.72
	Agricultural drainage	0.25	0.41	129.50	20.42
Fertilizer water	3 ml hydroponic	0.83	0.70	232.70	25.54
	6 ml hydroponic	1.29	1.20	367.90	21.64
	9 ml hydroponic	1.91	2.03	626.10	21.96
	3 ml A+B	1.88	1.68	435.80	22.65
	6 ml A+B	3.42	3.25	532.60	25.05
	9 ml A+B	4.94	5.25	535.10	24.74

From measured TDS and water temperature values in Table 1, the EC value is mathematically derived. The calculated EC value is then compared to the EC value obtained from the EC meter by Hanna Instrument. So, this can ensure that the equation used in this system is reliable and precise. Hence, each sensor performed in varying conditions, showcasing the consistency and reliability of the measurements. By comparing these sensor readings, this confirms that the developed IoT-AWMS can be effectively integrated with TDS and DS18B20 sensors for real-time agricultural wastewater monitoring. Moreover, this analysis helped in understanding the impact of different water sources and fertilizer concentrations on overall water quality, ensuring the system can provide accurate and useful information for agricultural wastewater management. The IoT-AWMS enables farmers to monitor water quality in near real-time, allowing them to adjust irrigation practices, reduce fertilizer wastage, and avoid contamination of nearby water bodies. Early alerts on excessive EC levels help prevent crop damage and promote compliance with environmental standards.

4.1. Data collection of total dissolved solids sensor

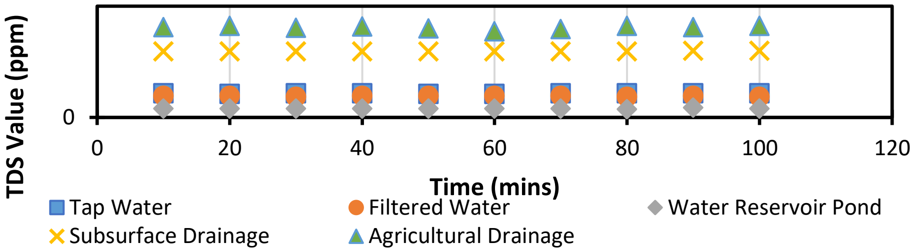
The data collection process for monitoring TDS value using a commercially available TDS sensor. The data was extracted from the Grafana dashboard and organized into an Excel spreadsheet for analysis. Measurements were taken every 10 minutes over a span of 100 minutes, providing a comprehensive set of data points in evaluating the water quality accurately. This regular sampling allows for precise tracking of TDS levels, ensuring the reliability and responsiveness of the monitoring system in detecting any fluctuations in water quality. Drinking water is used as a reference for uncontaminated water. Figure 8 provides a comprehensive comparison of TDS levels across drinking water, agricultural wastewater, and fertilizer water that is enriched with nutrients and monitored over time through IoT-AWMS.

In Figure 8(a), the TDS values are compared between drinking water and agricultural wastewater. These samples were observed over a 100-minute interval, and the results reveal stable TDS levels throughout the duration. Agriculture, drainage and subsurface drainage recorded high TDS values with 90 to 140 ppm. Thus, determine the presence of fertilizer in these samples. For the water reservoir pond, the EC value is lower than 40 ppm and is almost like tap water and filtered water parameters. Figure 8(b) shows the TDS value for fertilizer water under different fertilizer concentrations (3 ml, 6 ml, and 9 ml). Drinking water is used as a baseline to differentiate between uncontaminated and contaminated water. From the figure, TDS value for the hydroponics fertilizer and A+B fertilizer is above 200 ppm. The TDS levels in fertilizer water are considerably higher than those observed in drinking water. Notably, TDS values rise with increasing fertilizer concentrations, peaking in the 9 ml hydroponic and 9 ml A+B fertilizer samples. This pattern confirms that the addition of fertilizer significantly elevates the concentration of dissolved solids, with greater amounts of fertilizer leading to proportionally higher TDS levels. This correlation between fertilizer concentration and TDS suggests that TDS measurements can be an effective indicator for monitoring the concentration of dissolved substances in fertilizer water.

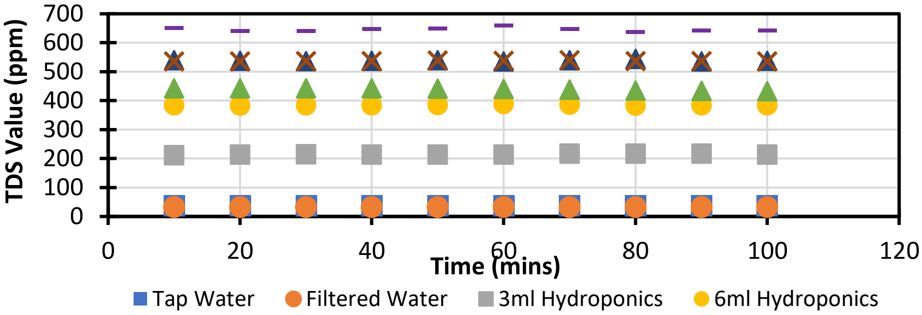
Figure 8(c) shows a summary of the mean TDS levels across all sample types, offering a visual comparison that highlights the differences between uncontaminated and contaminated water. Drinking water exhibits relatively low TDS values, approximately less than 40 ppm. Contaminated water (agricultural wastewater and fertilizer water) has TDS values above 90 ppm. For water reservoir pond at UTeM, the TDS value is identical to the tap water and filtered water. Hence, this water reservoir pond does not contain any fertilizer traces. High EC value exceeding 500 ppm has been obtained from 9 ml hydroponic fertilizer and 9 ml A+B fertilizer, confirming the EC value is proportional to fertilizer concentration. By looking into the average TDS values over all the sample fertilizers, the effectiveness of different TDS values can distinguish between untreated water and water enriched with fertilizer. So, the data demonstrates that as fertilizer concentration increases, so does the TDS value. Confidently making TDS a reliable metric for assessing dissolved solid content, particularly in Agricultural Wastewater and other fertilizer-intensive systems.

4.2. Data collection of water temperature by using DS18B20 sensor

The water temperature used in this work is a commercially available DS18B20 sensor. Figure 9 shows the data collection for water temperature at 100-minute intervals. This overview highlights the relatively uniform temperatures of the drinking water, agricultural wastewater, and fertilizer water samples. The temperature data was extracted from the Grafana dashboard and compiled into an Excel spreadsheet for thorough analysis. This consistent sampling allows for accurate tracking of temperature changes, ensuring the monitoring system can reliably detect and respond to any variations in the environmental conditions. Next, the obtained average water temperature and TDS value is used to determine the EC value.



(a)



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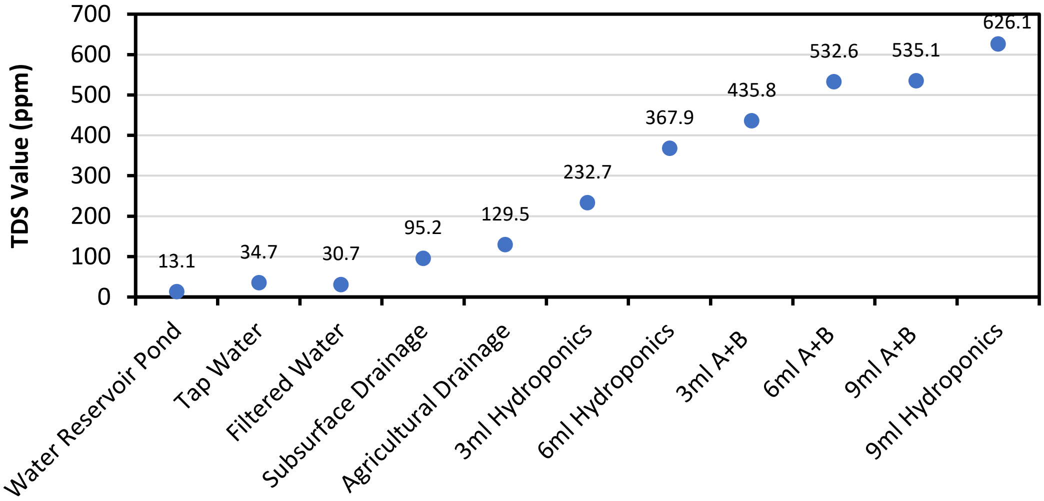

(c)

Figure 8. Performance of TDS sensor; (a) agricultural wastewater, (b) fertilizer water, and (c) average value for various water samples

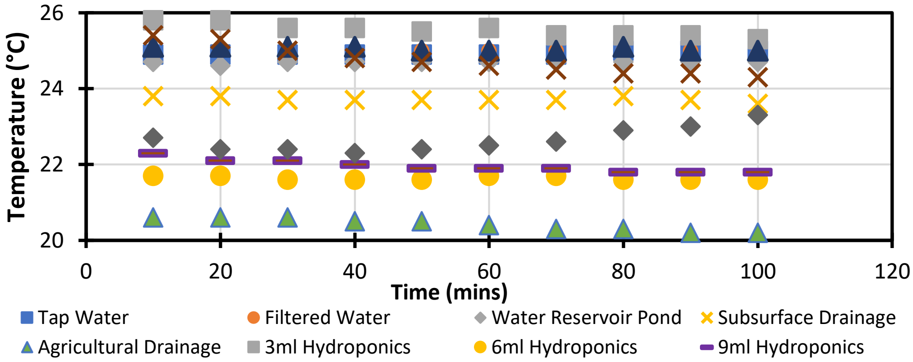

Figure 9. Performance of water temperature using DS18B20 sensor for 100 minutes

4.3. Data collection of electrical conductivity sensor

This section describes the calculation process for determining the EC using collected data. The EC value is calculated using (1):

$$EC = \left(\frac{TDS \times \frac{5}{4095}}{1+0.02 \times (Water\ Temperature - 25)} \right) \times 2.5 \quad (1)$$

TDS values and temperature readings from the DS18B20 sensor are incorporated into (1), which compensates for temperature effects, transforms the raw measurements, and scales the output to provide a precise estimation of EC as an indicator of water quality.

Figure 10 (in Appendix) illustrates the EC values ($mS\ cm^{-1}$) derived from the equation for different water samples in 100-minute duration. Agricultural wastewater and fertilizer water samples are always compared to drinking water to determine the difference between contaminated and uncontaminated water. The water reservoir pond has identical EC values to drinking water (tap water and filtered water), which is under 0.20 $mS\ cm^{-1}$. For agricultural wastewater, Figure 10(a) shows that subsurface drainage and agricultural drainage have high EC values of above 0.45 $mS\ cm^{-1}$ compared to tap water, filtered water, and water reservoir pond. Throughout the monitoring work, the EC values for each type of water remain less varied of data, indicating consistent water quality. Fertilizer water, as depicted in Figure 10(b), has a minimum EC value of 0.70 $mS\ cm^{-1}$, which is above the drinking water EC value. The Fertilizer Water has EC values ranging from 0.7 $mS\ cm^{-1}$ and up to 5.26 $mS\ cm^{-1}$. The concentration of fertilizer affects the EC value reading. For instance, hydroponics fertilizer and A+B fertilizer with 3 ml concentration have a lower EC value compared to 9 ml concentration. Another important observation is 3 ml A+B fertilizer has a near EC value to 9 ml hydroponic fertilizer. This indicates the A+B fertilizer has a strong fertilizer concentration compared to the hydroponic fertilizer.

The average EC value for all samples is shown in Figure 10(c). The uncontaminated water has less than 0.20 $mS\ cm^{-1}$ EC value, and contaminated water has EC value of 0.30 $mS\ cm^{-1}$. At UTeM agricultural site, agricultural wastewater has a higher EC value of 0.41 $mS\ cm^{-1}$ compared to subsurface drainage. Thus, suggesting the presence of more dissolved substances compared to the other samples. This higher EC value is likely due to the exposure of agricultural drainage to fertilizers used in the surrounding agricultural areas, which increases the concentration of dissolved solids in the water, as well as the in-situ measurement temperature. Despite the elevated levels, the stability of the EC values indicates consistent water quality conditions throughout the testing period. Overall, the graph demonstrates the stability of EC values in all samples, highlighting the impact of agricultural activities on water quality, particularly in agricultural drainage.

4.4. Percentage accuracy (%) for EC sensor

This section of the project focuses on assessing the accuracy of the EC values obtained compared to reference values from an EC Hanna device, as shown in Table 2.

Table 2. Percentage accuracy of EC value compared to the calculated value and EC Hanna

Samples		Measured EC ($mS\ cm^{-1}$)	Calculated EC ($mS\ cm^{-1}$)	Standard deviation ($mS\ cm^{-1}$)	Percentage error (%)	Percentage accuracy (%)
Drinking water	Tap water	0.15	0.17	0.002	11.62	88.38
	Filtered water	0.13	0.15	0.004	13.37	86.63
Agriculture wastewater	Water reservoir pond	0.07	0.06	0.002	8.73	91.27
	Subsurface drainage	0.37	0.3	0.01	24.06	75.94
	Agricultural drainage	0.25	0.41	0.027	38.76	61.24
Fertilizer water	3 ml hydroponic	0.83	0.7	0.009	18.11	81.89
	6 ml hydroponic	1.29	1.2	0.036	7.15	92.85
	9 ml hydroponic	1.91	2.03	0.061	6.14	93.86
	3 ml A+B	1.88	1.68	0.05	12.23	87.77
	6 ml A+B	3.42	3.25	0.009	5.29	94.71
	9 ml A+B	4.94	5.25	0.011	5.9	94.1

Initially, the percentage difference of EC values is calculated using (2):

$$Percentage\ Error\ (\%) = \left| \frac{(Average\ value\ of\ calculated\ EC - EC\ Hanna\ value)}{Average\ value\ of\ calculated\ EC} \right| \times 100 \quad (2)$$

This calculation determines how closely the average EC values derived from the project's monitoring system align with those measured by the EC Hanna device. Subsequently, the percent error for accuracy is computed using (3):

$$Percentage\ Accuracy\ (\%) = 100 - Percentage\ Error\ (\%) \quad (3)$$

From Table 2, this percentage error quantifies the accuracy of the project's EC measurements relative to the reference values provided by the EC Hanna device. Analyzing this data provides insights into the reliability and precision of the monitoring system in assessing water EC, essential for ensuring the system's effectiveness in agricultural applications.

For drinking water, the system achieved moderate accuracy, with values of 88.38% and 86.63% for tap and filtered water, respectively, and percentage errors of 11.62% and 13.37%. In agricultural wastewater, water reservoir pond exhibited a higher accuracy of 91.27% with an error of 8.73%, while subsurface drainage and agricultural drainage samples showed reduced accuracy of 75.94% and 61.24%, respectively, accompanied by higher percentage errors of 24.06% and 38.76%. The fertilizer water category demonstrated a progressive increase in accuracy with higher fertilizer concentrations. For instance, 6 ml and 9 ml hydroponic fertilizer yielded accuracies of 92.85% and 93.86%, respectively, with low percentage errors of 7.15% and 6.14%. A combination of A+B fertilizer further highlighted the system's capability, achieving the highest accuracy of 94.10% for 9 ml A+B fertilizer, with a minimal error of 5.90%. These findings validate the system's high reliability, particularly for high-concentration fertilizer, while identifying areas for refinement in more complex or diluted water matrices, such as agricultural drainage.

The lower accuracy observed in agricultural drainage (61.24%) compared to fertilizer water, which is up to 94.1% may be attributed to the presence of non-fertilizer dissolved solids, variable organic content, and temperature fluctuations due to open environmental exposure. These factors introduce inconsistency that affects EC calculations, as compared to controlled fertilizer solutions with predictable ion concentrations. Despite these temperature variations, the majority of the EC values for both systems exceeded the 85% accuracy target. In addition to accuracy, the standard deviation of each sample was analyzed over a 24-hour period. For instance, the 9 ml hydroponic fertilizer sample has a standard deviation of ±0.061 $mS\ cm^{-1}$, reflecting stable and repeatable EC measurements. This outcome underscores the system's integration as accurate and reliable for monitoring EC in varying environmental conditions.

5. CONCLUSION

This study successfully demonstrated an IoT-AWMS, achieving over 85% accuracy in EC estimation across diverse water samples. By integrating Raspberry Pi, Node-RED, InfluxDB, and Grafana with low-cost sensors, the system addresses key limitations in agricultural monitoring, including the absence of continuous insights and delayed response to water quality changes. Importantly, this work addresses current limitations in agricultural monitoring, such as the absence of continuous data insights and delayed response to water quality degradation. The robust integration of hardware and software components enhances automation and decision-making, contributing directly to resource efficiency and environmental protection in agriculture. Advancing this work further, future studies could leverage AI and machine learning to enhance the system’s capability in forecasting water quality variations and proactively detecting irregularities. Furthermore, the modular design ensures scalability, cost-effectiveness, and adaptability, making it suitable for precision farming such as corn farming and broader environmental monitoring. This research contributes a robust framework that can be extended through future work on calibration optimization, wider field validation, and integration into sustainable agricultural water management systems. Despite challenges such as limited plantation knowledge, environmental conditions, and network connectivity, the project overcame these hurdles to deliver a functional and effective monitoring solution. In conclusion, IoT-AWMS not only contributes to the advancement of agricultural technology but also offers a practical solution for improving crop production efficiency and sustainability.

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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

The authors declare no conflict of interest.

DATA AVAILABILITY

Data sets generated during the current study are available from the corresponding author on reasonable request.

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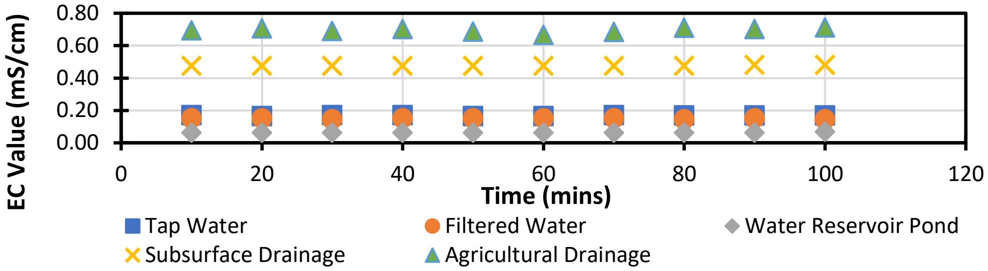
APPENDIX

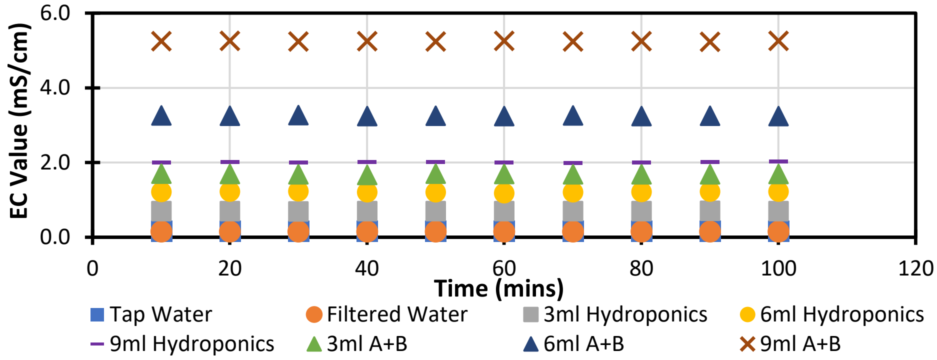
(a) (b)

(c)

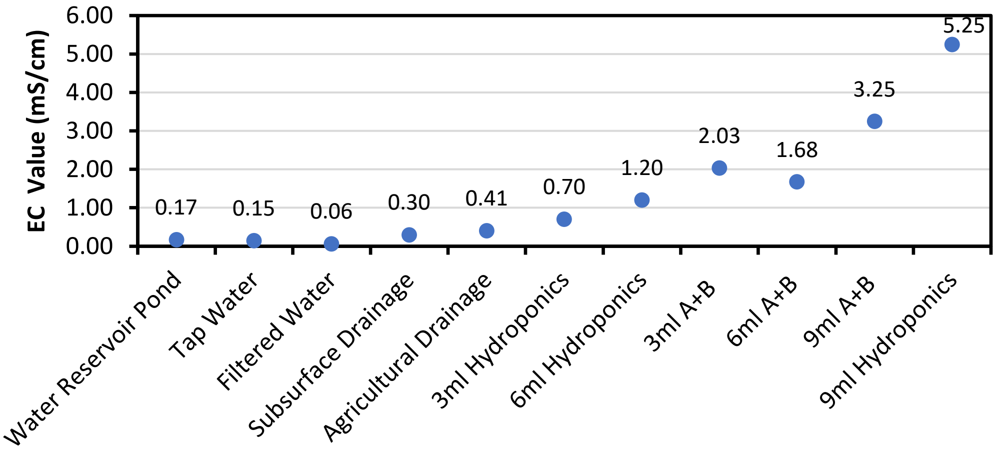
Figure 6. Dashboard displaying data from 9 ml A+B fertilizer stored in InfluxDB; (a) DHT11 sensor, (b) DS18B20 sensor, and (c) TDS sensor



(a)



(b)



(c)

Figure 10. Performance of EC sensor; (a) agriculture wastewater, (b) fertilizer water, and (c) average value for various water samples

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