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Original Research Article

Applicability of Low-Cost Sensors for Monitoring Floodwater pH and Temperature in Rice Fields

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Abstract: Data acquisition is crucial in agriculture for farmers to understand their systems and make informed decisions to improve overall productivity. However, the trade-off between data quality and the cost of technology needs to be addressed. In flooded rice fields, monitoring the floodwater pH and temperature is crucial, as they regulate ammonia emissions to the atmosphere. In this study, the applicability of the DS18B20 and SEN0161-V2 sensors for monitoring the temperature and pH of the floodwater in the rice fields was demonstrated. These sensors were selected as they are compatible with the Arduino microcontroller to develop a low-cost sensor system. Findings from the cumulative 38-day study demonstrated that the DS18B20 sensor is viable for monitoring the floodwater temperature in the rice fields. A high degree of inter-sensor precision, with a Pearson correlation coefficient, r=0.93 was observed during the field experiment. Following field deployment, accuracy verification yielded a mean absolute error (MAE) ranging from 0.95°C to 1.84°C when compared to a reference mercury thermometer. This confirms that the temperature sensors remained functional after prolonged exposure in the fields. Meanwhile, the SEN0161-V2 pH sensor showed poor inter-sensor precision (r=-0.02) and accuracy drift within a 72-hour window and therefore required recalibration each time the power banks were changed in the field. The subsequent post-deployment accuracy verification against the standard pH buffer solutions revealed reduced accuracy in one of the SEN0161-V2 pH sensors. In particular, a higher MAE was observed for pH Sensor 1, particularly in pH buffer 10 (MAE=3.53) compared to pH Sensor 2 (MAE=0.08). The lifespan of SEN0161-V2 was limited to about 24 days when subjected to constant submersion under field conditions. The 10,000 mAh power bank was used to power the system and needed to be charged every three days.

Keywords: Affordable sensor; Arduino; Water quality; DS18B20; SEN0161

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1. Introduction

Data acquisition plays a crucial role in modern agriculture as it enables stakeholders to make informed decisions, optimise resource allocation, reduce adverse impacts on the environment, and improve overall productivity (Karunathilake *et al.*, 2023). In data acquisition, various information about farms, such as soil moisture, temperature, pH, and nutrient levels, is typically collected either manually or by using remote or proximal sensing (Toselli *et al.*, 2023). Proximal sensing can be performed with sensors installed on moving vehicles or fixed sensors (Toselli *et al.*, 2023). The collected data will then be used to apply precision farming techniques, which aim at tailoring specific actions based on the needs of different areas within a farm (Vogel *et al.*, 2021). This action is a step towards Digital Twins in agriculture (Peladarinos *et al.*, 2023). In agriculture, a Digital Twin can be defined as a virtual representation of a physical farm or agricultural system, developed using advanced technologies such as sensors, IoT devices, and cloud computing (Peladarinos *et al.*, 2023). This approach enables farmers to simulate and optimise farming practices in a virtual environment, allowing improvements to be tested and refined before implementation in real-world conditions.

Despite the potential gains, data acquisition in agriculture poses several challenges that need to be addressed for it to be effective. Many agricultural lands are situated in rural regions, which may lack reliable internet connectivity (Yaacoub & Alouini, 2020). The harsh weather conditions in the open fields may damage the instruments (Sinha & Dhanalakshmi, 2021). More importantly, farmers have concerns about the trade-off between data quality, the uncertainty of the return on investment and the cost of technology (Rajak *et al.*, 2023). Advancements in technology have made less expensive instruments available (de Camargo *et al.*, 2023). However, the robustness of the low-cost instruments under harsh field conditions needs to be assessed. Therefore, addressing these challenges in data acquisition is crucial for the successful integration of technology into agriculture, especially in low- to middle-income countries, where farmers in crop sectors such as rice are still dependent on government subsidies due to high production costs (MOF, 2020).

Among the most frequently measured properties in water quality are temperature, pH, dissolved oxygen (DO), and turbidity (de Camargo *et al.*, 2023). In the case of flooded rice fields, monitoring of the floodwater pH and temperature is of interest as these factors regulate the rate of ammonia emissions (volatilisation) to the atmosphere (Zhong *et al.*, 2021). It was estimated that 9 to 45% of the applied total nitrogen (N) was lost to the atmosphere through ammonia volatilisation (Zhong *et al.*, 2021). The volatilised ammonia leads to the formation of particulate matter of less than 2.5 microns (PM2.5), which is known to be hazardous to the human respiratory system (Pommier *et al.*, 2025). The volatilised ammonia also represents monetary loss (Sabrina *et al.*, 2022). Ideally, the measurements of floodwater temperature and pH should be conducted at least at hourly time intervals for the data to be meaningful. This is because the floodwater temperature and pH fluctuate throughout the day, ranging from 19 to 40°C and pH 7 to 10, respectively (Fillery *et al.*, 1984). However, only a few studies reported the floodwater pH and temperature dynamics at hourly time intervals (Fillery *et al.*, 1984), while others reported them at daily time intervals (Liao *et al.*, 2023; Li *et al.*, 2021). This is likely due to the unavailability of affordable sensors for remote and frequent observations. Therefore, the challenge in data acquisition may be addressed through affordable sensor technology.

Relevant articles have been systematically reviewed, suggesting that there are few evaluations of low-cost sensor applicability in different environments (de Camargo *et al.*, 2023). For instance, the work by Huan *et al.*, (2020), who focused on the design of the aquaculture pond water quality monitoring system based on narrow band-IoT, where three sensors, namely the DHT12 temperature sensor, E-201-C pH sensor, and DOS-600 DO sensor, were used. The sensors were verified against the MS5-Hydrolab portable multi-parameter (HASH COMPANY) and showed reasonably good results. Meanwhile, Wu and Khan (2019) implemented four sensors on an unmanned service vehicle, particularly the SEN0169 pH sensor, SEN0189 turbidity sensor, Atlas Scientific DO sensor, and DS18B20 temperature sensor for measurements in a lake environment. The sensors were calibrated, but verification of measurements in the lake was not described. Xavier *et al.* (2022) evaluated the DS18B20 temperature sensor, SEN0189 turbidity sensor, Atlas ENV-50-DO sensor, and SEN0161-V2 pH sensor in both lab and lake environments. The study concluded that the sensors showed accurate results when tested in a controlled environment, but errors increased when tested under natural environmental/field conditions.

Given the limited number of studies on the applicability of low-cost sensors in field environments and the variation of sensors currently available, additional research that

demonstrates the effectiveness of low-cost sensors in different environments offers valuable insights into their applicability. Existing studies were mostly conducted in laboratories or freshwater and aquaculture systems (Xavier *et al.*, 2022; Huan *et al.*, 2020; Wu & Khan, 2019). Therefore, the objective of this study is to demonstrate the application of a low-cost sensor system for monitoring the temperature and pH of the floodwater in the tropical rice fields.

2. Materials and Methods

Arduino is a popular open-source hardware and software platform that has several advantages when it comes to data acquisition. Arduino boards and components are relatively inexpensive, making them accessible to a wide range of users, particularly those with limited budgets. Moreover, a wide range of sensors, modules, and communication protocols is available for users to tailor the data acquisition system to specific needs. In this study, the Arduino board and components were selected because it is accessible to users in terms of cost and easy to use for beginners, yet flexible enough for advanced users. In this study, the Arduino microcontroller is integrated with compatible sensors to monitor the floodwater temperature and pH in the floodwater of rice fields.

2.1. The Sensor and Microcontroller System

The Arduino UNO R3 (Arduino, Italy) was used as a microcontroller board. A shield data logger with DS1307 RTC was attached to the microcontroller board. A formatted micro-SD card (Kingston Technology, China) was inserted into the shield data logger to record all data measurements. The DS1307 was used to timestamp all data with the current time. An analogue pH sensor (Analogue pH meter V2 / SEN0161-V2, DFRobot, China) and a waterproof digital temperature (DS18B20) sensor were connected to the Arduino UNO R3 board. The pH sensor is laboratory-grade and has a working range from pH 0 to 14 with an accuracy of ± 0.1 pH at 25°C. Meanwhile, the accuracy of the temperature sensor is ±0.5°C with a working range from -10°C to +85°C. The temperature probe has a diameter of 0.6 cm and a length of 3cm and is suitable for use in a wet environment. The integrated system was powered by a 10,000 mAh rechargeable power bank (PINENG, Zhongshan Pineng Battery Co Ltd, China). The working temperature is -10°C to 45°C. Programming of the codes was performed using the Arduino IDE software. The total cost of the materials was around USD 75 (RM 358).

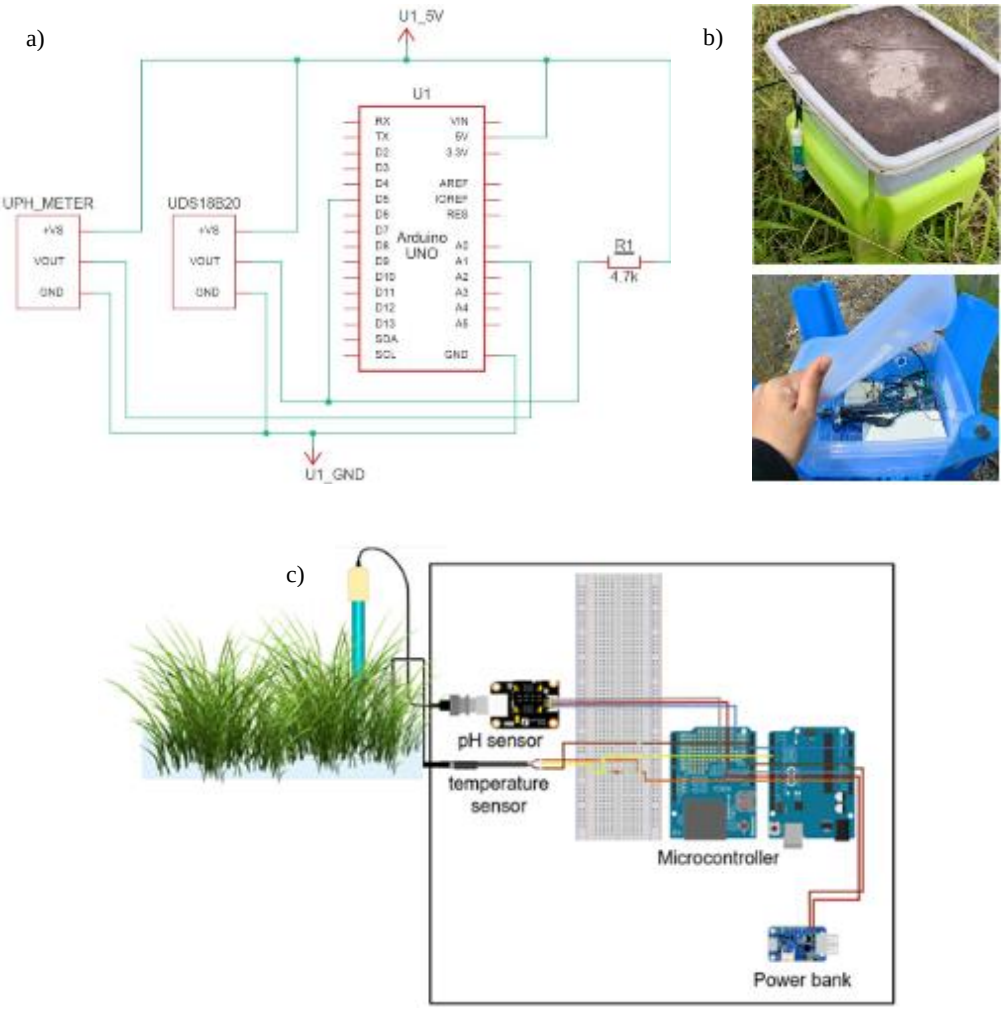


Figure 1. a) Circuit schematic diagram of the Arduino UNO R3 microcontroller connected to the pH (Analogue pH meter V2 DFRobot) and temperature (DS18B20) sensors. The shield data logger (DS1307 RTC) is plugged directly on top of the Arduino UNO R3, which then gives access to the pins. The drawing was produced using Tinkercad. b) Actual set-up in the field. c) Physical system configuration.

2.2. Calibration and Verification of pH and Temperature Sensors

The sensor calibration and verification protocol was executed in three phases to ensure data integrity before, during, and after the field experiment.

Phase 1: Pre-deployment verifications

Prior to the field experiments, the pH sensor was calibrated using the standard buffer solutions of pH 4 and 7 and subsequently verified using a buffer solution of pH 10. The temperature sensor was verified by comparing its observations with measurements made by a mercury thermometer. This initialisation phase confirmed that all sensors met the required baseline accuracy and conformed to the reference values prior to field deployment.

Phase 2: In-situ verifications

During the field experiment (detailed in Section 2.3), the pH sensors were checked for accuracy drift by dipping the sensors into the buffer solutions. It was observed that the accuracy of the pH sensor had drifted after three-day exposure in the field. Therefore, the pH sensors were recalibrated and reverified in the field each time the power banks were changed.

Phase 3: Post-deployment verifications

After the field experiments, sensor accuracy verifications were conducted under laboratory and outdoor conditions at Universiti Putra Malaysia to assess the sensors' performance following prolonged exposure to the harsh conditions of the rice fields. This phase was crucial for identifying the accuracy drift in the pH sensor and confirming that the temperature probes remained within functional tolerances after prolonged environmental exposure. The post-deployment verifications are detailed in Sections 2.2.1 and 2.2.2, respectively.

2.2.1. Laboratory verification of sensors after field deployment

The setup for laboratory verification is shown in Figure 2. A 500 mL beaker was filled with 400 mL of boiled water. Next, the water temperature was measured every 30 min using a mercury thermometer and the sensor systems. The mercury thermometer measurements were taken as reference values. When the water temperature equilibrated with the room temperature and became constant, the beaker was replaced with another beaker filled with boiled water. Meanwhile, the pH probes were submerged in the standard buffer solutions of pH 4 for about 2 days, followed by pH 7 and pH 10 for another 4 consecutive days. Similarly, the pH measurements were made every 30 min.

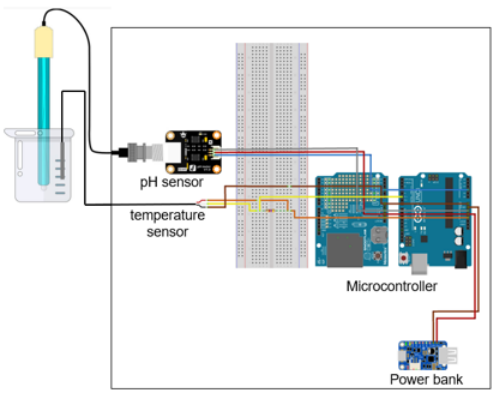


Figure 2. Schematic laboratory verification set-up.

2.2.2. Outdoor verification of sensors after field deployment

Next, the sensor systems were tested outdoors. The temperature and pH sensors were put inside a beaker filled with water at room temperature and placed outdoors. Measurements were conducted for about 1 ½ days. In addition, the temperature inside the microcontroller box and the surrounding air were also measured using a mercury thermometer every 30 min.

2.3. Deployment of the Sensor System in the Rice Fields

The field experiments were conducted at two rice field plots in Malaysia (Figure 3). Plot A was located at Sawah Sempadan, Tanjung Karang (3°27'10.1"N 101°13'44.9" E) from 14th July 2022 to 15th November 2022. The size of the study area was about 0.84 ha. Rice variety MRQ76 was transplanted by the farmer on 14th July 2022 and harvested on 28th October 2022. Meanwhile, Plot B was located at Sungai Besar (3°39'39.3"N 101°01'01.0" E) from 13th March 2023 to 20th June 2023. The size of the study area was about 1.1 ha. Rice variety MR 269 was transplanted by the farmer on 20th March 2023 and harvested on 28th June 2023. Both plots were flooded (5 to 15 cm depth) with water for most of the growing season. A weather station was installed adjacent to the study area to record the precipitation (ECRN-50 Precipitation, METER Group, mm) and surrounding temperature (ATMOS 14 Humidity/Temp/Barometer, METER Group, ºC).

The sensor systems were installed in the rice fields to record the floodwater pH and temperature. For Plot A, measurements were conducted from 1st to 8th August, and 16th to 29th August 2022. Meanwhile, for Plot B, measurements were conducted from 24th March to 4th April, and 7th to 10th April 2023. Measurements were made at a 30-min interval. Initially, only one sensor system (Sensor 1) was placed in Plot A. However, technical issues were observed with Sensor 1, and therefore, another set was added from 26th August onwards (Sensor 2). Based on insights from the initial field experiment, two sensor systems were installed in Plot B for the next field experiment. The power banks were replaced with fully charged power banks every 2 to 3 days.

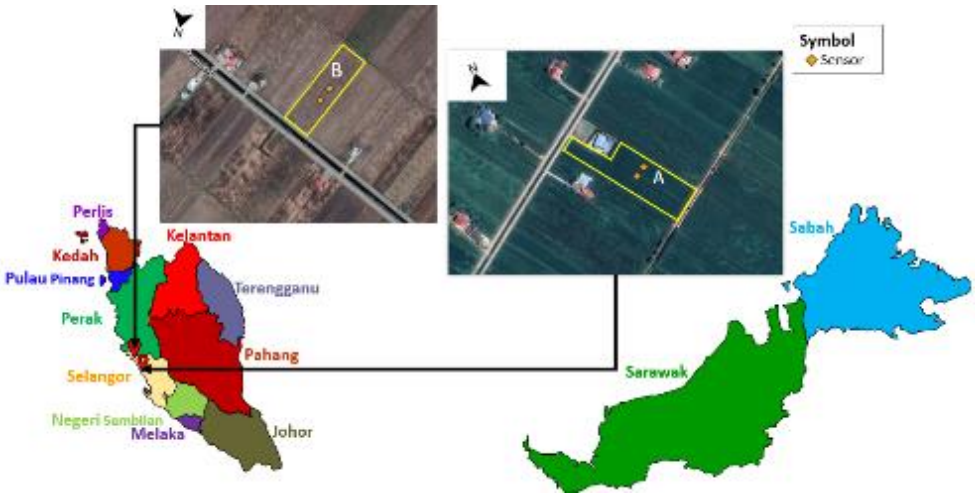


Figure 3. Plot A at Tanjung Karang and Plot B at Sungai Besar.

3. Results and Discussions

This study demonstrated the application of the DS18B20 waterproof temperature sensor and DFRobot SEN0161-V2 pH sensor for water quality monitoring in two rice fields for a total duration of 38 days.

3.1. Surrounding Air Temperature and Precipitation Data in Rice Fields

The air temperature ranged from 21.6 to 33.4°C during field experiments. High temperatures were observed at midday, while low temperatures were observed during the night, with a daily average temperature of 27°C. The total precipitation during the experiments was 264 and 108 mm at Plot A and Plot B, respectively (Figure 4).

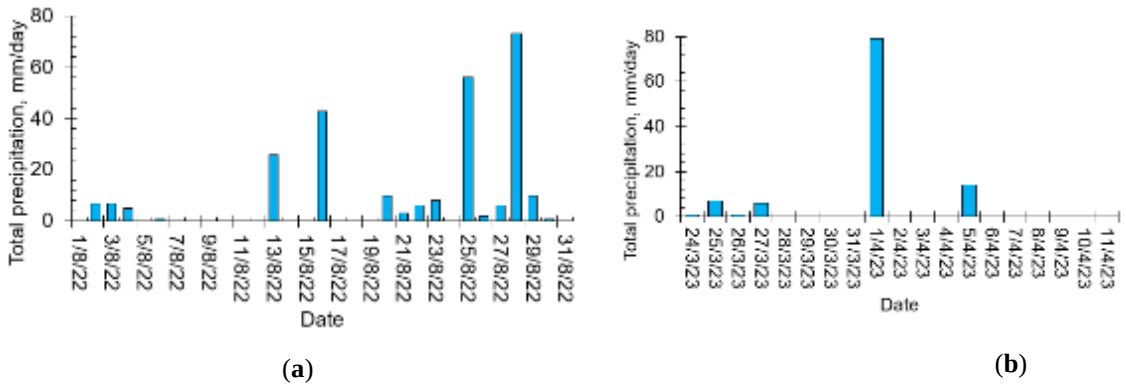


Figure 4. The daily precipitation (mm day^{-1}) at **(a)** Plot A and **(b)** Plot B in Selangor, Malaysia.

3.2. Floodwater Temperature Measurements in Rice Fields

Figure 5 and Figure 6 show the floodwater temperature measured by the sensors at Plot A and Plot B, respectively. Overall, reasonable values and trends were obtained for the floodwater temperature. The floodwater temperature gradually increased at midday due to the increase in ambient temperature and subsequently decreased towards the evening; the cycle repeats each day. The differences between the surrounding air temperature and the floodwater temperature are represented by the dashed line, where a negative value indicates greater floodwater temperature than the air temperature. Recurring differences in the magnitudes of +5°C were observed between the floodwater temperature and air temperature only around mid-day, speculated due to different specific heat capacities of water versus air. Water heats up slowly and holds that heat longer, especially on sunny days with little wind.

Nonetheless, unrealistic values were observed for some of the floodwater temperature readings by Sensor 2 (85°C and -127°C), for instance, from 24th to 27th March, 31st March to 3rd April and 7th to 10th April 2023 at Plot B (Figure 6). The 85°C value is the default value stored in the sensor's internal memory when it first powers up, suggesting a delay in value conversion. Meanwhile, the -127°C values indicate signal loss and were observed to coincide directly with the initial precipitation events at both Plot A and Plot B (Figure 4 vs. Figures 5 and 6). Except for these erroneous values, small differences were observed between the temperature readings measured by Sensor 1 and Sensor 2. After filtering out extreme outliers 85°C and -127°C, comparison between the two sensors demonstrated a high degree of linear consistency (inter-sensor precision) with a Pearson correlation coefficient, $r = 0.93$. The mean absolute error (MAE) was 1.01°C, further reflecting a small difference between the two sensors. The outliers 85°C and -127°C were excluded to ensure that the statistical analysis reflects the sensing inter-sensor precision of the devices during functional periods, rather than being skewed by temporary communication errors.

In addition, the floodwater temperatures ranged from 24.2 to 41.3°C at both plots, which was about the range reported for the tropical rice fields in the Philippines, i.e., 19 to 40°C (Fillery *et al.*, 1984). Meanwhile, the missing temperature readings were due to a drained power bank. Initially, the fully charged power bank lasted up to 3 days, but over time, the charging capacity of the power bank was reduced to two days and eventually one day after prolonged exposure to the hot weather environment.

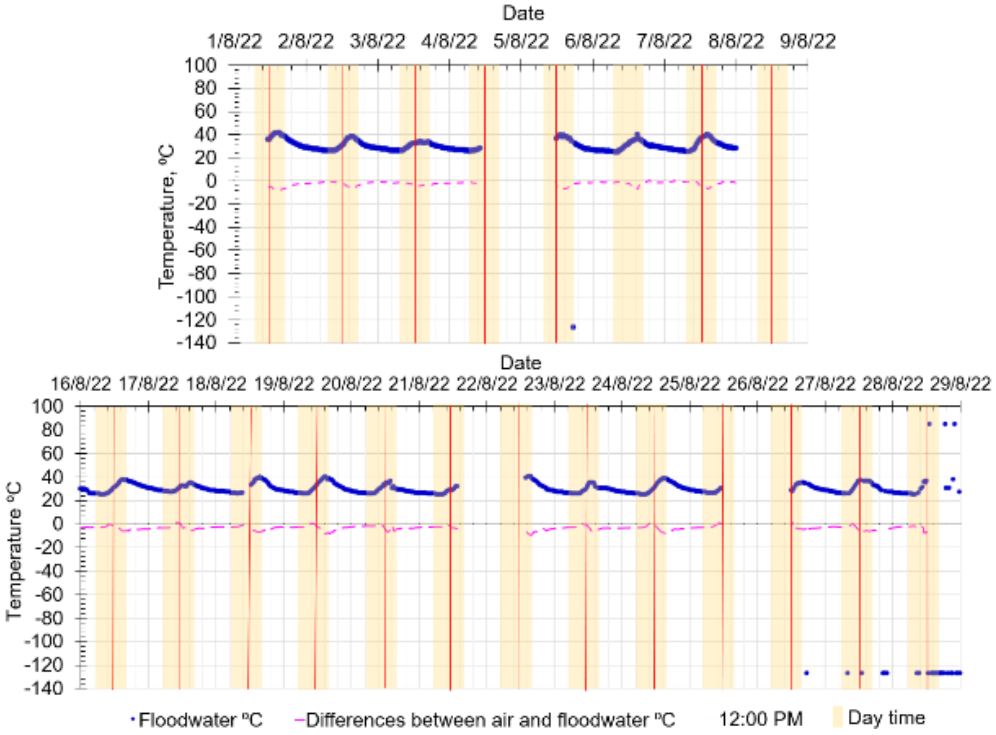


Figure 5. Floodwater temperature measured by the sensors and the surrounding air temperature at Plot A. The red vertical lines indicate 12.00 hrs (mid-day). The orange background indicates the daytime range from 8.00 to 18.00 hrs.

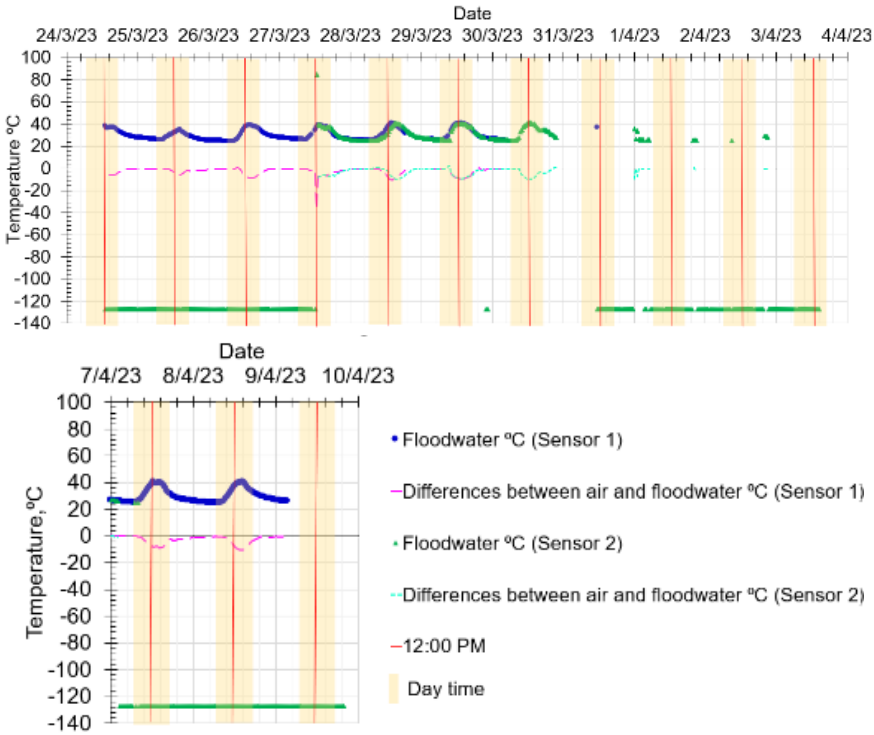
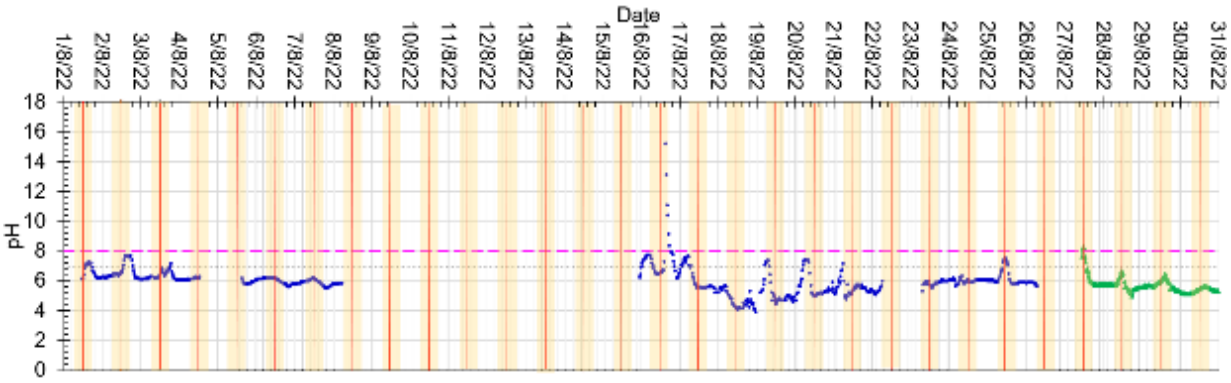


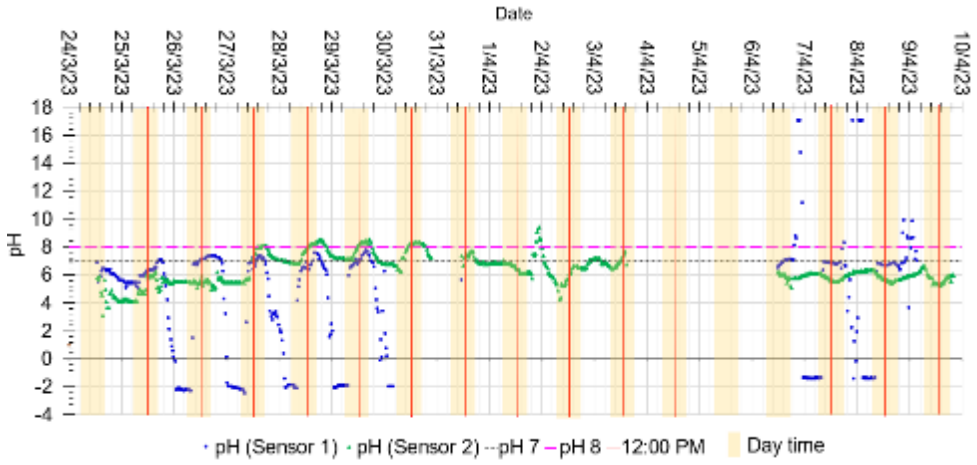
Figure 6. Floodwater temperature measured by the sensors and the surrounding air temperature at Plot B. The red vertical lines indicate 12.00 hrs. The orange background indicates the daytime range from about 8.00 to 18.00 hrs.

3.3. Floodwater pH Measurements in Rice Fields

Figure 7 shows the floodwater pH measured by the DFRobot SEN0161-V2 pH sensors at Plot A and Plot B. Sinusoidal trends were observed for the floodwater pH as reported in Fillery *et al.* (1984). The missing floodwater pH readings were also due to a drained power bank. At Plot A, the floodwater pH ranged from 3.12 to 15.68 and typically peaked after midday. Meanwhile, two sensors were installed at Plot B, and striking discrepancies in pH readings between the two sensors were observed. For instance, from 26th to 31st March 2023, the values recorded by Sensor 1 ranged from pH -2 to 7, but those observed by Sensor 2 ranged from pH 4 to 8.5. Unexpected values of floodwater pH (pH < 3 and pH > 14) were observed by Sensor 1, but not by Sensor 2. Unrealistic negative pH values were also observed by Sensor 1 at Plot B. Visual comparison revealed that most of the erroneous pH readings by Sensor 1 coincided with the erroneous temperature readings by Sensor 2 (Figure 6) and the occurrence of precipitation (Figure 4). The Pearson correlation coefficient between the two pH sensors was -0.02, which suggests very low inter-sensor precision. During the field experiment, the pH sensors were periodically checked for drift by dipping the sensor into the buffer solutions. It was observed that the accuracy of the pH sensor had drifted after about three-day exposure in the fields. Therefore, the pH sensors were calibrated each time the power banks were changed.



(a)



(b)

Figure 7. Floodwater pH measured by the sensors at **(a)** Plot A and **(b)** Plot B. The horizontal lines indicate neutral pH 7, and the orange background indicates a time range from about 8.00 to 18.00 hrs (day time).

3.4. Verification of Temperature Sensor After the Field Experiments and Comparative Analysis

Sensor 1 and Sensor 2 were exposed to harsh rice field environments for about 38 and 22 days, respectively. Following that, verification of the temperature and pH sensors was conducted to gain insights into the causes of erroneous readings during the field experiments and to check the sensors' accuracy after the field experiments.

It is observed that the water temperature readings measured using Sensor 1 and Sensor 2 closely followed the measurements using a mercury thermometer (Figure 8). The MAE for Sensor 1 and Sensor 2 in comparison with the thermometer readings were only 0.95°C and 1.16°C, respectively. The MBE for Sensor 1 and Sensor 2 were 0.54°C and -0.14°C, respectively. A bias of only 0.54°C is well within the manufacturer's tolerance of 0.50°C, suggesting the sensors are in good condition. The data suggest that both temperature sensors were very closely aligned with the true temperature of the water throughout the experiment. Results suggest that the sensors remained fully functional after the 38-day field experiment. It is further deduced that the erroneous temperature readings by Sensor 1 and Sensor 2 observed in the fields were not caused by the temperature sensor probes.

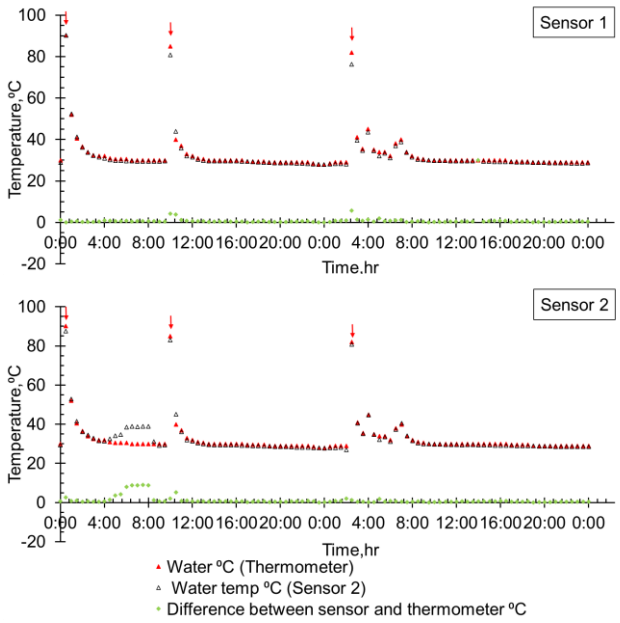


Figure 8. Laboratory verification of the temperature and pH sensors after long exposure duration in the fields. The red arrows indicate the transfer of boiled water poured into the beaker.

For further insights, the temperature sensors were also verified under outdoor conditions after the field experiments (Figure 9). The fluctuating water temperature was influenced by the surrounding air temperature as the depth of the water was shallow at about 10 cm. Except between 18:00 and 8:00 h, the water temperature readings measured using Sensor 1 and Sensor 2 closely followed the readings obtained using the mercury thermometer. By excluding the erroneous values (i.e., 85°C), the MAE for Sensor 1 and Sensor 2 in comparison with the thermometer readings were 1.59°C and 1.84°C, respectively. The MAE for both sensors increased slightly under outdoor conditions compared to the laboratory environment, suggesting the accuracy of the temperature sensors was slightly reduced outdoors. Nonetheless, the accuracy was still satisfactory for the specific application. Meanwhile, the MBE for Sensor 1 and Sensor 2 were 1.45°C and 1.67°C, respectively. The erroneous readings (85°C) were observed immediately after rain occurred for Sensor 2 at 17:00 h on the first day. The consistent 85°C value is the power-on reset value of the temperature register and occurs if a read operation is attempted before the initial conversion is complete. The connection was restored without intervention at 8:00 h the next day. Meanwhile, missing temperature readings for Sensor 1 from 17:00 to 8:00 h were due to a drained power bank. The power bank was replaced at 8:00 h on the following day. Figure 6 shows that erroneous floodwater temperature readings at Plot B occurred on 24th–27th March, 29th March, and 31st March–3rd April 2023, while Figure 4b shows that precipitation events were recorded on 24th–27th March, 1st and 5th April 2023. This temporal overlap suggests a

possible association between rainfall events and sensor errors. While a direct causal link was not established through controlled testing, the temporal coincidence of sensor errors with rainfall events suggests that environmental moisture likely affected the stability of the electrical connections, leading to the observed signal loss and reset values.

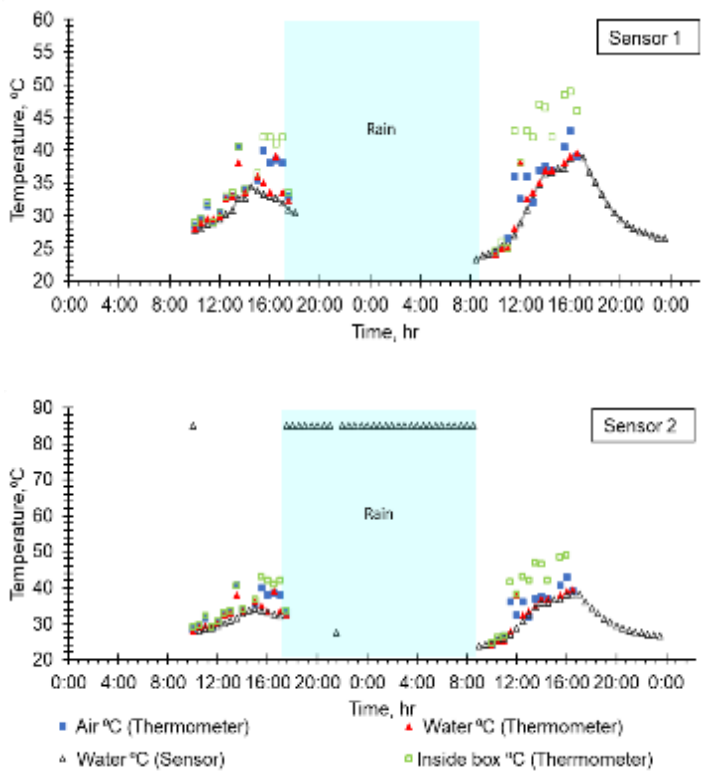


Figure 9. Outdoor verification. The temperature and pH of water measured by the sensors, and the temperature of air outside and inside the microcontroller housing. The blue background indicates the occurrence of rain.

It is further observed that the temperatures inside the microcontroller boxes were higher than the surrounding air temperature by up to 10°C around midday. The increase in internal housing temperature (Figure 9) suggests that thermal stress may have impacted the power bank efficiency and induced the sensor drift, reinforcing the need for passive ventilation or reflective shielding to maintain both sensor accuracy and power bank longevity.

3.5. Verification of pH Sensor After the Field Experiments and Comparative Analysis

Except for readings of Sensor 1 in pH buffer 10, all other pH readings measured using Sensor 1 and Sensor 2 closely followed the standard buffer solutions of pH 4, 7 and 10 (Figure 10). The MAE for Sensor 1 in comparison with pH 4, pH 7 and pH 10 buffer solutions were 0.89, 0.37 and 3.53, respectively. Meanwhile, the MAE for Sensor 2 compared to pH 4, pH 7, and pH 10 were 0.08, 0.39 and 0.08, respectively. The lower MAEs for Sensor 2 compared

to Sensor 1 suggest that the pH probe of Sensor 2 had good accuracy at the end of the field experiment. Sensor 1 was used sequentially for both Plot A and Plot B experiments, and this prolonged exposure led to sensor degradation and an inability to observe pH values above 10. This explains the discrepancies between the floodwater pH measured by Sensor 1 and Sensor 2 at Plot B.

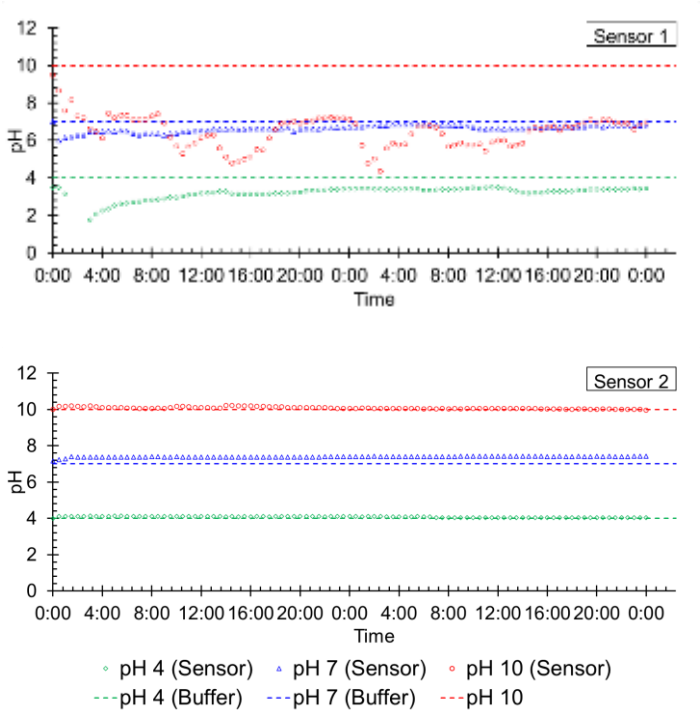


Figure 10. Verification of the SEN0161-V2 pH sensors after long exposure duration in the fields.

Many studies used either the SEN0161, SEN0161-V2 or SEN0169 pH sensor for low-cost sensor systems, but verification of these sensors' readings against reference equipment or standard buffer solutions during or after experiments was not reported (Morales *et al.*, 2023; Tolentino, 2021; Wu & Khan, 2019). Adriman *et al.*, (2022) evaluated a low-cost pH sensor that is compatible with ESP32 under six pH treatments with three replicates in a laboratory experiment and found a low average error of 3.15%, but the model of the pH sensor was not mentioned, and the experiment was not long-term. In contrast to our field experiments, a quick inspection by dipping the DFRobot SEN0161-V2 pH sensor into the buffer solutions showed that the accuracy of the pH sensor had drifted after a three-day exposure in the field. Sensor drift is a time-varying offset, which means that the sensor performance deviates from the original calibration formula (Li *et al.*, 2020). As a quick solution, the pH sensors were recalibrated each time the power bank was changed during the field experiments. The use of power banks in this case may have led to accuracy drift due to unstable voltage, drained power supply, or heat from sun radiation when placed in the open

rice fields. The need for recalibration was briefly mentioned in Bórquez López *et al.* (2020). Algorithms are being developed to overcome the drift in calibrated sensors (Goparaju *et al.*, 2021).

It was observed that Sensor 1 provided reasonable pH values at Plot A when compared to the data in Fillery *et al.* (1984), but the sensor's reliability had been reduced at Plot B, where unrealistic negative pH values were observed (Figure 7). Subsequently, the laboratory verification confirms that the lifespan of the pH Sensor 1 had been reduced (Figure 10). Interpreting these observations in tandem suggests that the SEN0161-V2 pH sensor may be viable only for 24 days when subjected to constant submersion under field conditions. In contrast, Lin *et al.* (2021) reported no increase in the accuracy drift for the SEN0161-V2 pH sensor after 20 consecutive days of on-site monitoring activity when compared with the reference pH 6.86 buffer solution. However, the power source for their system was not described. The contradictory findings suggest that further investigation is needed to evaluate the viability of the SEN0161-V2 pH sensor for long-term monitoring

3.6. Synthesis of Findings

While a true reference value was not continuously available in the fields, comparing Sensor 1 against Sensor 2 allowed quantification of consistency and reliability of sensors (Sections 3.2 and 3.3). Subsequently, the sensors' accuracy after prolonged exposure in the fields was assessed by comparing the sensor outputs against known standards (pH buffers and a mercury thermometer) (Sections 3.4 and 3.5).

For the field deployment, the high Pearson correlation (r = 0.93) between the two DS18B20 temperature sensors suggests that the sensors consistently tracked the same environmental trends with minimal noise. The subsequent post-deployment accuracy verification against a mercury thermometer in the laboratory experiment showed that the MAEs were 0.95°C and 1.16°C for each sensor, confirming that the temperature sensors remained highly reliable after prolonged exposure (Section 3.4). A slight increase in the MAE (1.59°C and 1.84°C) were observed when the sensors were verified outdoors. The MAE were not far off from the DS18B20 manufacturer's specified tolerance of ±0.5°C, indicating that temperature data quality obtained from the low-cost system was still satisfactory for agricultural system monitoring. Our results corroborate the findings of Méndez-Barroso *et al.* (2020), who compared the DS18B20 temperature sensor with a scientific-grade multiparameter probe (YSI-EXO3) in a tidal channel for 45 days and found a high Pearson correlation for the DS18B20 sensor (r=0.91). Lin *et al.* (2021) assessed the accuracy drift for

the DS18B20 sensor after a 20-day on-site monitoring process and found only a slight increase in the error metrics (i.e., a 3% increase in the RMSE) when compared with the reference HEL-711 RTD. Collectively, these data suggest that the DS18B20 is a reliable, cost-effective candidate for monitoring in tropical rice field ecosystems under short-term deployment.

In contrast, the Pearson correlation between the two SEN0161-V2 pH sensors for the field deployment was low (r=-0.02), suggesting poor inter-sensor precision and reliability. The low correlation may be due to different conditions of the two sensors; Sensor 2 was newly added at Plot B (22 days of exposure), while Sensor 1 had been exposed at Plot A before Plot B (38 days of exposure). The subsequent post-deployment accuracy verification against the standard pH buffer solutions revealed reduced accuracy in pH sensor 1 in comparison with Sensor 2. A higher MAE was observed for pH Sensor 1, particularly in pH buffer 10 (MAE=3.53) compared to Sensor 2 (MAE=0.08). Details in Section 3.5. The reduced accuracy after prolonged exposure and accuracy drift observed within the 72-h window and the low inter-sensor precision observed during the field experiment, suggest that the reliability of the pH sensor probes is influenced by the cumulative exposure time.

The interest in low-cost sensors for monitoring agricultural systems has gained traction as they may enable high temporal-resolution data collection in settings where cost of equipment is a primary barrier. While the limited number of spatial replicates may constrain the generalisability of these findings, this pilot deployment study provides a necessary baseline knowledge on the reliability of DS18B20 and SEN0161-V2 sensors in a tropical paddy environment. Overall, results showed that while the temperature sensors remained reliable, the pH sensors reached an operational limit after prolonged exposure.

3.7. Comparative Performance of the Portable Power Bank

In this study, the rechargeable power banks were used to power the low-cost sensor system due to the power bank’s compact size for ease of transportation and installation in remote rice fields. The sensor system was powered by a 10,000 mAh rechargeable power bank and included an Arduino UNO R3 microcontroller, two sensors, a DS1307 RTC and an SD card. The system logs data every 30 min, and the power bank can keep the sensor system running for up to three days. It was then observed that the power bank's capacity gradually declined over time, reducing its duration to two days and eventually one day. It was suspected that the LED battery percentage display and blinking light on the power banks may increase power consumption. The running duration of the power systems used by Shete *et al.* (2024)

and Hawari and Hazwan (2022) were comparable to that of the system in our study. Shete *et al.* (2024) report that their battery (backup) power system lasted up to 2 days with a 15-min resolution. This system included the ATmega328 microcontroller and three sensors. Hawari & Hazwan (2022) reported that their system, which was powered by a monocrystalline solar panel and the energy generated by the solar panel (12V and 30Wp) was stored in five lead-acid batteries (60,000 mAh), can last up to 3 or 4 days. This system included the Orange Pi and Arduino microcontroller and three sensors. In contrast, Méndez-Barroso *et al.* (2020) used three 3.7 V, 10,000 mAh rechargeable LiPo batteries connected in parallel to power their low-cost sensor system and reported the potential for 33 days of continuous data monitoring with 1-h resolution. Their power system included a Sparkfun PRT-10255 LiPower boost converter that was used as a boost regulator to increase the voltage from 3.7 to 5 V. While Méndez-Barroso's LiPo setup lasted 33 days, the use of a power bank system prioritised portability and plug-and-play deployment for users who may not be able to wire up complex LiPo boost converters.

4. Conclusions

This study provides valuable insights into the applicability of the low-cost DS18B20 temperature sensor and SEN0161-V2 pH sensor for field-based monitoring under short-term deployment. Findings from the cumulative 38-day study demonstrated that the DS18B20 sensor was viable for monitoring the floodwater temperature, provided that potential mechanical connection issues are mitigated via soldered joints. Meanwhile, the SEN0161-V2 pH sensor showed accuracy drift within a 72-hour window and required recalibration. In addition, the lifespan of SEN0161-V2 was limited to about 24 days when subjected to constant submersion under field conditions. A single power bank charge supported continuous data logging for 72 h. The power bank's capacity gradually declined over time, reducing its duration to two days and eventually one day. The replacement interval is a known constraint, but the approach represents a strategic trade-off to maintain the low-cost system and ease of maintenance for end-users.

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