Portable LoRaWAN-Based Real-Time Drinking Water Quality Monitoring System for Public Spaces

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Declaration of Authorship:

I, Wenhao Yang, confirm that the work presented in this assessment is my own and that all sources have been acknowledged.

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Abstract

Access to safe drinking water remains a global issue, with approximately 2 billion people relying on contaminated drinking water sources according to the World Health Organization. Public drinking facilities, such as water fountains in universities, parks, and commercial spaces, often lack real-time water quality assessment, instead, relying heavily on periodic laboratory testing which is time-consuming and may not detect contamination immediately.

Studies have shown that Internet of Things (IoT) technologies have the potential to offer continuous and automated surveillance that would improve the safety of the overall health of the public. Due to the widespread distribution of public drinking facilities, the deployment of drinking water monitoring devices is hard to achieve comprehensive coverage as this device are usually fixed and expensive.

This paper presents an innovative portable monitoring system integrating multiple sensors (pH, turbidity, electrical conductivity, temperature) with LoRaWAN communication to The Things Network (TTN). The low-cost IoT device features multi-level user interaction through LED indicators, e-paper display, and web dashboard, providing immediate water quality assessment based on WHO standards and categorizing safety as "Excellent", "Marginal", "Unsafe". The effectiveness of the system has been demonstrated in the field testing across UCL East area drinking points with successful testing results gained for public space implementation.

Acknowledgements

I would like to express my gratitude to my supervisor, Martin de Jode, for his constant inspiration and assistance throughout this process. His invaluable design advice, encouragement, detailed guidance in providing appropriate equipment, and comprehensive thesis supervision have been instrumental in the successful completion of this project.

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1. Introduction

1.1 Research Background

In the United Kingdom, drinking water quality is generally maintained at a high standard, with public water supply systems achieving a compliance rate of over 99.98%(Drinking Water Inspectorate, 2024). However, challenges exist, particularly with public drinking facilities such as water fountains and taps, which can pose health risks if not properly maintained.

Research indicates that inadequate cleaning can lead to bacterial contamination in these facilities, especially in high-traffic areas like schools, parks, and train stations (The Guardian, 2018). Additionally, aging infrastructure, such as lead pipes in older buildings, contributes to localised contamination risks, with lead compliance rates slightly lower at 99.6%(Drinking Water Inspectorate, 2024). Recent concerns have also emerged regarding the presence of per- and polyfluoroalkyl substances (PFAS), or "forever chemicals," in some English drinking water sources, prompting calls for stricter regulations(*The Guardian*, 2025).These issues highlight the need for enhanced monitoring to ensure public water safety.

Public drinking fountains, as the main source for providing drinking water in the public place, face significant safety concerns due to potential contamination. Studies indicate that water fountains can harbour bacteria, and the bacterial colony counts in public drinking fountains can be alarmingly high, particularly in high-traffic areas like airports and shopping malls(Bichelman, 2024). For instance, a 2018 investigation found that some public fountains in London had disappeared due to poor maintenance and concern about health risks(*The Guardian*, 2018).

To solve the potential contamination problem of public facilities, water quality testing is essential for the public health. Traditional laboratory-based water quality testing, while essential, has notable limitations. This approach has several drawbacks, including the high cost of labour and equipment, along with a lack of real-time information about drinking water quality that can facilitate critical decisions to ensure public safety(Vijayakumar and Ramya, 2015). Moreover, periodic sampling fails to capture real-time fluctuations in water quality, limiting the ability to respond promptly to contamination events(Zainurin *et al.*, 2022). These limitations underscore the need for more real-time monitoring solutions in public spaces.

This research aims to design and build a real-time water quality tester for public drinking facilities through the communication of LoRaWAN with multi-parameter sensors. The system shows water quality results via LED indicators and an e-paper display for immediate feedback, alongside a web-based dashboard for detailed visualization of water quality parameters. Public drinking fountains in the areas near UCL East Marshgate were selected as the study area for this research. The project will generate a dataset accessible in the project repository, with the assumption that the information presented on the web dashboard may benefit stakeholders, including local authorities and future water quality studies.

1.2 Research Questions and Objectives

1. Can a portable, low-cost, drinking water monitoring device be developed to provide the public with immediate water quality safety information in urban areas such as the UCL East Marshgate?

2. What are the water quality differences between different public drinking facilities, such as university campus and commercial places, and can portable monitoring effectively characterise these variations?

The objective of the project is to design and implement a portable, low-cost drinking water quality monitoring system utilising LoRaWAN technology, alongside an interactive web platform, to actively monitor and improve public awareness of water quality safety at public drinking facilities near UCL East area.

1.3 Structure of the Dissertation

This dissertation is structured into six chapters, beginning with an Introduction that outlines the research context and objectives. After the Introduction, a critical review of literature on water quality monitoring and IoT-based sensor systems is presented (Chapter 2), followed by a detailed design and implementation of the portable drinking water monitoring system (Chapter 3), The collected data and experimental results are presented in Chapter 4, with Chapter 5 discussing key findings, limitations, and reflections, while Chapter 6 concluding this project while identifying possible future research opportunities.

2. Literature Review

2.1 Water Quality Monitoring Methods: Evolution and Comparison

Drinking water quality monitoring is critical for safeguarding public health and ensuring sustainable water resources. Since the late 20th century, drinking water quality monitoring has evolved significantly, transitioning from reliance on traditional laboratory testing to advanced, real-time technologies. Traditional methods, involving chemical and biological analyses, offer high precision but are time-consuming and costly (Vijayakumar and Ramya, 2015). The advent of electronic sensors enabled rapid measurement of parameters like pH, turbidity, residual chlorine, and dissolved oxygen, improving response times and data accuracy(Badger Meter, 2023). In the 21st century, IoT technologies, leveraging low-power, long-range communication protocols such as LoRaWAN and GSM, have transformed monitoring by enabling smart sensors to transmit real-time data to cloud platforms, suitable for both urban and remote settings(Zainurin *et al.*, 2022). Remote sensing technologies, including satellites and drones, have emerged as powerful tools for large-scale water quality assessment, offering broad spatial coverage despite limitations in parameter specificity (Li et al., 2021). Optical and spectroscopic methods, such as ultraviolet-visible spectroscopy (UV-Vis) and fluorescence spectroscopy, offer non-invasive, rapid detection of turbidity, dissolved organic matter, and microbial contaminants, minimizing chemical reagent use (Jiang and Meng, 2015). The integration of artificial intelligence (AI) and machine learning (ML) has further enhanced monitoring capabilities by enabling predictive analytics and anomaly detection. These technologies analyse large datasets to identify potential contamination risks before they escalate, improving proactive management(Zainurin *et al.*, 2022). These advancements collectively underscore a shift toward scalable, efficient systems prioritizing real-time data and public safety.

To comprehensively evaluate current drinking water quality monitoring strategies, the following table compares five primary methods based on their advantages and disadvantages.

Table 1. Summary of water quality monitoring approaches

Monitoring Method	Pros	Cons
Traditional Laboratory	High accuracy	Time-consuming, manual, high cost, less effective for continuous

Testing		monitoring (Vijayakumar and Ramya, 2015)
On-Site Sensors	• Real-time data collection • monitors multiple parameters, • cost-effective(Badger Meter, 2023)	• Requires regular calibration and maintenance • accuracy may degrade over time • limited to specific parameters • needs power supply(Zainurin *et al.*, 2022)
IoT Monitoring Systems	• Real-time wireless data transmission and quick alert • cost-effective in long-term	• Reliant on network coverage • potential cybersecurity risks • high initial investment(Fields, no date)
Remote Sensing	Large-scale and real-time monitoring and non-contact	• Limited parameter(turbidity and algae) measurement(NASA, 2023) • affected by weather and resolution, • high application cost(Yang *et al.*, 2022)
Optical/Spectroscopic Methods	• High sensitivity and rapid • reagent-free detection of turbidity and organic matter • real-time monitoring(Thomas, Delpla and Thomas, 2017)	• Requires calibration • susceptible to interference • high equipment costs(Hossain *et al.*, 2020)

2.2 Related Work

Recent research has demonstrated the technical feasibility of portable water quality monitoring. Kelechi et al. (2021) developed portable systems integrating temperature, pH, and turbidity sensors with microcontroller processing and Bluetooth connectivity for Android applications, achieving high measurement accuracy (97-100%) while demonstrating cost-effective monitoring capabilities for the community but suffering from limited communication range(Hilary Kelechi *et al.*, 2021). The WaterScope platform by Bedell et al. (2024) further validated this approach through extensive laboratory and field testing. Through the introduction of open-source portable testing with machine learning-enhanced classification technology, it can establish equivalent measurement with conventional laboratory methods(Dabrowska *et al.*, 2024).

Most existing portable monitoring research focuses on natural water environments such as rivers and lakes. Liu et al. (2018) developed a solar-powered LoRaWAN system achieving stable data transmission every 30 minutes with minimal data loss, though their focus remained on controlled water bodies rather than public drinking facilities(Liu *et al.*, 2018). Pires et al. (2024) implemented practical river monitoring solutions measuring temperature, pH, conductivity, and turbidity with real-time LoRaWAN transmission, achieving average RSSI of -94 dBm and SNR of 7.33 dB during 4-hour field deployments(Pires and Gomes, 2024). (Jabbar *et al.*, 2024). Demetillo et al. (2019) deployed buoy-based systems for large aquatic area monitoring that maintained stability even under extreme weather conditions, including tropical cyclones with 95 km/h winds. (Demetillo, Japitana and Taboada, 2019).

Limited research has addressed portable monitoring specifically for public drinking facilities. Kelechi et al. (2021) developed portable systems with Bluetooth connectivity for community monitoring, but their approach suffered from limited communication range requiring manual data collection, making it unsuitable for distributed public facility monitoring.(Hilary Kelechi *et al.*, 2021). Miao et al. (2022) implemented campus-wide monitoring systems using LoRaWAN for both air and water quality, noting cost-effectiveness and scalability potential, though their work lacked detailed accuracy validation and focused primarily on environmental monitoring rather than public drinking safety assessment(Miao *et al.*, 2022).

Critical Research Gap: Existing portable water quality monitoring research focuses primarily on natural water bodies or laboratory conditions, with limited investigation of public drinking facilities. This gap represents a missed opportunity for the public to understand drinking water quality variations across different facility types, such as in the shopping mall and university campus, which could be valuable information for public health.

3. Methodology

3.1 System Overview

This section provides an overview of the portable water quality monitoring system architecture and its operational workflow. The hardware system comprises four main components: a multi-parameter sensor system for water quality measurement, an Arduino MKR WAN 1310 microcontroller with integrated LoRaWAN connectivity, a dual-feedback user interface with LED indicators and ePaper display. In terms of the software system, a database is used for data storage and Web platform to visualise water quality information and histories.

The main objectives of this research were to measure water quality parameters, provide immediate user feedback, and transmit data for longitudinal analysis. To achieve these goals, a portable device was developed that integrates four water quality sensors (pH, EC, turbidity, temperature) with Arduino MKR WAN 1310. The device was programmed to provide instant visual feedback through tri-colour LED indicators and ePaper display, while simultaneously transmitting data via LoRaWAN to The Things Network (TTN) gateway. Following this, a configured webhook handler processes the data from TTN and stores it in a Neon PostgreSQL database, while a Next.js web application was developed to provide historical data visualization and water source tracking capabilities.

The documentation of this research, which includes sensor calibration procedures, hardware schematics, embedded software code, web application source code, and deployment guidelines, can be accessed through the project repository at GitHub. The Appendix A presents a bill table for the component list.

3.2 Sensors and Calibration

Four sensors were used to measure key water quality parameters: pH, electrical conductivity, turbidity, and temperature. Some of these sensors need to be calibrated before testing.

DS18B20 Temperature Sensor

The DS18B20(Figure 1) is a low-cost, robust digital temperature sensor which operates underwater with ±0.5°C accuracy. This waterproof sensor was chosen due to its reliability, direct digital output compatibility with Arduino platforms, and elimination of analogue-to-digital conversion errors. No calibration was required for this sensor, and it can provide temperature data for water quality and enable temperature compensation for other sensors which are affected by temperature when testing.

Figure 1. DS18B20 Waterproof Temperature Sensor

pH Sensor

The DFRobot SEN0161 analogue pH sensor was selected for measuring water acidity and alkalinity levels due to its cost-effectiveness and easy-to-use features. This probe-based sensor operates in the pH range of 0-14 with ±0.1 pH accuracy at 25°C, suitable for drinking water assessment. The sensor requires 5V power supply. Prior to use, the probe was conditioned in storage solution for 12-24 hours to activate the glass electrode membrane. As shown in Figure 2, there are pH electrode storage solution to maintain the accuracy of the probe at the bottom of the glass. The sensor needs to be calibrated to use. Figure 3 shows the standard buffer solutions (pH 4.00, 7.00, and 10.01) and electrode storage solution used for the three-point calibration performed at approximately 25°C. The experimental data revealed an unusual voltage trend where voltage increased with pH (pH 4.0: 1.73V, pH 7.0: 1.98V, pH 10.01: 2.21V). A linear calibration equation was derived as below:

$$\mathbf{pH = 12.521 \times Voltage - 17.79}$$

$R^2 = 0.9982$

Figure 2. pH sensor with storage solution at the probe

Figure 3. Standard buffer solutions (pH 4.00, 7.00, and 10.01)

For detailed information, the table 3 below presents the complete calibration results with a calibration curve in Figure 4.

Table 2. pH sensor calibration results

Standard pH	ADC Reading	Voltage (V)	Calculated pH	Error	Error (%)
4.00	536	1.73	3.87	+0.13	+3.25%
7.00	615	1.98	7.00	0.00	0.00%
10.01	687	2.21	9.88	+0.13	+1.30%

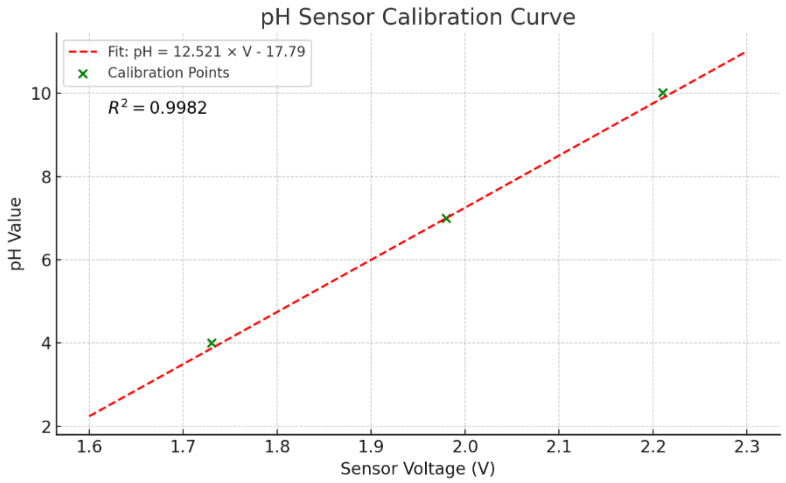


Figure 4. pH sensor Calibration Curve

TDS and EC sensor

Total Dissolved Solids (TDS) and Electrical Conductivity (EC) (shown in Figure 5) are critical parameters for assessing drinking water quality. TDS measures the total concentration of dissolved substances in water, while EC measures the solution's ability to conduct electrical current. These parameters are closely related, as conductivity is proportional to the ionic concentration in water, and TDS is typically estimated through conductivity measurements combined with conversion factors.

However, during laboratory testing, significant interference was observed when both sensors operated simultaneously in the same water sample. This interference manifested as reading deviations of 50-150 ppm TDS compared to individual measurements to both sensors. The likely mechanism is electric field interference. Both sensors apply AC signals to measure ionic conductivity. When operating in close proximity, their electric fields interact and alter ion distribution in the solution, creating cross-talk that affects measurement accuracy(Vernier, 2019).

To eliminate sensor interference while maintaining measurement capability for both parameters, the electrical conductivity sensor was selected as the only measurement device and TDS values are calculated from conductivity readings using the established relationship: TDS (ppm) = Conductivity (μS/cm) × 0.65. This conversion factor of 0.65 is based on empirical studies and represents a commonly accepted approximation for natural waters and drinking water applications(Environmental Measurement Systems, 2014).

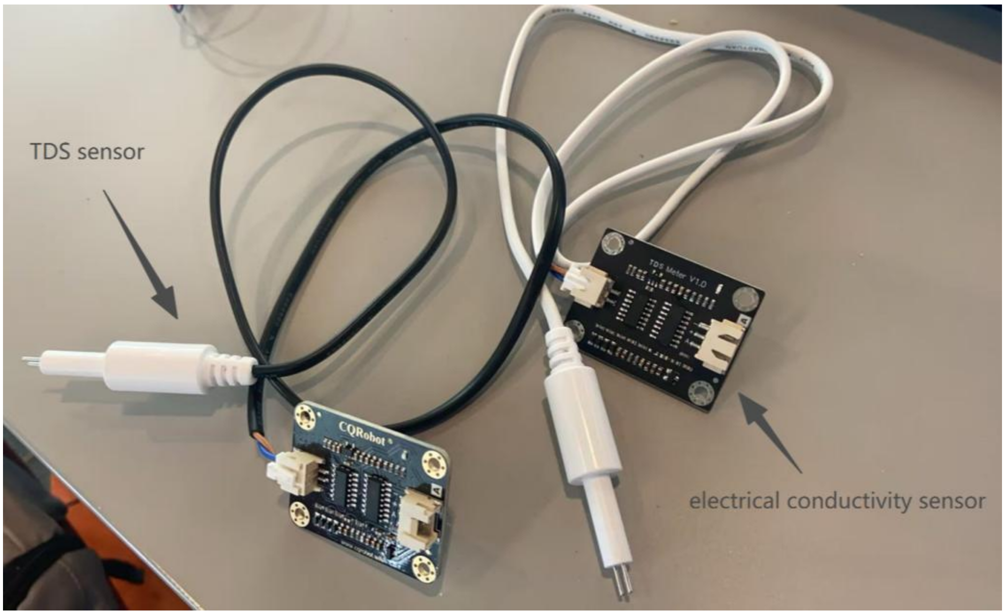


Figure 5. TDS sensor and EC sensor

Turbidity Sensor

The DFRobot SEN0189 analogue turbidity sensor (Figure 6) was chosen to measure water clarity by detecting suspended particles using light scattering detection method. The sensor operates in the range of 0-1000 NTU, suitable for drinking water analysis. It operates in a range of 0–4.5V while the maximum ADC voltage output for the MCU (Arduino MKR1310) is 3.3V. To prevent this damage, a voltage divider using two 6.4kΩ resistors, reducing the voltage by half. This makes the input range 0–2.25V, which is safe for the 3.3V ADC. Voltage readings were taken and converted back to original sensor voltage by multiplying by 2.

The system was calibrated using a linear regression model based on the two standard points using 20 NTU and 500 NTU turbidity solutions which is shown below in Figure 7.

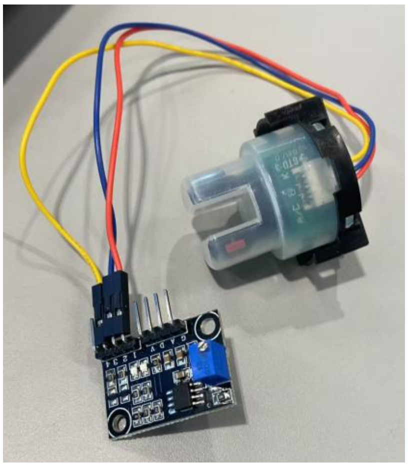


Figure 6. DFRobot SEN0189 Turbidity Sensor (Left)

Figure 7. Turbidity Solution (20 NTU 50NTU) (Right)

The experimental data revealed a trend which is shown in Figure 8 where the voltage decrease with NTU (NTU 20: 2.167, NTU500: 0.485V). A linear calibration equation was derived as below and the detailed results is in Table 4:

$$\mathbf{NTU = -142.68 \times Voltage + 638.92}$$

Table 3 Turbidity Sensor Calibration Results

Standard NTU	ADC Reading	A5 Voltage (V)	Sensor Voltage (V)	Calculated NTU	Error (NTU)	Error (%)
20.0	672	2.167	4.334	20.73	+0.73	+3.65%
500.0	150	0.485	0.970	498.32	-1.68	-0.34%

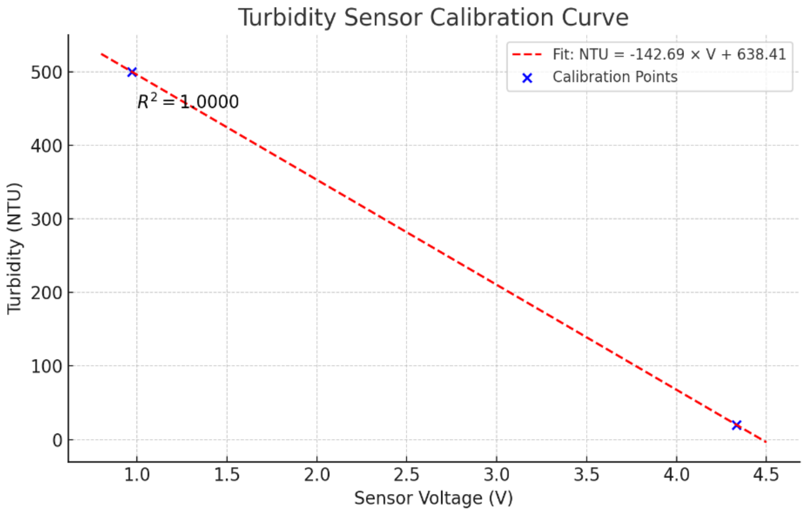


Figure 8. Turbidity Sensor Calibration Curve

3.3 Hardware Design

The water quality monitoring system was designed for portable applications and also remote access, allowing immediate water quality assessment with real-time feedback and cloud connectivity. The device was based on a microcontroller Arduino MKR WAN 1310 with integrated LoRaWAN connectivity (https://docs.arduino.cc/hardware/mkr-wan-1310) to send data to the TTN as a cloud platform.

Hardware overview

The hardware of the device comprises the aforementioned four water quality sensors (pH, TDS, turbidity, temperature), a tri-colour LED indicator system activated by a push button for measurement update, and a 2.9-inch ePaper display for detailed parameter information. The system operates via USB power supply to ensure consistent power delivery during measurement sessions.

Table 4 provides an explanation of the components and wiring connections, whereas Figure 9 shows the workflow of the whole system while Figure 10 shows the complete system schematic.

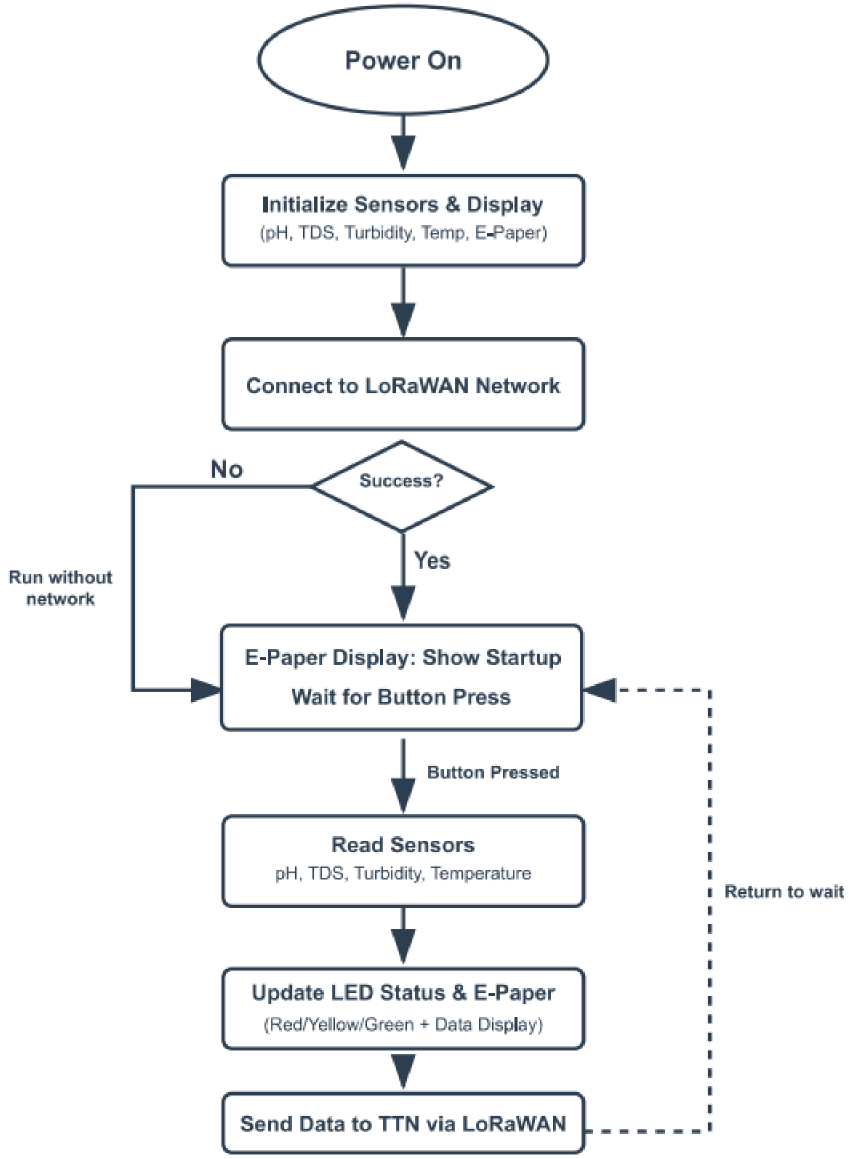


Figure 9. Workflow chart of the Hardware System

Table 4. Components and Wiring List

Component	Pin	Arduino Pin	Other Connection
pH Sensor Module (U2)	VCC	+5V	
	GND	GND	
	P0	A1	
Turbidity Sensor (U4)	VCC	+5V	
	A0	A2	Via voltage divider (6.4kΩ + 6.4kΩ)
	GND	GND	
EC Sensor (U3)	VCC	+5V	

	A0	A0	
	GND	GND	
DS18B20 Temperature (U5)	VCC	+5V	
	DATA	D6	Via 4.7kΩ pullup resistor (R3)
	GND	GND	
Red LED (LED1)	+	D2	Via 10kΩ resistor (R4)
	-	GND	
Green LED (LED2)	+	D3	Via 10kΩ resistor (R5)
	-	GND	
Yellow LED (LED4)	+	D4	Via 10kΩ resistor (R7)
	-	GND	
Push Button (SW1)	1	D1	
	3	GND	
ePaper Display (U6)	GND	GND	
	VCC	+3V3	
	DIN	D11/MOSI	
	CLK	D9/SCK	
	CS	D7	
	DC	D8	
	RES	D12	
	BUSY	D10	

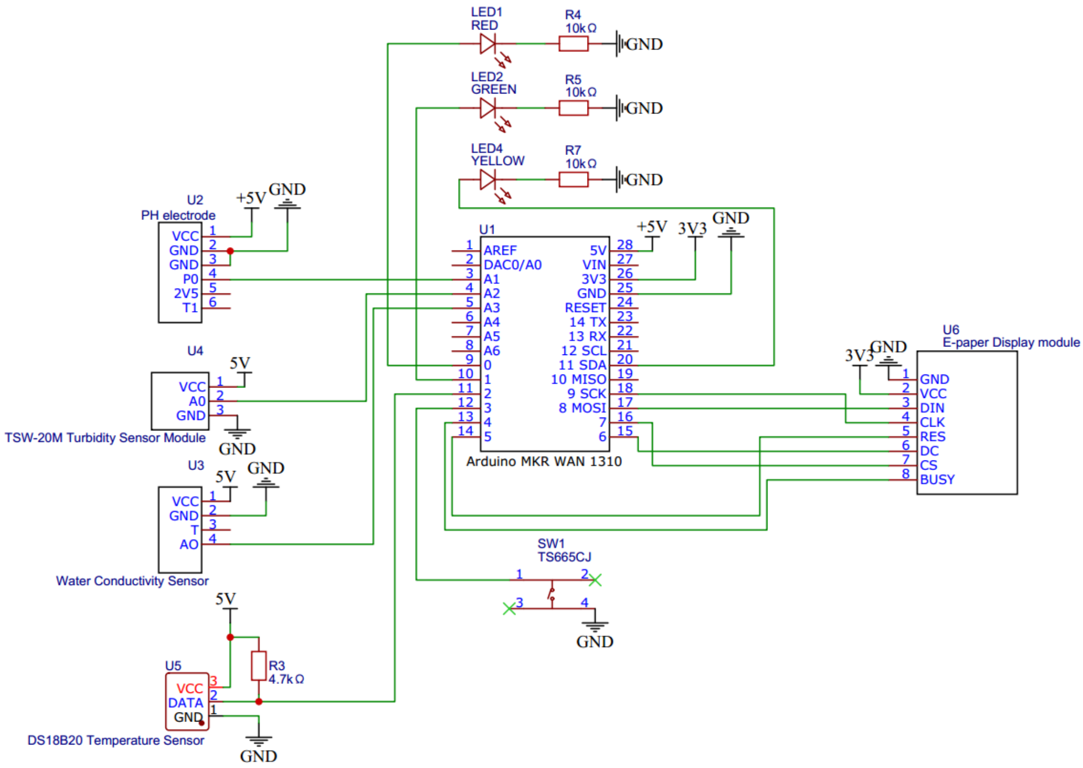


Figure 10. System Circuit Schematic

Display Interface

The 2.9-inch ePaper display module (https://www.waveshare.com/2.9inch-e-paper-module.htm) connects via SPI interface using multiple pins for comprehensive control (Figure 11). The display provides detailed water quality parameters and system status while consuming minimal power, updating only when data changes to extend the display's lifespan.

Figure 11. 2.9-inch E-Ink display module (Source: waveshare.com)

The e-paper follows a two-stage display logic in which the home screen shows the project title, system description, and readiness status, prompting the user to press the button to begin measurement (Figure 12a). After activation, the display transitions to the measurement screen, presenting the analysed results and an overall water quality assessment (Figure 12b).

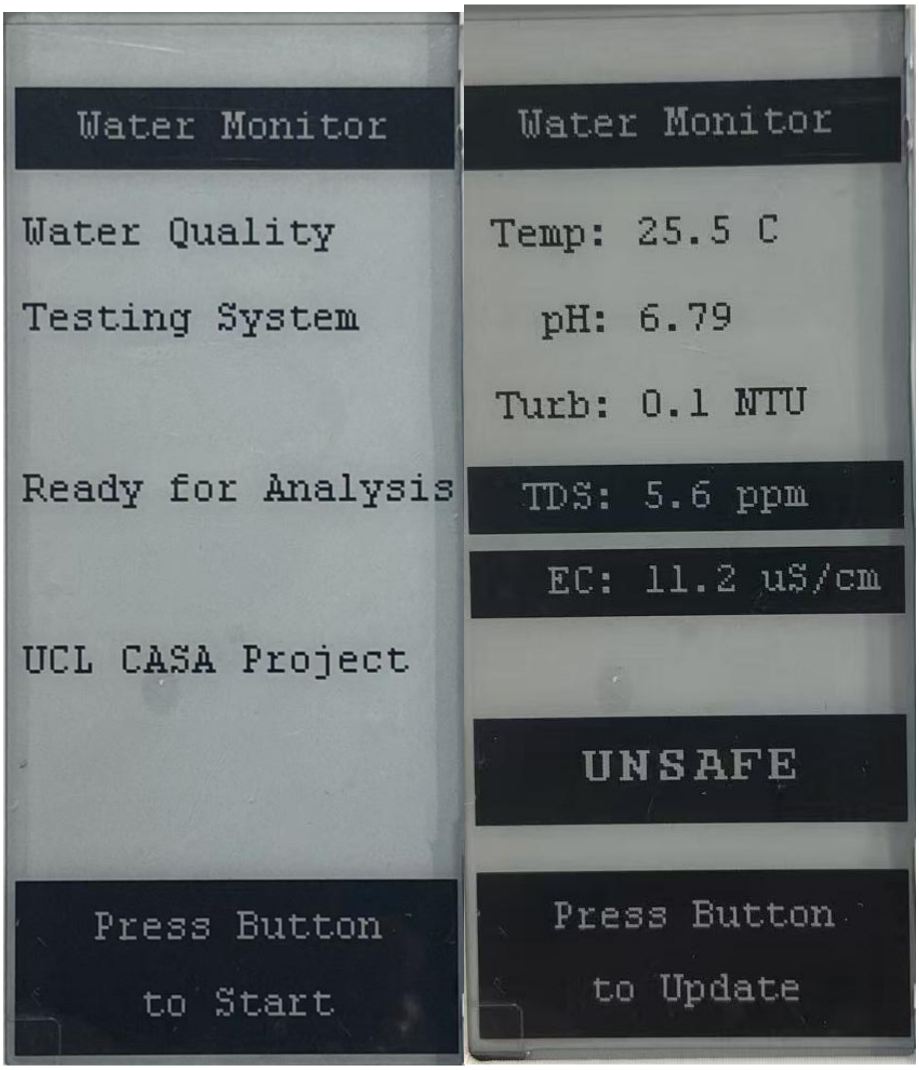


Figure 12a. Home Screen of the E-paper Display (Left)

Figure 12b. Water Quality Measurement in E-paper Display (Right)

LEDs and Push Button

The tri-colour LED system provides immediate visual feedback using LEDs in three different colours with resistors to limit current. The LED indication logic is detailed below:

Red → Unsafe water quality,

Yellow → Marginal water quality,

Green → Excellent water quality.

To achieve power-saving goals, the LEDs only updates when push button is triggered. This design prevents automatic updates of both the ePaper display and LED indicators, significantly reducing update frequency to protect the ePaper display's lifespan while conserving power.

Figure 13 illustrates the complete user interface featuring the tri-colour LED system, push button, and ePaper display for immediate water quality feedback.

Figure 13. User Interface Components (LEDs, Button and E-paper)

3.4 Enclosure

The enclosure of the portable water quality testing system is fabricated using 3D printing technology (Figure 14a). It consists of two main components: an upper housing and a lower protective base. The upper housing contains the MCU, sensor circuits, and all the remaining electronic components with four holes at its base designed to accommodate four sensors, allowing them to pass through for direct user measurements (shown in Figure 14b). The lower section (Figure 14c) serves as a stable platform to protect the exposed sensor probes. This design enables users to directly view and identify the four water quality sensors before inserting them into water samples for testing.

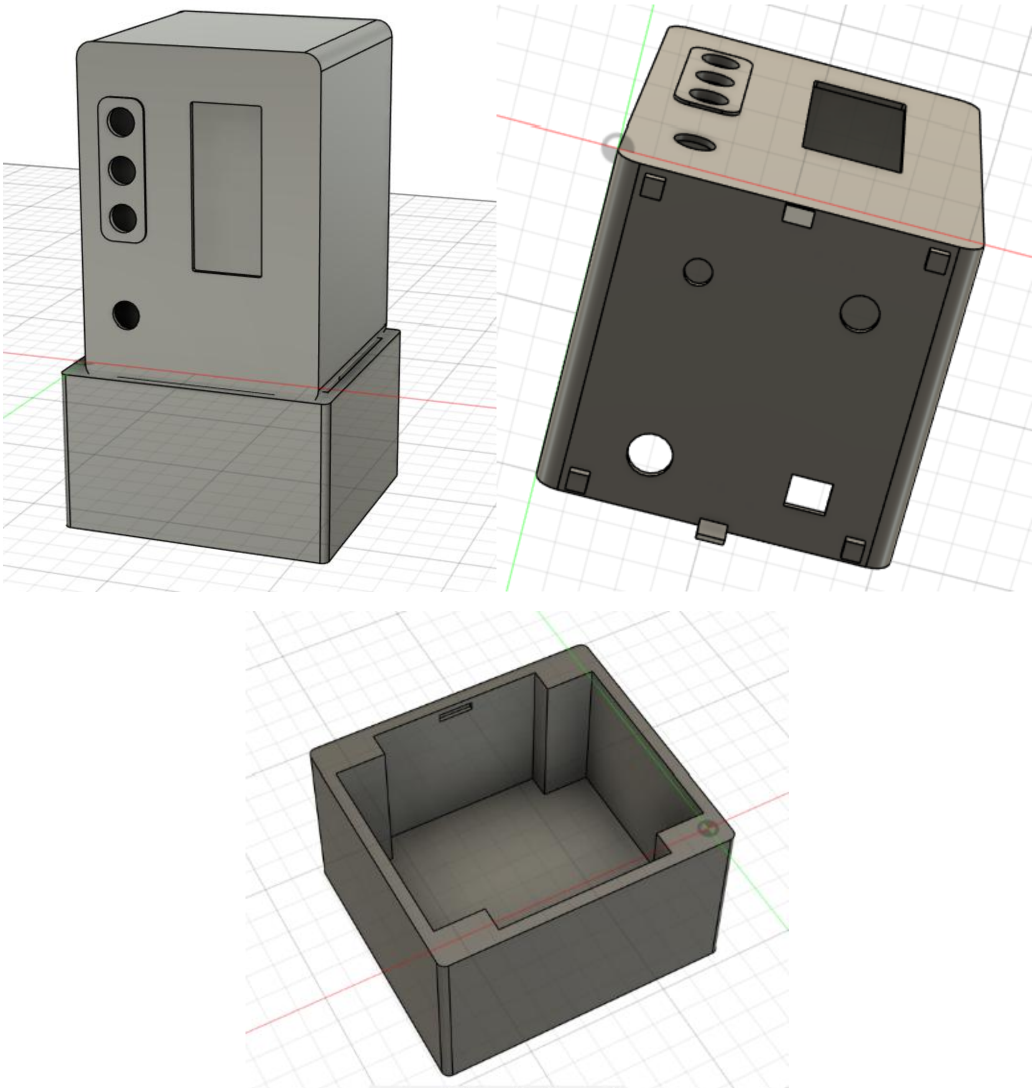


Figure 14a. 3D Model for Enclosure of the System (top-left)

Figure 14b. 3D Model Four precise openings for sensors (top-right)

Figure 14c. 3D Model for the lower base (bottom)

Although the upper device itself does not require water immersion, the four sensor openings present a waterproofing challenge potentially. A Rubber Grommets Kit (260 Pcs, 7 Sizes) (Figure 15a) was used to address this issue. These grommets can not only create effective water seals around each sensor while mechanically securing them in position (picture is shown in Figure 15b). The design utilises standard 3D printing materials (PLA) rather than specialized waterproof materials, focusing protection specifically at sensor penetration points to achieve cost-effectiveness goals while ensuring the reliable operation. The overall wiring and electronical components in the box are shown in Figure 16 while the complete physical device is displayed in Figure 17.

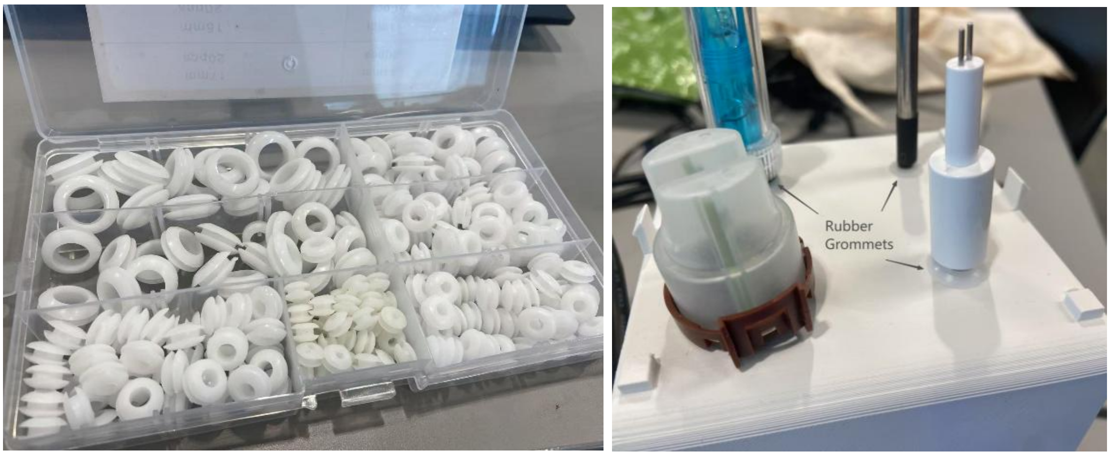


Figure 15a. Rubber Grommets Kit (Left)

Figure 15b. Sensors with grommets fixed (Right)

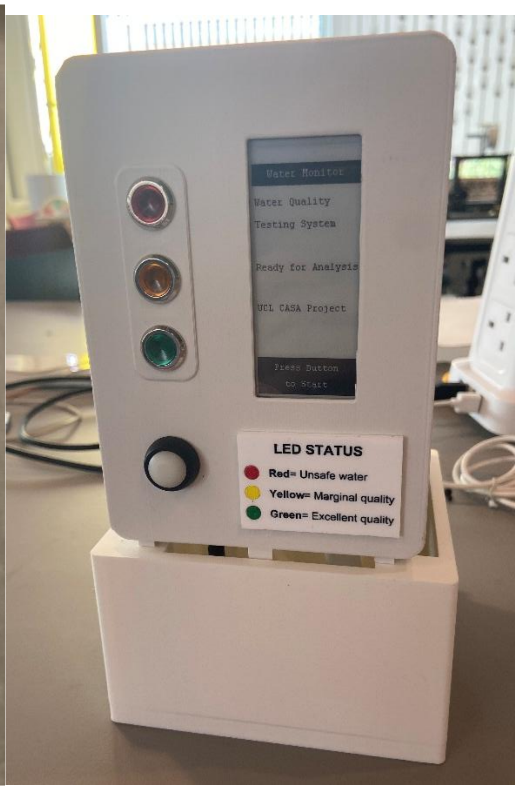


Figure 16 The Wiring in the Box (Left)

Figure 17. Complete Physical Device (Right)

3.5 Programming

The water quality monitoring system operates through a carefully designed software architecture that coordinates sensor data acquisition, user interaction, display management, and wireless communication.

Sensor Data Acquisition and Processing

The embedded software architecture implements a modular design pattern with separate modules for sensor management, data processing, and communication handling. The software framework is built upon the Arduino IDE environment. The sensor data acquisition is a sequential reading process to minimize electromagnetic interference between sensors.

Sensor Data code process is shown in Figure 18 below:

```
void readAllSensors() {
    // Temperature sensor (digital, highest priority)
    if (!readTemperature()) {
        handleSensorError("Temperature sensor fault");
    }

    // pH sensor with temperature compensation
    float rawpH = analogRead(PH_SENSOR_PIN) * (VREF / ADC_RESOLUTION);
    pHValue = 12.521 * rawpH - 17.79;

    // Turbidity with voltage division compensation
    float turbidityVoltage = analogRead(TURBIDITY_PIN) * (VREF / ADC_RESOLUTION) *
2.0;turbidityNTU = -142.68 * turbidityVoltage + 638.92;

    // Electrical conductivity with TDS calculation
    readConductivity();
    calculateTDSFromConductivity();
}
```

Figure 18. Code Snippets of Sensors Data Acquisition

Water Quality Classification Algorithm

The water quality assessment is based on comprehensive standards for drinking water safety of WHO, EPA(World Health Organization, 2017; US EPA, no date). There is three- classification water quality levels corresponding to the LED indicator colours as mentioned before: Excellent quality (Green LED) for all optimal ranges for drinking water, and marginal quality (Yellow LED) for safe to consumption, but one or more parameters is only in the acceptable ranges while the unsafe quality (Red LED) for at least one parameter exceeding established safety thresholds, meaning the water is unsuitable for drinking. The detailed Table 5 shows the water quality assessment methods for four water quality parameters according to WHO, EPA and the corresponding code in Figure 19. The measurement result in Arduino IDE serial monitor is shown in Figure 20.

Table 5. Water Quality Assessment Thresholds

Parameter	Excellent (Green)	Marginal (Yellow)	Unsafe (Red)
pH	6.5 - 8.0	6.0-6.4, 8.1-9.0	<6.0, >9.0
Turbidity (NTU)	0 - 1.0	1.1 - 4.0	>4.0
TDS (ppm)	80 - 300	50-79, 301-500	<50, >500
EC (μS/cm)	100 - 400	50-99, 401-800	<50, >800

```
int evaluateWaterQuality(float pH, float turbidity, float tds, float ec)
{   // Priority 1: Check for unsafe conditions
    if (pH < 6.0 || pH > 9.0 || turbidity > 4.0 ||
        tds > 500 || tds < 50 || ec > 800 || ec < 50) {
        return RED_LED;     // Unsafe for consumption
    }

    // Priority 2: Check for marginal conditions
    if ((pH >= 6.0 && pH < 6.5) || (pH > 8.0 && pH <= 9.0) ||
        (turbidity > 1.0 && turbidity <= 4.0) ||
        (tds >= 50 && tds < 80) || (tds > 300 && tds <= 500) ||
        (ec >= 50 && ec < 100) || (ec > 400 && ec <= 800)) {
        return YELLOW_LED; // Marginal quality
    }

    return GREEN_LED;      // Excellent quality
}
```

Figure 19. Code Snippets of Water Quality Evaluation

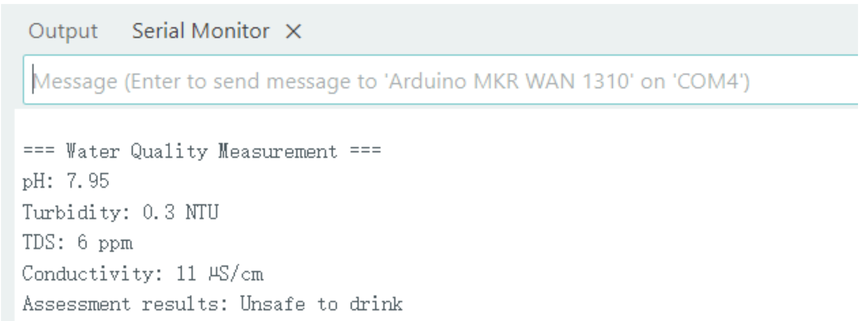


Figure 20. Water Quality Measurement displayed in Serial Monitor

3.6 Communication

The communication part of this system creates a clear and smooth process for data to move from sensor readings to the final display in both physical and digital forms for users.

Figure 21 illustrates the complete data flow architecture: The sensors collect water quality data, which moves through LoRaWAN to TTN platform. After that, through webhook, the sensor data stores into the professional database which will be directly shown in the web interfaces to users.

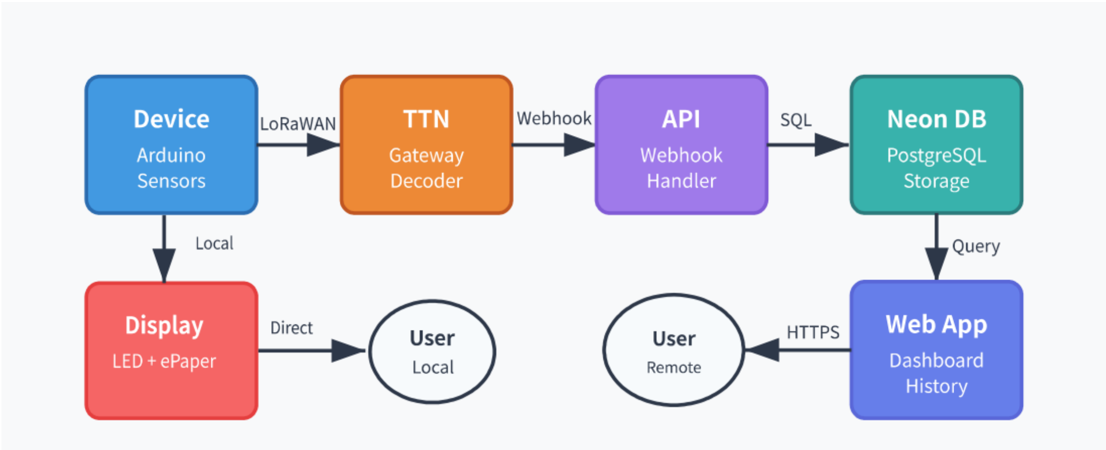


Figure 21. Data Flow of the System

LoRaWAN Selection and Configuration

LoRaWAN was selected for this portable water quality monitoring system based on the testing result across UCL East area for cost-effectiveness and efficiency purpose. LoRaWAN has advantages when compared with other communication tools, such as Wi-Fi and cellular. The testing locations span approximately 2km radius, which exceeds the range of Wi-Fi (50-100m) and would require access to different network credentials at each facility while LoRaWAN provides 5-15km coverage through The Things Network's existing gateway infrastructure at UCL East. Besides, unlike cellular solutions that require high annually subscription fees, LoRaWAN operates in free. The system only needs to transmit 4 sensor values plus metadata (~20 bytes) per measurement, which fits well within the data rate capacity. Additionally, the robust signal of LoRaWAN ensures reliable connectivity in various public spaces, from indoor facilities to outdoor fountains, making it an ideal communication tool in this research.

The LoRaWAN utilises The Things Network (TTN) to transmit sensor data. There existing gateway infrastructure in the Marshgate building which can provide reliable long-range communication for the monitoring applications. The system operates in the EU868 frequency band to achieve the optimal performance. Each Arduino MKR WAN 1310 board contains a unique DevEUI that must be retrieved before network registration. The code snippet shown below Figure 22 present how to get the DevEUI in Arduino IDE Serial Monitor.

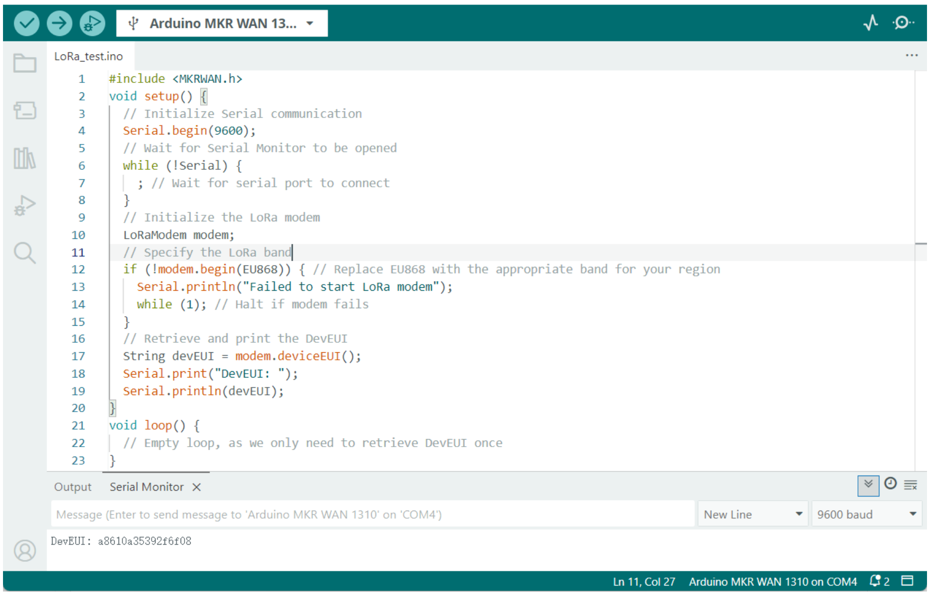


Figure 22.Code and Serial Monitor output for Retrieving DevEUI

TTN Integration

The TTN requires device registration and payload configuration for data transmission from the Arduino MKR WAN 1310 to the cloud database. The configuration process begins with device identification, followed by network registration, payload formatting, and transmission optimization. The retrieved DevEUI is registered in TTN console under the water-quality-monitor application, with the system automatically generating AppKey and AppEUI values for OTAA authentication. The registration process requires specifying the device name, DevEUI, and selecting the EU868 frequency plan for European deployment (shown in Figure 23).

The system attempts to connect using the AppEUI and AppKey generated during TTN device setup. Once authentication succeeds, the device can transmit sensor data to the network infrastructure with code snippet shown in Figure 24.

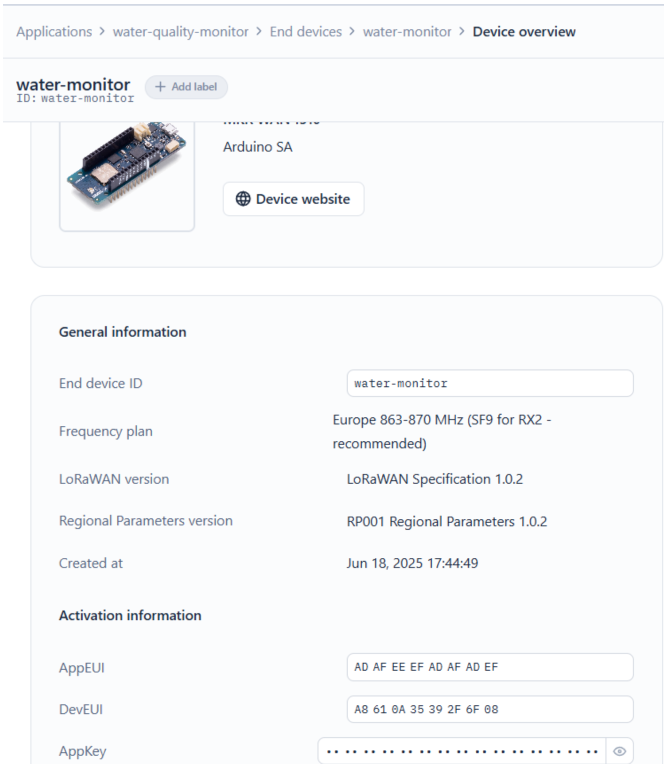


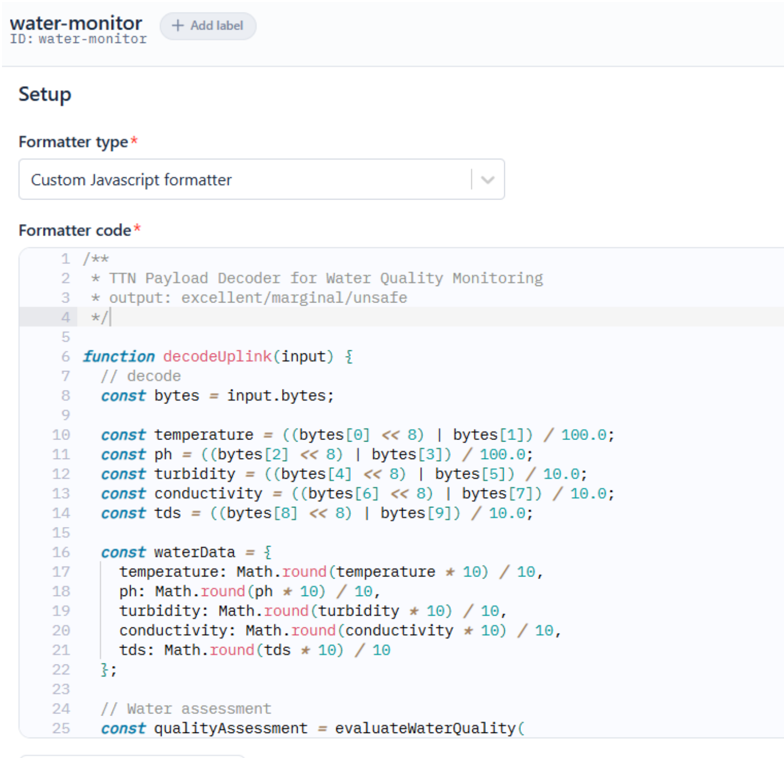
Figure 23. End Device Registration

```
bool connectToNetwork() {
    String appEui = "70B3D57ED0000000";  // From TTN application
    String appKey = "A8A2FB5D5F9C5A1E2D3B4C5D6E7F8A9B";  // Generated by TTN

    Serial.println("Attempting OTAA join...");
    int connected = modem.joinOTAA(appEui, appKey);

    if (connected) {
        Serial.println("Successfully joined LoRaWAN network");
        return true;
    } else {
        Serial.println("Join failed");
        return false;
    }
}
```

Figure 24. Code Snippet for Network Join

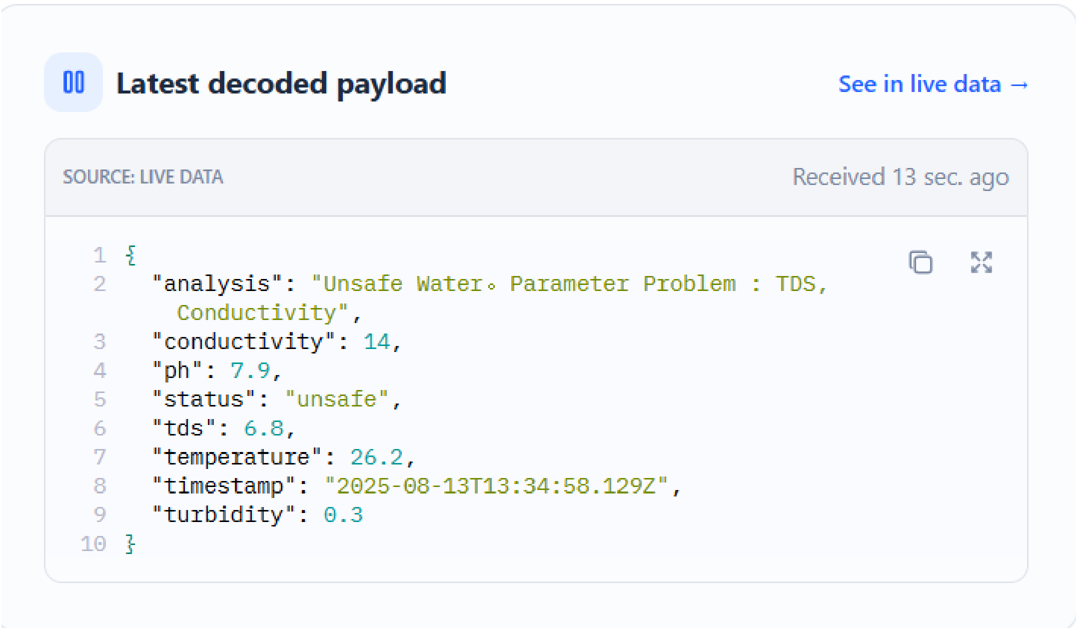
Payload Formatter Configuration

The sensor data transmitted via LoRaWAN requires conversion from binary format to human-readable values. A custom JavaScript payload formatter (Figure 25) is implemented within the TTN application to decode the sensor payload. After the binary format data is decoded, the TTN payload will display live data message of water quality parameters that human can understand, which is shown in Figure 26.




```javascript
/**
 * TTN Payload Decoder for Water Quality Monitoring
 * output: excellent/marginal/unsafe
 */

function decodeUplink(input) {
  // decode
  const bytes = input.bytes;

  const temperature = ((bytes[0] << 8) | bytes[1]) / 100.0;
  const ph = ((bytes[2] << 8) | bytes[3]) / 100.0;
  const turbidity = ((bytes[4] << 8) | bytes[5]) / 10.0;
  const conductivity = ((bytes[6] << 8) | bytes[7]) / 10.0;
  const tds = ((bytes[8] << 8) | bytes[9]) / 10.0;

  const waterData = {
    temperature: Math.round(temperature * 10) / 10,
    ph: Math.round(ph * 10) / 10,
    turbidity: Math.round(turbidity * 10) / 10,
    conductivity: Math.round(conductivity * 10) / 10,
    tds: Math.round(tds * 10) / 10
  };

  // Water assessment
  const qualityAssessment = evaluateWaterQuality(
```

Figure 25. JavaScript Payload Formatter (part)




```json
{
  "analysis": "Unsafe Water。Parameter Problem : TDS, Conductivity",
  "conductivity": 14,
  "ph": 7.9,
  "status": "unsafe",
  "tds": 6.8,
  "temperature": 26.2,
  "timestamp": "2025-08-13T13:34:58.129Z",
  "turbidity": 0.3
}
```


Figure 26 Decoded Payload Live Data Display

Webhook Configuration and Database Integration

The data in TTN can be decoded to the cloud database through HTTP POST requests by webhook. The webhook configuration specifies the target URL, authentication headers, and data format requirements (Figure 27). Neon PostgreSQL was chosen as the database and the Vercel serves as the hosting platform for the webhook API, offering deployment of Next.js applications.

The webhook connects TTN to the Neon PostgreSQL database through a Vercel-hosted API endpoint. The webhook is configured with ID "water-quality-webhook" using JSON format (Figure 28). When TTN receives device transmissions, it automatically forwards the decoded data to this endpoint for processing and database storage.

The Neon database stores complete sensor measurements with timestamps and the corresponding water quality status (Figure 29), enabling both real-time monitoring and historical trend analysis.

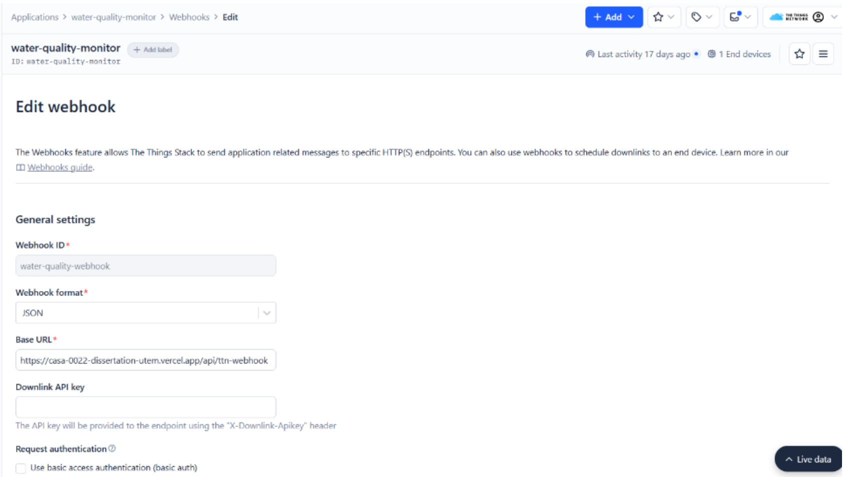


Figure 27 Create the Webhook

```
export default async function handler(req, res) {
    const data = req.body;
    const deviceId = data.end_device_ids?.device_id || 'water-monitor';
    const payload = data.uplink_message?.decoded_payload;

    const waterData = {
        temperature: parseFloat(payload.temperature) || 0,
        ph: parseFloat(payload.ph) || 0,
        turbidity: parseFloat(payload.turbidity) || 0,
        conductivity: parseFloat(payload.conductivity) || 0,
        tds: parseFloat(payload.tds) || 0
    };

    const status = evaluateWaterQuality(waterData);
    await WaterQualityDB.saveReading({ device_id: deviceId, ...waterData, status });

    return res.status(200).json({ success: true });
}
```

Figure 28. Code Snippet in JSON Format for Data Storage in DB

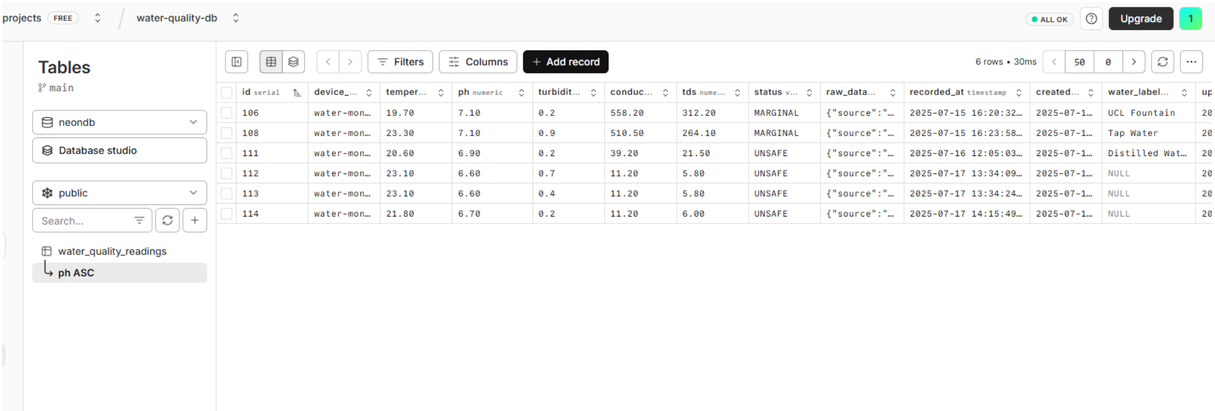


Figure 29. Screenshot of Neon Water Quality DB Tables

Web Platform Implementation

Following the data storage process described in Section 3.6, a web-based data access system was developed to present the water quality information stored in the Neon PostgreSQL database. The platform architecture utilises Next.js framework with serverless deployment on Vercel (Figure 30), enabling direct database connectivity through API routes that query the sensor measurements received via TTN webhook integration. The backend implementation includes data processing functions that convert raw sensor values into standardized formats and apply the water quality classification algorithm described in Section 3.5 to generate safety assessments. Database queries retrieve both real-time measurements and historical records. The serverless architecture automatically handles scaling requirements while Vercel's deployment ensures reliable public access.

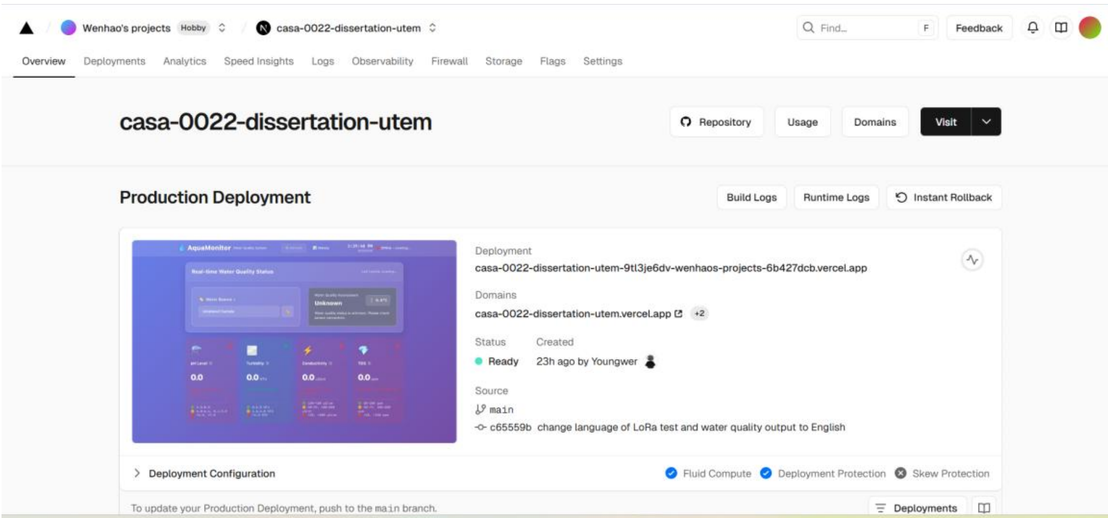


Figure 30 Screenshot of the Vercel Platform

4. Results

This project has three main contributions, with the first two representing the core scientific contributions: 1.) A validated portable water quality monitoring system capable of real-time assessment and classification; 2.) A comprehensive dataset of water quality measurements from diverse sources and public drinking infrastructure around UCL East Marshgate; 3.) A public web platform that effectively communicates the research findings to the community, embodying the principles of "Sense, Deploy, and Communicate" goals in Connected Environments Module.

4.1 System Performance and Sensor Validation

The designed IoT water quality monitoring system successfully demonstrated its capability to measure four key water parameters (pH, turbidity, electrical conductivity, and temperature) and transmit data through LoRaWAN to TTN gateway. The system was tested on various water sources in multiple locations near UCL East Marshgate to validate sensor accuracy and system reliability.

Prior to testing, calibration was performed for sensors requiring linearization to ensure measurement accuracy. The pH and turbidity sensors were calibrated while the DS18B20 temperature sensor and EC sensor were used with manufacturer specifications due to their digital output and inherent calibration. The calibration results are shown in Table 6.

Table 6. Sensor Calibration and Specification Results

Parameter	**Sensor Type**	**Calibration Status**	**Calibration Range**	**Accuracy**	**R^2 Value**
pH	DFRobot SEN0161	**Calibrated**	4.00 - 10.01 pH	±0.13 pH	0.9982
Turbidity	DFRobot SEN0189	**Calibrated**	20 - 500 NTU	±1.68 NTU	1*
Temperature	DS18B20	Manufacturer Spec	-55 to +125°C	±0.5°C	N/A
EC/TDS	Conductivity Probe	Manufacturer Spec	0-1000 µS/cm	±2% reading	N/A

**Note: The turbidity calibration R^2 = 1.0000 because only two calibration points (20 NTU and 500 NTU) were used.*

The pH sensor demonstrated excellent linearity with $R^2 = 0.9982$(as shown in Figure), confirming the reliability of the derived calibration equation: pH = 12.521 × Voltage - 17.79. The turbidity sensor required voltage division using two 6.4kΩ resistors to prevent ADC damage, achieving stable readings with the linear relationship: NTU = -

142.68 × Voltage + 638.92. The DS18B20 temperature sensor provided direct digital readings with factory calibration, eliminating the need for additional calibration procedures. Similarly, the electrical conductivity sensor was used with manufacturer specifications, with TDS values calculated using the standard conversion factor: TDS (ppm) = EC (μS/cm) × 0.65.

4.2 Water Source Testing and Classification Results

The device demonstrated immediate response to different water quality conditions, with the tri-colour LED system providing instant visual feedback and e-paper display updating detailed parameter readings within 3 - 5 seconds of sensor immersion. Figure 25 shows the system's real-time performance during testing of different water sources.

4.2.1 Real-time Device Performance and Classification

The device demonstrated immediate response to different water quality conditions, with the tri-colour LED system providing instant visual feedback and e-paper display updating detailed parameter readings within 3-5 seconds of sensor immersion. Figure 31 shows the system's real-time performance during testing of different water sources.

Figure 31. Device Testing Results

Bottled water(top-left) - UCL Fountains Water(top-right)

UCL Tap Water(bottom-left) – Distilled Water(bottom-right)

Bottled water from the supermarket test shows **Green LED** illuminated with Excellent water quality. UCL Water Fountain and tap water tests both show **Yellow LED** illuminated with Marginal water quality while the distilled water test showing **Red LED**, meaning UNSAFE water quality due to the low TDS and EC values (lack of minerals in water).

The physical system run smoothly with push-button activation system and the LED classification proved highly effective. Users are able to obtain immediate water quality assessments by simply immersing the sensors and pressing the measurement button performed consistently, correctly identifying water safety levels according to the established WHO/EPA thresholds across all test scenarios.

Following extensive field testing across different water sources, comprehensive data was collected to validate the system's classification accuracy. Each water source was tested multiple times (ranging from 4 to 15 measurements per source) depending on accessibility and availability. The complete dataset (Table 8) demonstrates the device's ability to discriminate between water quality levels effectively.

Table 7. Comprehensive Water Quality Measurements and Classifications (Average values from multiple tests)

Water Source	pH	Turbidity (NTU)	TDS (ppm)	EC (µS/cm)	Temp (°C)	Water Status	Test Count

UCL Water Fountains	7.4	0.6	187	287	21.8	Excellent	15
Brita Filtered	7.2	0.3	124	191	21.3	Excellent	12
Volvic Bottled	7.6	0.1	95	146	21.1	Excellent	6
Distilled Water	6.9	0.1	12	18	21.1	Unsafe	10
Tap water	8.2	0.8	342	526	19.4	Marginal	8
Rainwater	6.3	2.1	23	35	18.9	Unsafe	4

The system can successfully differentiate between water sources. Testing the same source multiple times showed consistent results, with parameter variations under 5%, confirming the sensor system's reliability and repeatability.

4.3 Public Space Water Quality Assessment

The portable feature of the system makes it possible to test across diverse public drinking facilities in the UCL East Marshgate area, which allows for comparative analysis of water quality across different types of public infrastructure and usage environments. The areas near London Olympic Park were selected to test different categories of public water infrastructure. Figure 32 illustrates the geographical distribution of testing sites, spanning from UCL East Campus facilities including water fountain (Figure 33) and bathroom tap (Figure 34), to major public venues including the Olympic Park (Figure 35) and Westfield shopping Ave (Figure 36). Table 8 presents the complete dataset from the multi-location assessment.

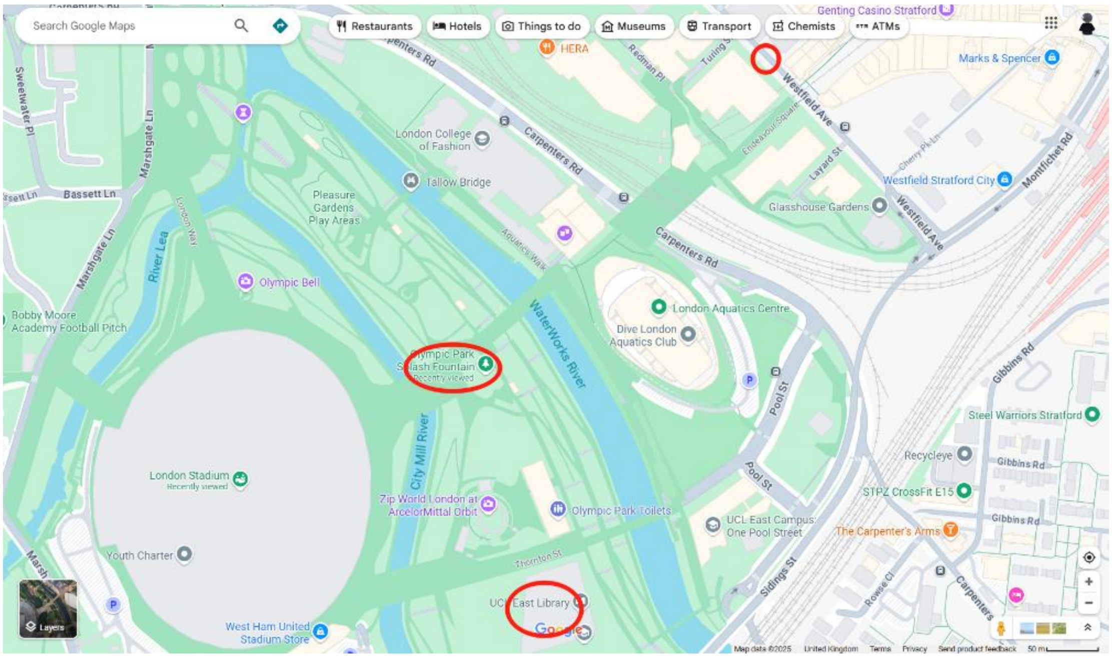


Figure 32. Map showing testing locations

Figure 33. Water Source 1: UCL Marshgate Water Fountain (Top-Left)

Figure 34. Water Source 2: Marshgate Bathroom Tap (Top-Right)

Figure 35. Water Source 3: Westfield Water Fountains (Bottom-Left)

Figure 36. Water Source 4: Water Fountains in the Queen Elizabeth Olympic Park (Bottom-Right)

Table 8. Public Space Water Quality Assessment Results

Specific Site	pH	Turbidity (NTU)	TDS (ppm)	EC (μS/cm)	Temp (°C)	Classification
Marshgate Water Fountain	7.3	0.8	176	271	21.5	Excellent
Marshgate Washroom Tap	7.4	0.6	187	287	21.8	Excellent
Olympic Park Plaza Fountain	7.6	1.2	203	312	20.3	Excellent
Westfield Ave Public Fountain	7.2	1.8	245	377	22.1	Excellent

4.3 Web-based Data Visualization Platform for Public Access

A Next.js web application was developed for remote monitoring of water quality data on both desktop and mobile devices. Unlike traditional laboratory-based testing that provides delayed results to authorities only, the web platform is publicly accessible via Vercel hosting, enabling users to monitor water quality measurements and historical trends from any location. On the homepage, users can view real-time water quality status with coloured background and access detailed parameter readings including pH, turbidity, TDS, and temperature measurements (Figure 37). It uses the same three-level system as the embedded device: green for excellent quality, yellow for acceptable conditions, and red for unsafe water. Historical data is shown in a structured table (Figure 38), listing past measurements with timestamps, quality ratings, and data source details, allowing users to track water quality trends and spot patterns over time. The water source tracking feature allows users to categorize and compare measurements from various public infrastructure types, directly supporting the core research finding that different facility categories exhibit distinct water quality characteristics. Users can choose from predefined water sources (e.g., tap, river, lake, well) or input a custom source name via a dropdown menu and text field in the interface (Figure 39).

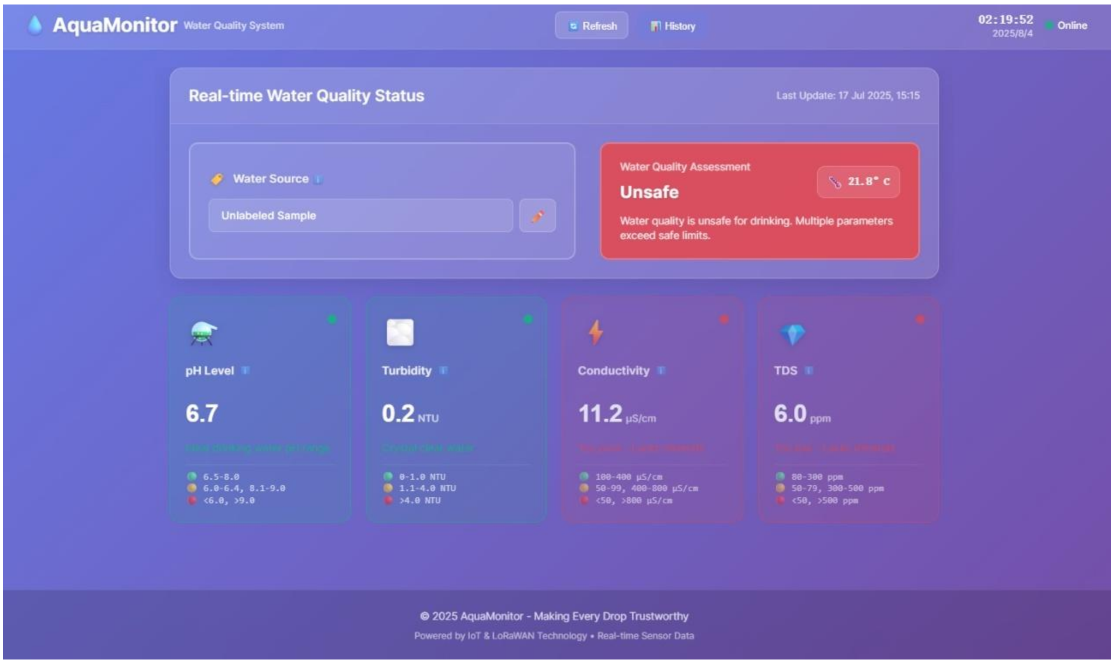
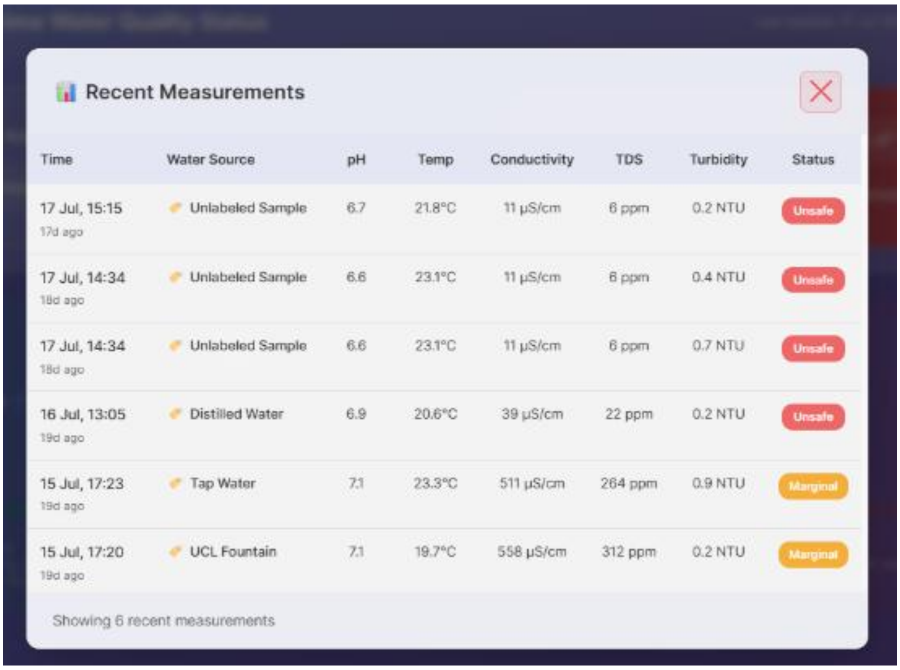


Figure 37. Web Application Screenshot



Recent Measurements

Time	Water Source	pH	Temp	Conductivity	TDS	Turbidity	Status
17 Jul, 15:15 17d ago	Unlabeled Sample	6.7	21.8°C	11 µS/cm	6 ppm	0.2 NTU	Unsafe
17 Jul, 14:34 18d ago	Unlabeled Sample	6.6	23.1°C	11 µS/cm	6 ppm	0.4 NTU	Unsafe
17 Jul, 14:34 18d ago	Unlabeled Sample	6.6	23.1°C	11 µS/cm	6 ppm	0.7 NTU	Unsafe
16 Jul, 13:05 19d ago	Distilled Water	6.9	20.6°C	39 µS/cm	22 ppm	0.2 NTU	Unsafe
15 Jul, 17:23 19d ago	Tap Water	7.1	23.3°C	511 µS/cm	264 ppm	0.9 NTU	Marginal
15 Jul, 17:20 19d ago	UCL Fountain	7.1	19.7°C	558 µS/cm	312 ppm	0.2 NTU	Marginal

Showing 6 recent measurements

Figure 38. Historical Records Table

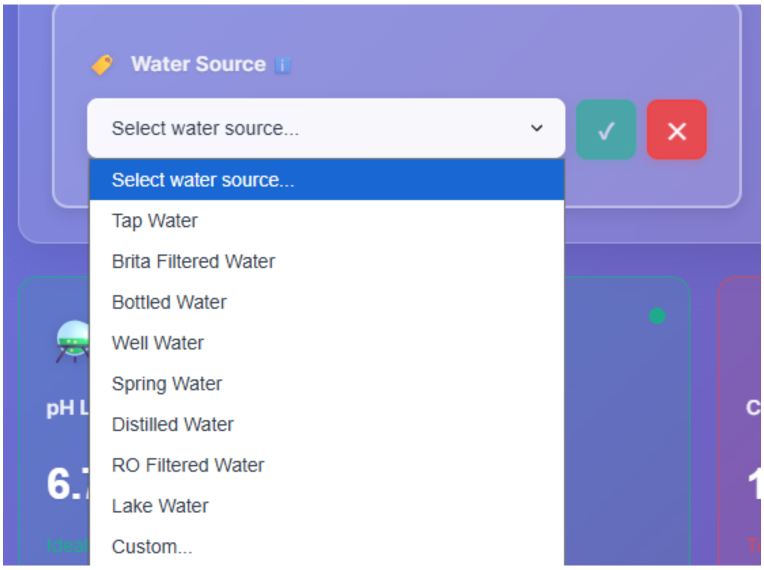


Figure 39. Water Source Tracking and Record

5. Discussion

5.1 Observations and Key Findings Analysis

The experimental results demonstrate that the portable water quality monitoring system successfully achieved its primary objectives of providing immediate water quality assessment through both physical and digital user interfaces. There are some key findings:

1) The most significant finding of this research is the water quality variations detected across different types of public drinking infrastructure in the UCL East area. The results revealed small but consistent differences in water quality between facility types. University campus water sources averaged 182 ppm TDS, while fountains in shopping centre and park averaged 245 ppm TDS, representing a 35% difference in mineral content between educational and commercial infrastructure networks. Furthermore, it was observed that spatial variability exists even within the same infrastructure type. Municipal tap water measurements showing an 83% inconsistence in TDS levels (shown in Table 7 and 8) between different sources (ranging from 187 ppm at Marshgate Washroom Tap to 342 ppm in general tap water samples from other locations) This finding demonstrates that public drinking facilities are not uniform in water quality at UCL East area and exhibit complex water quality patterns across different locations.

2) The system demonstrated comprehensive water safety assessment beyond traditional contamination detection. Notably the system classified both distilled water and rainwater as "Unsafe" due to extremely low mineral content (12 ppm TDS and 23 ppm TDS respectively) which is consistent with the WHO guidelines that adequate mineral content in drinking water is essential for optimal health(World Health Organization, 2017). While neither of water is not harmful in short-term for people, the World Health Organization notes that prolonged consumption of demineralized water may lead to mineral deficiencies and electrolyte imbalances, particularly affecting calcium and magnesium levels(*Nutrients in drinking water*, 2005; Kozisek, 2024). Additionally, the rainwater sample additionally exhibited slightly acidic conditions (pH 6.3) and turbidity (2.1 NTU). It is in unsafe classification due to potential atmospheric contaminants and surface collection impurities. This classification demonstrates the system's ability to detect both over-contamination and under-mineralization scenarios, representing a more holistic approach to water safety than conventional monitoring systems that primarily focus on contaminant detection.

3) Across all tested water sources, the system demonstrated consistent water quality classification classifies the drinking water quality according to WHO/EPA standards (Excellent/Marginal/Unsafe). The system successfully differentiated between high-quality sources (bottled water, filtered water) standard municipal supplies (tap water, fountain water), and problematic sources (distilled water, rainwater) in accordance with established standards although the laboratory-based validation work was not conducted

as part of the study, which remains a future work. The LoRaWAN communication infrastructure proved reliable and achieved consistent data transmission across all testing locations within the UCL East area, suggesting that existing TTN gateway infrastructure provides reliable coverage for portable monitoring applications.

5.2 Limitations and Reflections

From both technical performance and practical deployment perspectives, several significant limitations emerged that require honest acknowledgment and critical analysis.

1) The large size is one of the device's main limitations, measuring 15cm × 10cm × 8cm and weighing 450g, making it too bulky for pocket-sized use. Because of the four water quality sensors, especially the 12cm-long pH probe and the 8cm × 5cm turbidity sensor housing, it requires a bigger enclosure for proper placement and circuitry. This conflicts with the "lightweight and compact" benefits claimed by Zainurin et al. (2022) for portable systems, showing a trade-off between including multiple sensors and keeping the device portable.
2) The USB power requirement presents a significant limitation for true portable deployment. While USB power ensures reliable measurements during testing, it restricts the system's ability to operate independently in locations without power sources. The current device requires USB power sources to work, which is conflicts with the autonomous operation capabilities highlighted by Demetillo, Japitana and Taboada (2019) for remote monitoring applications. It has not achieved the portable purpose that "true portability should be able to be distributed to public facility without any dependencies on infrastructure".
3) Despite eliminating TDS/EC sensor interference through design modifications, the system still requires periodic recalibration to maintain accuracy, particularly for pH and turbidity sensors. This maintenance requirement contradicts the "plug-and-play" installation advantages promoted in the literature and represents a practical barrier to widespread deployment in public spaces where technical maintenance access may be limited.

5.3 Future Work

From the limitation and reflection mentioned in Section 5.2, some future works emerge from the analysis: 1) Investigation of miniaturized sensor alternatives or sensor multiplexing approaches to reduce device footprint while maintaining measurement comprehensiveness; 2) Implementation of battery-powered operation with integrated power management systems, including deep sleep functionality and potentially solar charging capabilities, to enable autonomous deployment without infrastructure dependencies; 3) Integration of automated calibration verification systems to reduce manual maintenance requirements and ensure sustained accuracy in unsupervised deployments.

6.Conclusion

In response to the research questions posed, this study successfully demonstrates that a portable, low-cost drinking water monitoring device can effectively provide immediate water quality safety information to the public, while an interactive web platform can deliver real-time data visualization and historical trend analysis for enhanced public awareness. This research makes three principal contributions to the field of IoT-based water quality monitoring. First, the study addresses critical sensor interference challenges through innovative design modifications, eliminating TDS/EC sensor cross-talk while achieving exceptional calibration accuracy (R^2 = 0.9982 for pH) that surpasses many existing portable systems. Second, the integrated system demonstrated high accuracy classification of drinking water quality according to WHO/EPA standards across diverse public drinking facilities, with real-time assessment capabilities that significantly outperform traditional laboratory-based approaches requiring hours or days for results. Third, the research establishes a comprehensive IoT infrastructure successfully integrating LoRaWAN communication, multi-level user feedback system (LED indicators, e-paper display, and web dashboard), and cloud-based data storage, enabling public health monitoring that achieved data transmission across all tested locations within the UCL East area where the LoRaWAN network is covered. The successful testing across varied public infrastructure types, from campus to major commercial venues, validates the system's practical viability for widespread public space implementation.

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Appendix A

Bill of Materials and Components

MCU, Sensors and Calibration Solutions Parts	
DS18B20 Temperature Sensor Module Kit (Waterproof)	12.59
Water Conductivity Sensor	10.23
Turbidity Sensor Module	18.49
pH Sensor Module	25.99
pH Calibration Solution and Buffer (pH 4.0, 7.0, 10.01)	16.79
Turbidity Solution (20 NTU 500 NTU)	15.69
MKR1310	40.00
Visualisation and Customised Components	
LED Lights	7.99
2.9inch E-paper Module	21.19
Waterproof Momentary Push Button	5.99
Rubber Grommets Kit (260 Pcs, 7 Sizes)	15.00
Total	189.95

The table showed above is based on the price in Aug 2025.

**Over 70% of the cost is the MCU, Sensors and Calibration Solutions part.*

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I acknowledge the use of Claude (Claude Sonnet 4, https://claude.ai) as an assistive tool in accordance with UCL's Category 2 guidelines. Specifically:

1. To receive structural suggestions for some part of the dissertation.

Prompts used: My dissertation is a portable water quality testing device using multiple water parameters sensor, present the initial outline of the of the dissertation.

2. To ensure grammar and style consistency.

Prompts used: Check the grammar of the dissertation and correct the wrong ones, and some sentences with unclear expression.

All content, analysis, and ideas presented are my own, and AI was used solely as a supportive resource, not to generate original ideas or replace my own work.

Wenhao Yang

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