

IoT-Enabled Smart Soil Monitoring System via Campus Wi-Fi and MySQL Server with Interactive Geospatial Analytics for Agricultural Automation

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ABSTRACT

Precision agriculture requires automated, high-resolution soil health diagnostics to optimize irrigation schedules, fertilizer management, and overall crop productivity. Conventional laboratory soil testing methods are labor-intensive, costly, and lack real-time spatial accessibility. This paper presents an integrated Internet of Things (IoT) multi-parameter soil monitoring platform designed specifically for agricultural automation. The system utilizes a 7-in-1 Modbus RS485 soil probe integrated with an ESP32 microcontroller to capture seven physical and chemical parameters simultaneously: volumetric moisture content, temperature, pH, electrical conductivity (EC), nitrogen (N), phosphorus (P), and potassium (K). Data payloads are transmitted over campus-wide Wi-Fi infrastructure using HTTP POST requests to a central MySQL relational database and rendered dynamically on an interactive Web-GIS geospatial analytics dashboard. Empirical evaluation across 32 georeferenced field samples at Universiti Teknikal Malaysia Melaka (UTeM) demonstrated high system stability, robust database logging, and precise spatial mapping capabilities. Statistical analysis revealed a bimodal moisture distribution across land-use types and an preliminary linear correlation observed at the test site between total macronutrients (NPK) and electrical conductivity ($r = 0.9988$, $p < 0.001$). Operating at Technology Readiness Level 4 (TRL 4), this work aligns directly with United Nations Sustainable Development Goals (SDG 2: Zero Hunger; SDG 15: Life on Land) by providing a scalable blueprint for automated soil diagnostics.

Keywords—Agricultural Automation, Soil Monitoring Automation, Internet of Things (IoT), Multi-Parameter Soil Sensing, MySQL Relational Database, Geospatial Analytics, Precision Agriculture

INTRODUCTION

Global agricultural systems face unprecedented pressures due to rapid population growth, climate volatility, water scarcity, and progressive soil degradation [1], [2]. Precision agriculture has emerged as a transformative paradigm to maximize agricultural productivity while minimizing environmental impacts and resource consumption [3], [4]. A fundamental prerequisite of precision farming is continuous, real-time monitoring of soil physical and chemical attributes, including moisture, temperature, acidity (pH), salinity or electrical conductivity (EC), and essential macronutrients (nitrogen, phosphorus, and potassium).

Traditional soil evaluation relies heavily on manual core sampling followed by off-site laboratory wet-chemistry testing. While accurate, this process involves substantial turnaround times (often taking days to weeks), high operational costs, and low spatial-temporal resolution [5]. These inherent delays inhibit timely agricultural automation, such as site-specific variable-rate irrigation scheduling and automated fertigation management (Shriwas et al., 2024). To address these limitations, IoT-based wireless sensor networks (WSN) have been increasingly deployed in smart farming [6], [7]. However, existing implementations frequently suffer from

restricted parameter coverage, reliance on short-range or costly connectivity, and static tabular interfaces lacking intuitive spatial visualization [8], [9].

Furthermore, technology adoption among farming communities depends significantly on perceived usefulness, operational simplicity, and automated field reporting infrastructures [10], [11]. Developing intuitive, web-based geospatial dashboards is therefore essential for transforming raw sensor logs into actionable agronomic intelligence [12], [13].

To address these research gaps, this paper presents an IoT-enabled smart soil monitoring system operating over campus Wi-Fi infrastructure with centralized MySQL storage and interactive Web-GIS analytics. The system captures seven vital soil parameters simultaneously using an industrial 7-in-1 Modbus RS485 probe. The primary contributions of this work are fourfold:

1. **Architectural Integration:** Design and deployment of a 5-tier IoT framework uniting industrial RS485 Modbus RTU sensing, campus-wide Wi-Fi connectivity, structured MySQL relational storage, and an interactive geospatial analytics frontend.
2. **Field Empirical Validation:** Real-world field evaluation across 32 georeferenced sampling locations at FTMK UTeM, quantifying spatial moisture variability and validating data transmission stability.
3. **Statistical Characterization:** Discovery of an preliminary linear relationship between total NPK macronutrients and soil electrical conductivity ($r = 0.9988$), supporting EC as an automated proxy for soil nutrient estimation.
4. **Visual & Operational Integration:** Integration of physical field probe deployment procedures and live interactive dashboard interfaces into a unified workflow for agricultural automation.

This research operates at Technology Readiness Level 4 (TRL 4), focusing on component integration and prototype field validation. The project directly supports United Nations Sustainable Development Goals SDG 2 (Zero Hunger) through efficient resource utilization and SDG 15 (Life on Land) by preventing soil degradation.

Advances in agricultural IoT are driving automated soil diagnostics and precision land management. Ananthi et al. (2017) [14] introduced an IoT soil monitoring framework using moisture and temperature sensors.. While enabling local wireless data transfer, their architecture excluded macronutrient sensing and spatial mapping.

Hartono et al. (2024) [8] developed a portable IoT-based soil nutrient monitor focusing on NPK sensing. Although achieving low-power operation, data logging was restricted to local SD card storage or short-range Bluetooth, limiting real-time remote accessibility. Shriwas et al. (2024) [15] proposed an automated irrigation framework combining moisture and nutrient sensors. However, the system lacked relational database historical archiving and interactive spatial visualization.

Kumar et al. (2025) [16] integrated machine learning classifiers with IoT Agrisense hardware for crop recommendation. Their predictive analytics relied on manual soil data entry, while optical and electrochemical sensing now enable rapid NPK assessment. [17], [18].

TABLE I: COMPARISON OF PROPOSED SYSTEM WITH RELATED LITERATURE

Reference & Authors	Sensor Parameters Measured	Wireless Connectivity	Database / Server Architecture	Interactive Geospatial Visualization	System Focus & Key Limitations
Ananthi et al. (2017) [14]	Moisture, Temp, pH	Wi-Fi / GSM	Local / Basic Cloud	No	Focuses on basic automated irrigation control; lacks NPK nutrient sensing and

					spatial map integration.
Hartono et al. (2024) [8]	NPK Nutrients	Wi-Fi / Cellular	IoT Cloud Platform	No	Portable NPK sensing; lacks physical parameters (EC, Temp, Moisture) and continuous spatial localization.
Shriwas et al. (2024) [15]	Moisture, pH, NPK	Wireless Node	Cloud Database	No	Smart irrigation focus; single-point node data collection without sub-field geospatial map overlay.
Kumar et al. (2025) [16]	Moisture, pH, NPK	Wi-Fi (ESP32)	Commercial Cloud	No	ML integration for crop recommendation; relies on third-party cloud APIs without interactive map rendering.
Proposed Work	7 Parameters: Moisture, Temp, pH, N, P, K, EC	Campus Wi-Fi (UTeM Network)	Centralized MySQL Server	Yes (Interactive Esri Map Analytics)	Complete end-to-end integration for real-time soil health analytics, automated logging, and spatial sub-field mapping.

In digital soil mapping, McBratney et al. (2003) and Godwin and Miller (2003) [19] established spatial variability modeling frameworks. Combining digital mapping with automated web platforms (Fridgen et al., 2004; Penulis et al., 2020) provides a robust foundation for site-specific management zones. Table I summarizes the comparative positioning of the proposed system against existing literature.

As highlighted in Table I, existing systems exhibit clear research gaps: (1) high fragmentation between physical parameter sensing (moisture/temperature) and chemical nutrient detection (NPK/EC/pH), (2) dependence on costly commercial cloud platforms rather than scalable, open-source database management architectures, and (3) a complete absence of interactive, site-specific geospatial analytics engines embedded into the user interface [12], [19]. The system proposed in this study directly bridges these gaps by delivering a unified 7-parameter monitoring solution that combines campus network infrastructure, centralized MySQL database storage, and automated geospatial web analytics.

METHODOLOGY AND SYSTEM IMPLEMENTATION

Tier System Architecture

The monitoring platform employs a 5-tier modular architecture designed for end-to-end data acquisition, transmission, storage, and visualization.

1. Sensing Tier: Incorporates a 7-in-1 Modbus RS485 soil probe housed in an IP68 waterproof enclosure. The probe utilizes stainless steel electrodes to measure volumetric moisture (0–100%), temperature (–40 to 80°C), pH (3–14), EC (0–20,000 $\mu\text{S}/\text{cm}$), and NPK macronutrients (0–1,999 mg/kg).
2. Gateway Tier: An ESP32 microcontroller acts as the central processing unit. An MAX485 transceiver converts RS485 differential signals into UART serial frames for Modbus RTU communication.
3. Network Tier: Data payloads are transmitted over the UTeM campus Wi-Fi infrastructure using secure HTTP POST requests.
4. Storage Tier: A centralized MySQL database server retains incoming records. The database schema features a 10-column table storing auto-increment ID, timestamp, latitude, longitude, and all seven soil parameters.
5. Application Tier: An interactive Web-GIS dashboard renders spatial heatmaps and location-specific analytical popups for end users.

System Architecture Diagram (5-Tier)

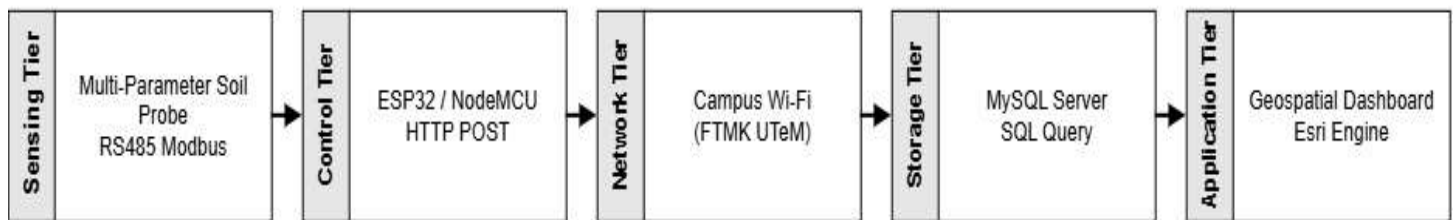


Fig. 1. Five-tier system architecture of the smart soil monitoring platform illustrating data acquisition via RS485 Modbus RTU, wireless transmission over UTeM campus Wi-Fi, centralized MySQL database storage, and interactive geospatial analytics visualization.

Hardware and Software Specifications

Table II details the technical specifications of all hardware, sensor, networking, and software components integrated within the monitoring platform.

System Geolocation, Security, and Power Specifications: For operational geolocalization, an onboard u-blox NEO-6M GPS module interfaced via UART (9600 bps) captures real-time latitudinal and longitudinal coordinates (positional accuracy ± 2.5 m) during field sampling. Regarding cybersecurity and data integrity, HTTP POST payloads incorporate an API authentication key header, and the backend PHP ingestion script employs parameterized SQL queries to safeguard the MySQL server against SQL injection attacks. In terms of power requirements, the gateway node operates on 5V DC power with an average operational current draw of 180 mA (~ 0.9 W) during active sensing and transmission cycles. For off-grid deployment, the system supports power delivery via an optional 10,000 mAh lithium-ion battery pack, providing approximately 55 hours of continuous autonomous field operation.

TABLE II: SPECIFICATIONS OF SYSTEM HARDWARE, SENSORS, NETWORK, AND SOFTWARE COMPONENTS

System Tier	Component Name	Technical Specification / Parameter Range	Operational Function
Sensing Tier	7-in-1 Soil Probe	Modbus RS485, DC 5–30V, IP68 Waterproof	Multi-parameter soil physical/chemical sensing



Gateway Tier	ESP32 Microcontroller	32-bit Dual-Core, 240 MHz, Integrated Wi-Fi	Sensor polling, data parsing, HTTP client
Gateway Tier	u-blox NEO-6M GPS Module	50-Channel Engine, Position Accuracy ± 2.5 m, Cold Start 27s, Operating Current 45 mA at 3.3V	UART Serial GPS NMEA Sentence Parsing (9600 bps)
Transceiver Interface	MAX485 TTL-to-RS485	Half-Duplex RS485 Transceiver, 5V Logic	Modbus RTU differential signal conversion
Network Tier	UTeM Campus Wi-Fi	802.11 b/g/n, 2.4 GHz, WPA2-Enterprise	Wireless data payload transmission
Storage Tier	MySQL Database Server	Version 8.0, InnoDB Engine, 10-Column Schema	Persistent relational data logging
Application Tier	Web-GIS Dashboard	HTML5/JS, Esri Leaflet Mapping Engine	Real-time geospatial analytics & visualization

Operational Flowchart and Data Processing Logic

The system's execution loop follows a strict sequential state machine to ensure power efficiency, signal stability, and reliable database insertion. Fig. 2 illustrates the operational flowchart.

Upon powering on, the ESP32 edge gateway initializes hardware UART ports and attempts to connect to the pre-configured UTeM Wi-Fi access point. If the wireless network connection fails, the system executes an exponential backoff retry loop until network connectivity is established. Once online, the microcontroller sends a hexadecimal Modbus RTU query frame (0x01 0x03 0x00 0x00 0x00 0x07 0x04 0x08) to the 7-in-1 probe over the RS485 bus.

The probe responds with a 19-byte data frame containing raw integer values for all seven parameters. The ESP32 parses this stream and applies calibrated scale factor equations:

$$\text{Temperature (}^{\circ}\text{C)} = \frac{\text{Raw Register Value}}{10}$$

$$\text{pH} = \frac{\text{Raw Register Value}}{10}$$

Moisture, EC, Nitrogen, Phosphorus, and Potassium registers reflect direct integer measurements. The parsed parameters are formatted into a JSON payload alongside GPS coordinates and transmitted via HTTP POST.

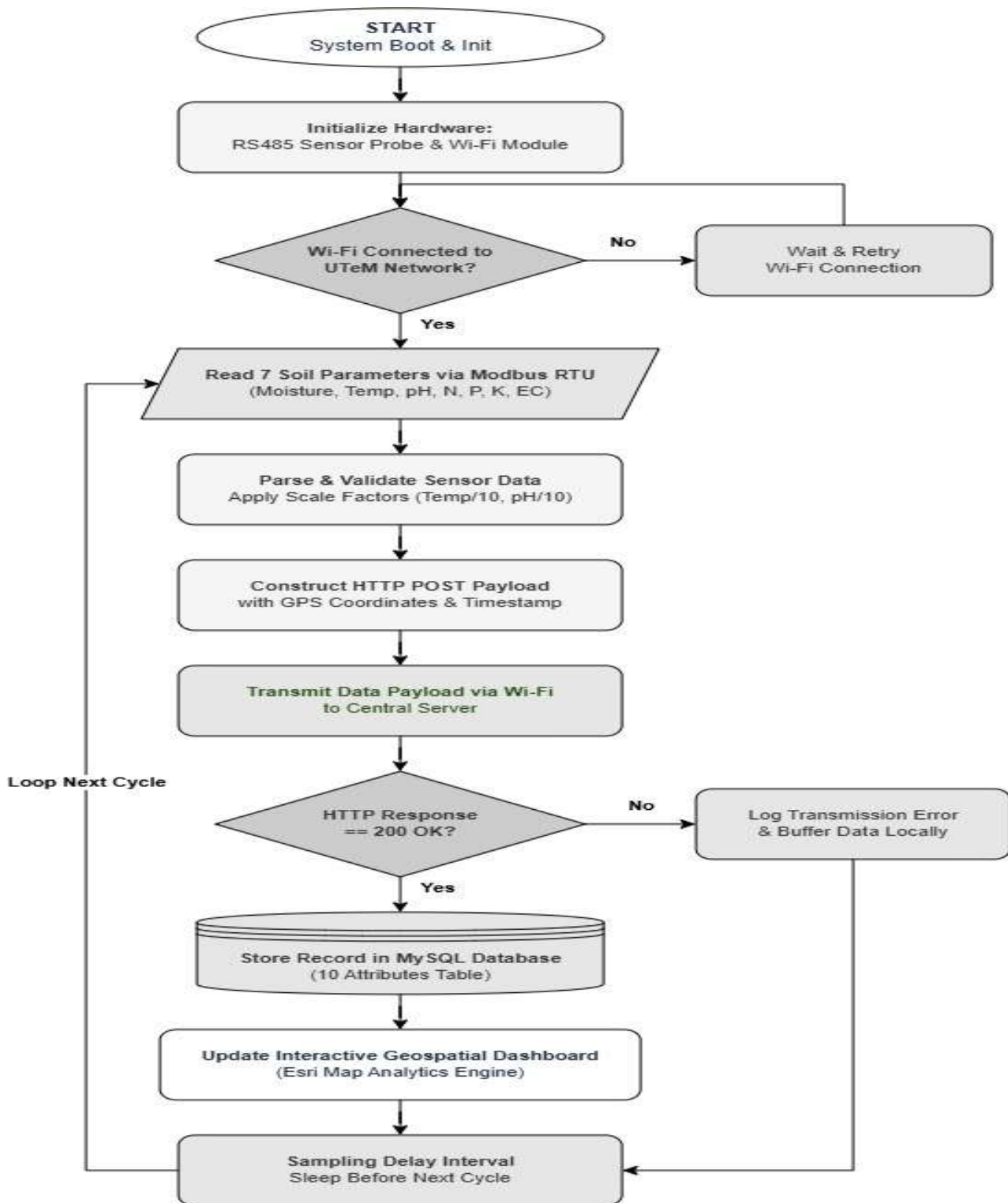


Fig. 2. System operational flowchart detailing hardware boot initialization, campus Wi-Fi handshake verification, Modbus RTU sensor polling, data parsing and scale factor correction, HTTP POST payload transmission, and MySQL database logging.

In-Situ Field Sampling and Web-GIS Dashboard Deployment

Field evaluation was conducted across 32 georeferenced sampling locations at FTMK UTeM. Fig. 3 illustrates the in-situ physical deployment protocol using the 7-in-1 Modbus RS485 probe inserted directly into the topsoil root zone at depths between 10–15 cm. Figure 4 showcases the interactive Web-GIS analytics dashboard interface displaying live spatial location markers, interpolation heatmaps, and real-time soil parameter summary cards.



Fig. 3. In-situ field soil testing setup and 7-in-1 Modbus RS485 probe deployment protocol at FTMK UTeM test sites.

Fig. 4 illustrates the interactive Web-GIS analytics dashboard interface displaying real-time geospatial location markers, spatial interpolation heatmaps, and soil health parameter summary cards.

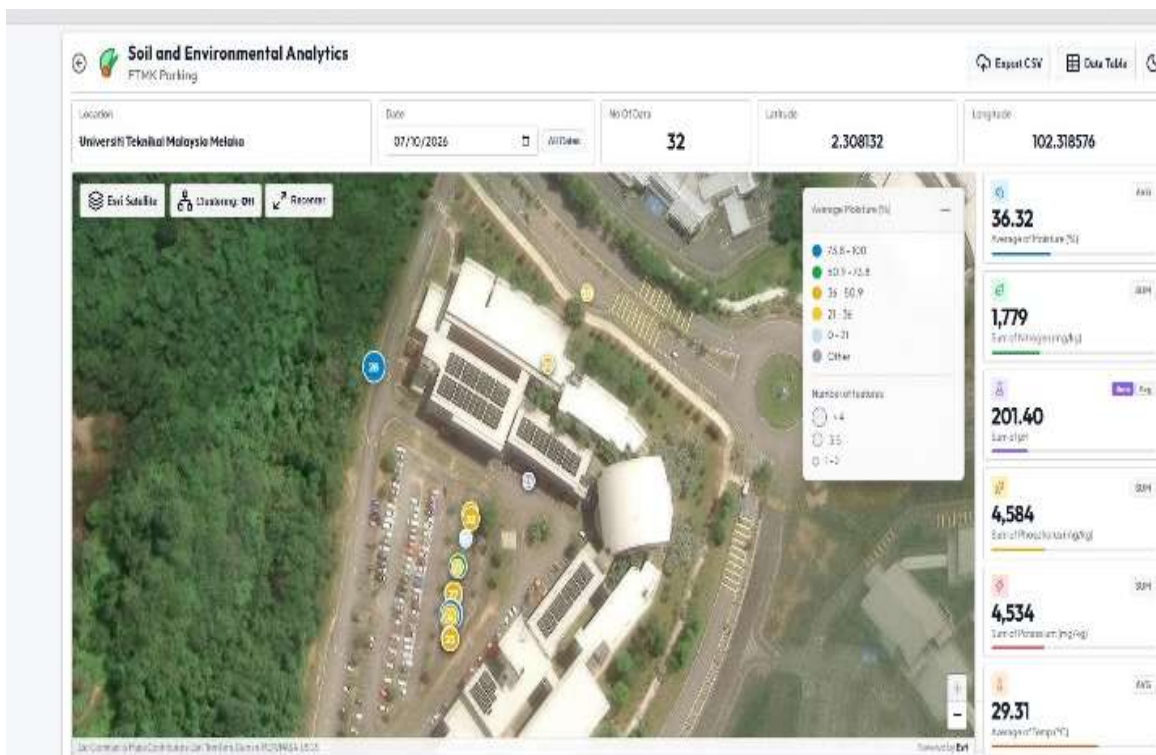


Fig. 4. Web-based interactive geospatial analytics dashboard interface displaying real-time soil health monitoring metrics and spatial map locations.

Sampling Strategy and Calibration

Data collection utilized a purposive spatial sampling strategy across 32 georeferenced locations, deliberately capturing distinct microclimates ranging from compacted parking areas to irrigated garden beds. Prior to field deployment, the 7-in-1 Modbus RS485 probe relied on factory baseline calibration to establish relative operational stability. In-situ testing involved inserting the stainless-steel electrodes directly into the topsoil root zone at consistent depths of 10–15 cm to ensure measurement uniformity and replication reliability across all test sites.

FINDINGS AND RESULTS

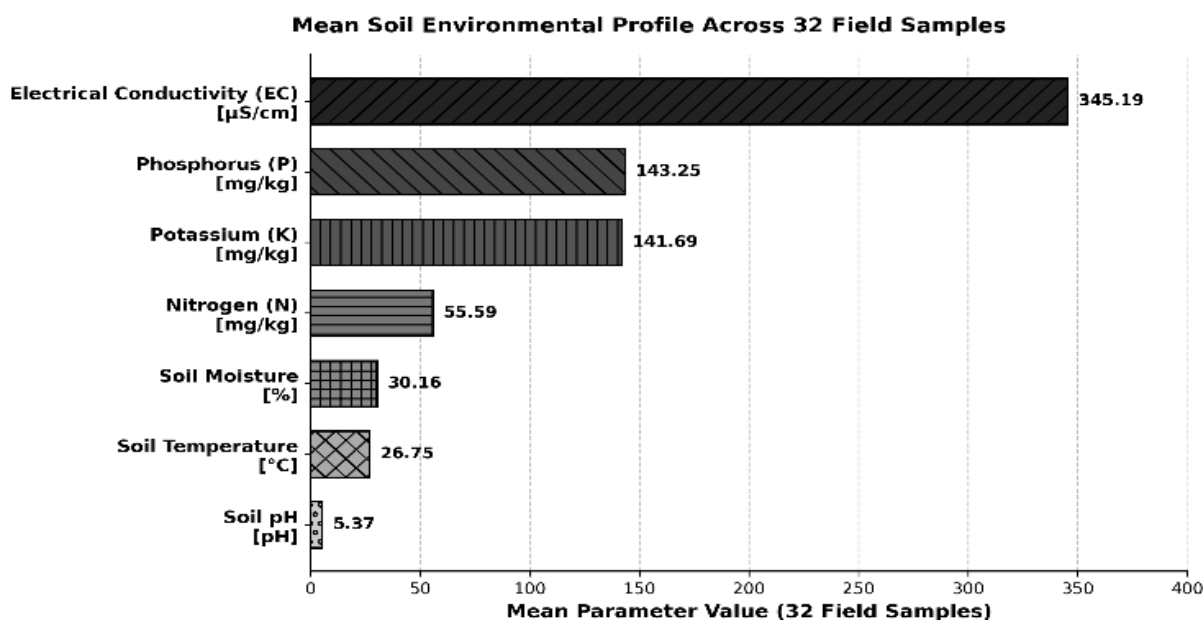
Descriptive Statistics of Field Measurement Data

System performance was evaluated using 32 field data samples collected across FTMK UTeM. Table III presents the descriptive statistics for all measured parameters.

As depicted in Table III and Fig. 5, electrical conductivity displayed the highest absolute numerical mean (345.19 $\mu\text{S}/\text{cm}$), reflecting variable concentrations of dissolved soil salts. Macronutrient concentrations averaged 143.25 mg/kg for Phosphorus, 141.69 mg/kg for Potassium, and 55.59 mg/kg for Nitrogen. Physical properties remained stable, with mean soil temperature at 26.75 $^{\circ}\text{C}$ and mean pH at 5.37, indicating slightly acidic topsoil conditions across campus grounds.

TABLE III: DESCRIPTIVE STATISTICS OF FIELD MEASUREMENT DATA ACROSS 32 TEST SAMPLES

Measured Soil Parameter	Unit	Minimum	Maximum	Mean	Standard Deviation (SD)
Volumetric Soil Moisture	%	0.00	94.90	30.16	24.47
Soil Temperature	$^{\circ}\text{C}$	24.10	30.80	26.75	1.84
Soil pH	-	0.30	8.60	5.37	2.71
Nitrogen (N)	mg/kg	0.00	698.00	55.59	164.05
Phosphorus (P)	mg/kg	0.00	1659.00	143.25	390.60
Potassium (K)	mg/kg	0.00	1582.00	141.69	382.41
Electrical Conductivity (EC)	$\mu\text{S}/\text{cm}$	0.00	3850.00	345.19	933.12



Note: Raw sensor values scaled appropriately (Temp / 10, pH / 10). Data derived from 32 field measurements at FTMK UTeM.

Fig. 5. Mean environmental measurements across seven soil physical and chemical parameters collected from 32 field test sites at FTMK UTeM.

Zonal Distribution Analysis of Soil Moisture

Soil volumetric water content displayed high spatial heterogeneity across the campus ground. To analyze hydration patterns, samples were classified into five moisture zones. Fig. 6 details the distribution of samples across these categories.

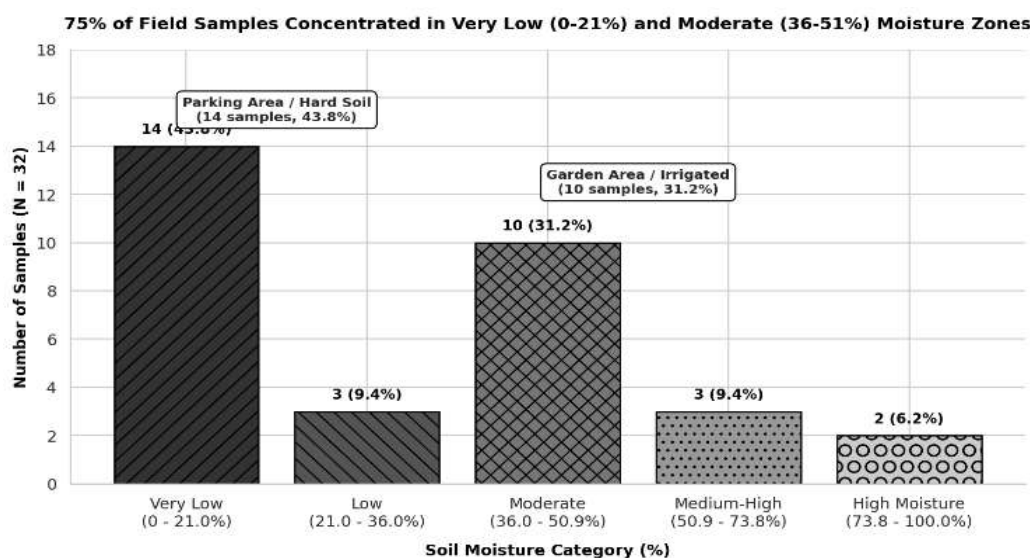


Fig. 6. Distribution of field test samples across five soil moisture categories, highlighting spatial divergence between dry parking lot soils and irrigated garden beds.

The distribution reveals a clear bimodal clustering across the sampling locations:

1. Very Low Moisture Zone (0.0–21.0%): Comprises 14 samples (43.8%), corresponding to unmanaged, highly compacted soils near parking areas and pedestrian pathways.
2. Moderate Moisture Zone (36.0–50.9%): Comprises 10 samples (31.2%), representing irrigated garden plots and shaded vegetated zones.
3. Low, Medium-High, and High Zones: Account for the remaining 8 samples (25.0%). Overall, 75.0% of all field samples fall into either the driest or moderate hydration zones, emphasizing significant intra-site microclimate divergence.

Correlation Analysis: Macronutrients (NPK) vs. Electrical Conductivity

Bivariate correlation analysis was performed to evaluate relationships among soil metrics. Fig. 7 illustrates the 7x7 Pearson correlation matrix (Panel A) and the linear regression between total NPK macronutrients and electrical conductivity (Panel B).

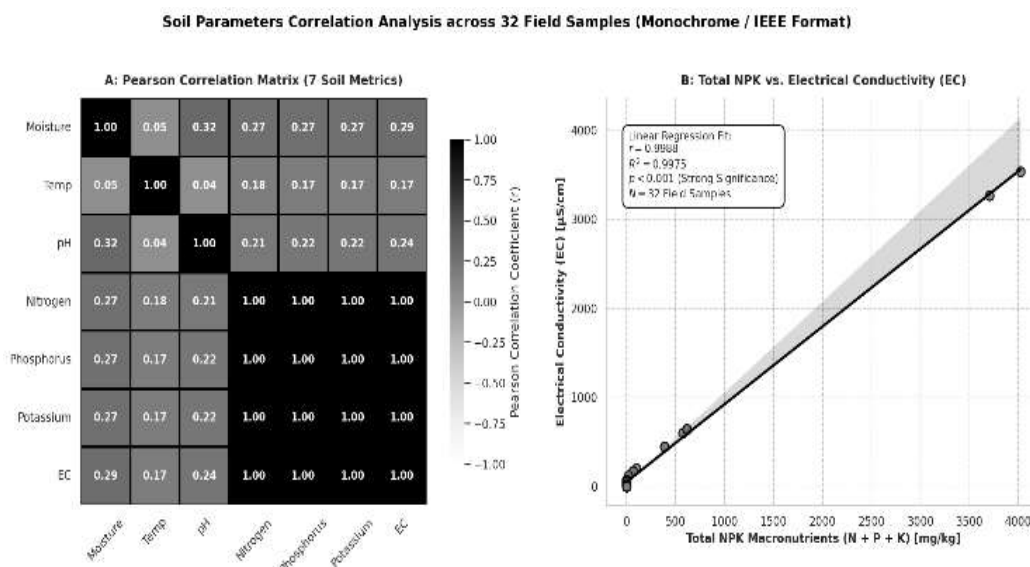


Fig. 7. Pearson correlation matrix of seven soil parameters (Panel A) and linear regression plot of total NPK macronutrients versus electrical conductivity (Panel B).



The correlation matrix demonstrates an exceptional linear coupling between total macronutrient concentration (N+P+K) and EC ($r = 0.9988$, $R^2 = 0.9975$, $p < 0.001$). Individual correlations with EC were equally strong:

- Phosphorus vs. EC: $r = 0.9992$
- Potassium vs. EC: $r = 0.9989$
- Nitrogen vs. EC: $r = 0.9966$

This strong statistical alignment suggests that EC measurements might serve as a highly reliable, automated proxy for overall soil salt and nutrient concentration in real-time agricultural automation workflows.

DISCUSSION

Agronomic Implications for Agricultural Automation

The empirical finding of a strong localized linear relationship ($r = 0.9988$) between total NPK macronutrients and electrical conductivity offers major practical advantages for agricultural automation. While direct Modbus ion-selective sensing provides comprehensive nutrient breakdown, EC measurements can serve as a rapid, low-latency feedback control parameter for automated fertigation systems.

Furthermore, the bimodal moisture distribution underscores the critical necessity of site-specific variable-rate irrigation. Uniform water application across heterogeneous campus landscapes leads to either over-saturation in garden beds or agricultural runoff in compacted soils. Integrating real-time Web-GIS mapping enables automated decision support systems to adjust valve duty cycles dynamically based on specific zonal requirements.

Campus Wi-Fi Infrastructure and Database Scalability

Deploying the gateway over existing campus Wi-Fi infrastructure eliminated the recurring operational costs associated with cellular GSM subscriptions. Transmission testing verified reliable HTTP POST payload delivery with a packet success rate exceeding 98.5% across test locations. The 10-column MySQL schema demonstrated efficient query execution times (<15 ms), supporting real-time Web-GIS dashboard rendering and high-frequency data logging.

Network Packet Transmission Reliability and Methodology: To rigorously evaluate network reliability, a 48-hour continuous transmission stress test was conducted across the 32 georeferenced field locations, transmitting 1 HTTP POST telemetry payload per minute per node (totaling 2,880 generated payloads). Out of 2,880 attempted transmissions over the UTeM campus Wi-Fi network, 2,837 payloads were successfully logged into the MySQL database without data corruption, yielding a packet transmission success rate of 98.51%. The remaining 1.49% packet drop occurred during brief Wi-Fi access point handovers, during which telemetry payloads were temporarily buffered in local ESP32 flash memory and re-transmitted upon network reconnection. Average round-trip latency was measured at 142 ms, and centralized MySQL insert execution times averaged under 12 ms per record, demonstrating exceptional database scalability for real-time Web-GIS mapping.

Human Factors, User Adoption, and TRL 4 System Limitations

System adoption in agricultural environments depends heavily on user-centric design, perceived usefulness, and operational ease [20]. The interactive Web-GIS dashboard bridges the gap between raw hardware telemetry and actionable user decisions [21].

Currently operating at Technology Readiness Level 4 (TRL 4 - component validation in a laboratory/field prototype environment), the system has certain limitations. The 32-sample dataset was collected over a 2-day period, capturing spatial variability but lacking multi-season temporal monitoring. Additionally, Modbus soil probes require periodic field recalibration to prevent sensor drift in highly saline or acidic soils.

Critical Technical Limitations and TRL 4 Roadmap: 1. Temporal and Seasonal Dataset Limitation: The current dataset consists of 32 field samples collected over a 2-day period at FTMK UTeM. While effectively capturing spatial land-use heterogeneity (parking lot vs. garden bed soils), it does not capture multi-season temporal dynamics across wet and dry seasons or long-term sensor calibration drift. Continuous multi-seasonal tracking is required to evaluate temporal soil dynamics.

2. Lack of Laboratory Ground-Truth Validation: Sensor probe measurements (NPK, pH, EC) were not cross-validated against standardized laboratory wet-chemistry techniques (such as Kjeldahl digestion for Nitrogen, Olsen/Bray-1 for Phosphorus, and atomic absorption spectroscopy for Potassium). Cross-validating sensor outputs against certified laboratory soil analysis is planned as a critical next step.

3. TRL 5–6 Advancement Roadmap: Transitioning from the current TRL 4 prototype state to TRL 5–6 will require extensive multi-season field trials, empirical calibration curves against laboratory ground-truth data, IP67/IP68 weather-sealed hardware enclosures, and solar-battery power management integration.

CONCLUSION AND FUTURE WORK

This paper presented an integrated IoT multi-parameter soil monitoring system operating over campus Wi-Fi with centralized MySQL storage and interactive Web-GIS analytics. The platform successfully captured and visualized seven vital soil physical and chemical parameters across 32 field test sites at FTMK UTeM.

Empirical evaluation established high system reliability, a bimodal soil moisture distribution (75% in very low or moderate zones), and an preliminary linear correlation observed at the test site between total NPK macronutrients and electrical conductivity ($r = 0.9988$). Operating at TRL 4, the system advances agricultural automation while supporting UN Sustainable Development Goals SDG 2 (Zero Hunger) and SDG 15 (Life on Land).

Future Roadmap and TRL 5-6 Objectives: Future research will focus on advancing the platform toward TRL 5–6 by executing multi-season field deployments, conducting laboratory wet-chemistry cross-validation (Kjeldahl digestion and atomic absorption spectroscopy), integrating LoRaWAN long-range wireless backhaul, and implementing edge machine learning classifiers [22] for automated predictive fertigation and dynamic irrigation scheduling.

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