

DEVELOPMENT OF AUTOMATED SOIL PARAMETER MONITORING EQUIPMENT FOR PRECISION AGRICULTURE

DESENVOLVIMENTO DE EQUIPAMENTO DE MONITORAMENTO
AUTOMATIZADO DE PARÂMETROS DO SOLO PARA AGRICULTURA DE
PRECISÃO

DESARROLLO DE EQUIPOS AUTOMATIZADOS PARA EL MONITOREO DE
PARÁMETROS DEL SUELO EN LA AGRICULTURA DE PRECISIÓN

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ABSTRACT

The integration of technologies has opened new avenues for precision agriculture. These technologies enable dynamic monitoring, predictive analysis, and automated decision-making, thereby increasing the efficiency and sustainability of agricultural practices. Accordingly, the objective was to develop automated monitoring equipment for soil parameters (pH, temperature, electrical conductivity, and soil moisture) for precision agriculture. Sensors were deployed directly in the field, combining data transmission with the precise acquisition of information regarding soil quality. Following the assembly of the soil monitoring equipment, testing phases were initiated through benchtop analysis of soil samples, enabling parameter readings, data storage, and data transmission. The soil used for equipment validation was classified as a dystroferic Red Latosol (LVdf) with medium texture. Once sensor readings were obtained, the maximum absolute error, non-linearity, hysteresis, and repeatability error of the sensors were determined. This soil parameter monitoring equipment automates precision agriculture, transforming farming from manual practices into dynamic operations that increase crop productivity, improve the sustainability of agricultural production, and reduce human labor.

Keywords: Technology. Sensors. pH. Temperature. Electrical Conductivity. Humidity.

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RESUMO

A integração de tecnologias abriu novos caminhos para a agricultura de precisão. Essas tecnologias permitem o monitoramento dinâmico, a análise preditiva e a tomada de decisões automatizada, aumentando assim a eficiência e a sustentabilidade das práticas agrícolas. Com isto, objetivou-se realizar o desenvolvimento do equipamento de monitoramento automatizado de parâmetros do solo (pH, temperatura, condutividade elétrica e umidade do solo) para agricultura de precisão. Os sensores foram aplicados diretamente no campo, aliando a transmissão de dados com a aquisição precisa de informações sobre a qualidade do solo. Posteriormente a montagem do equipamento de monitoramento de solo foi iniciada as etapas de testes do dispositivo por meio das análises das amostras de solo em bancada, possibilitando a leitura dos parâmetros, seu armazenamento e transmissão de dados. O solo que foi utilizado para o teste de validação do equipamento foi o solo classificado como Latossolo Vermelho distroférrico (LVdf) de textura média. Uma vez obtida a leitura dos dados por intermédio dos sensores foram determinados o erro máximo absoluto, não-linearidade, histerese e o erro de repetitividade do sensor. O equipamento de monitoramento de parâmetros do solo automatiza a agricultura de precisão, transformando a agricultura de práticas manuais em operações dinâmicas que aumentam a produtividade das culturas, melhora a sustentabilidade da produção agrícola e reduz os esforços humanos.

Palavras-chave: Tecnologia. Sensores. pH. Temperatura. Condutividade Elétrica. Umidade.

RESUMEN

La integración de tecnologías ha abierto nuevas vías para la agricultura de precisión. Estas tecnologías permiten el monitoreo dinámico, el análisis predictivo y la toma de decisiones automatizada, aumentando así la eficiencia y la sostenibilidad de las prácticas agrícolas. Por lo tanto, el objetivo fue desarrollar un equipo de monitoreo automatizado para parámetros del suelo (pH, temperatura, conductividad eléctrica y humedad del suelo) para la agricultura de precisión. Los sensores se aplicaron directamente en el campo, combinando la transmisión de datos con la adquisición precisa de información sobre la calidad del suelo. Tras el ensamblaje del equipo de monitoreo del suelo, se inició la prueba del dispositivo mediante el análisis de muestras de suelo en un banco de pruebas, lo que permitió la lectura de parámetros, el almacenamiento y la transmisión de datos. El suelo utilizado para la prueba de validación del equipo se clasificó como un Latosol Rojo Distrófico (LVdf) con textura media. Una vez obtenidas las lecturas de datos a través de los sensores, se determinaron el error absoluto máximo, la no linealidad, la histéresis y el error de repetibilidad del sensor. El equipo de monitoreo de parámetros del suelo automatiza la agricultura de precisión, transformando la agricultura de prácticas manuales a operaciones dinámicas que aumentan la productividad de los cultivos, mejoran la sostenibilidad de la producción agrícola y reducen el esfuerzo humano.

Palabras clave: Tecnología. Sensores. pH. Temperatura. Conductividad Eléctrica. Humedad.



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INTRODUCTION

The rapid development and widespread application of devices have driven improvements in current agricultural practices, primarily through automation and computerization (Munteanu *et al.*, 2024). The precise experimental determination of soil parameters is of great importance across various scientific fields, such as agronomy, soil physics, hydraulics, and soil mechanics (Ovanisof *et al.*, 2018). Integrating devices into soil monitoring systems has revolutionized data accessibility, enabling the use of mobile devices or computers.

In this context, the integration of IoT, WSN, and ML has opened new avenues for precision agriculture. These technologies enable dynamic monitoring, predictive analysis, and automated decision-making, thereby enhancing the efficiency and sustainability of agricultural practices (Bauer-Marschallinger *et al.*, 2019). The convergence of smart sensors, advanced data analytics, and sustainable technologies is revolutionizing agriculture, aligning with global efforts to achieve the Sustainable Development Goals.

The collected data can also be analyzed to gain insights into soil health and make future predictions, facilitating management strategies (Udrea *et al.*, 2020).

Recent innovations have improved the energy efficiency and longevity of wireless sensor networks deployed in agricultural fields, achieving superior monitoring performance (Kavitha *et al.*, 2025). IoT-based frameworks provide farmers with data on soil conditions, enabling resource-efficient practices and reducing environmental impact (Bhardwaj *et al.*, 2024). Furthermore, integrating IoT with blockchain technologies has enhanced data security and transparency within smart agriculture ecosystems (Singh and Musale, 2024). By understanding the specific nutritional needs of crops, fertilizers can be applied more precisely, reducing the risk of nutrient loss (Alreshidi, 2019). Despite these new agricultural technologies, several challenges persist; for instance, deploying sensors across various soil types often involves difficulties regarding calibration, maintenance costs, and data accuracy (Kavitha *et al.*, 2025). Furthermore, managing the vast amounts of heterogeneous data generated by sensors requires robust frameworks for data fusion and interoperability (Benameur *et al.*, 2024). Against this backdrop, the objective was to develop automated monitoring equipment for soil parameters (pH, temperature, electrical conductivity, and soil moisture) for precision agriculture.

METHODOLOGY

The equipment was developed by the company Acanto LTDA in the municipality of Rio Verde, Goiás (GO). The region's climate is classified according to Köppen and Geiger (1928) as Aw (tropical), with rainfall from October to May and a dry season from June to September. The average annual temperature ranges from 20 to 35°C, annual precipitation varies between 1,500 and 1,800 mm, and the terrain is gently undulating (6% slope).

Soil parameters were collected using an Arduino integrated with sensors for pH, temperature, conductivity, and soil moisture. The sensors were inserted directly into the soil, sending data to the Arduino, which processed the information and forwarded it to a NodeMCU. Continuous data collection was performed, with the data subsequently stored on the Ubidots service; the system thus comprised two distinct applications, each with a specific function: one was responsible for data centralization, while the other handled management tasks.

The automated soil monitoring system for precision agriculture utilized two distinct hardware platforms: the Arduino UNO and the NodeMCU. Arduino was responsible for collecting sensor data (pH, temperature, conductivity, and soil moisture), capturing soil quality information at two-second intervals. The NodeMCU received the data collected from the Arduino via the I2C protocol and managed the system by analyzing the information. Additionally, it is connected to a local wireless network to transmit data to the Ubidots platform using the MQTT protocol.

The sensors were deployed directly in the field, combining data transmission with precise soil quality data acquisition, obtained directly without the need for sample transport, personnel costs, or laboratory infrastructure.

Following the assembly of the soil monitoring equipment, testing began with benchtop analysis of soil samples, enabling parameter readings, data storage, and data transmission. The soil used for the equipment validation test was classified as a dystroferric Red Latosol (LVdf) with medium texture (Embrapa, 2013). To establish the equipment's reliability and validate the results, commercial equipment was used to obtain reference data, which served as the fundamental benchmark for the validation process.

To ensure a valid analysis of the parameters measured by the sensors (pH, temperature, conductivity, and soil moisture), calibration was required to improve measurement precision; this was performed using standard solutions. Furthermore, to validate the results, the precision of

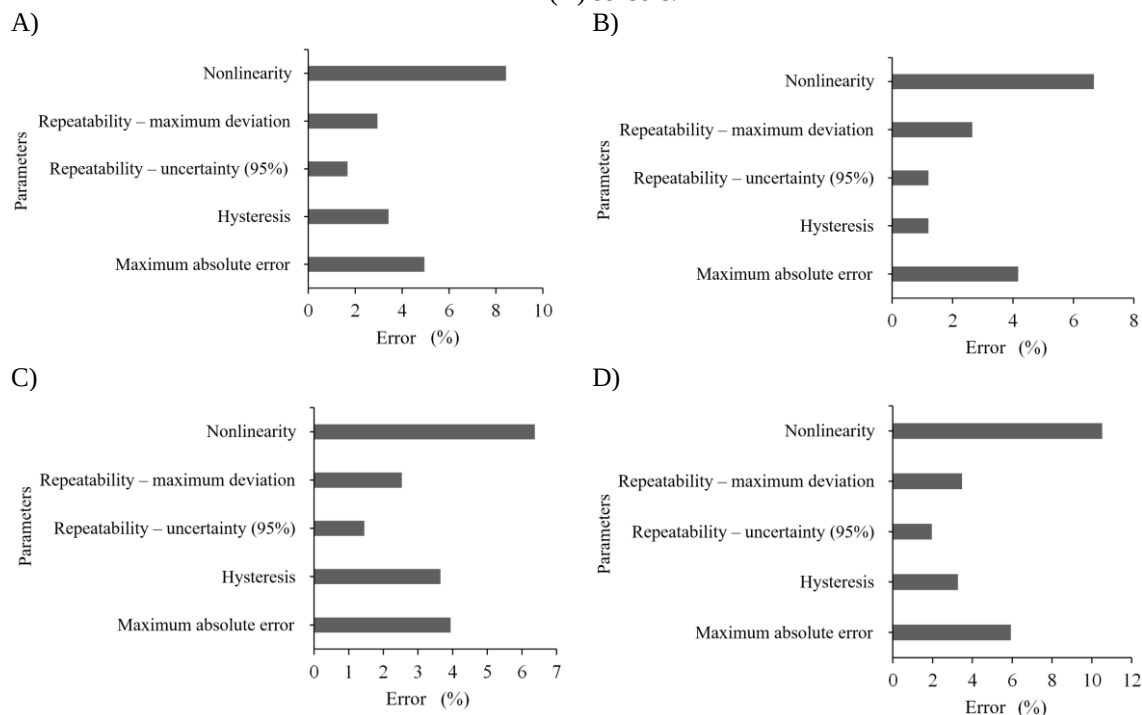
each sensor—defined as the acceptable degree of variation in measurement results—was determined. Once data readings were obtained from the sensors, the maximum absolute error, non-linearity, hysteresis, and repeatability error were calculated (Wheeler & Ganji, 1996; Vellame *et al.*, 2011).

The data obtained was subjected to descriptive statistics and analysis of variance (ANOVA) using the F-test. For results showing significant differences, Tukey's test was applied at a 5% probability level using the SISVAR statistical software (Ferreira, 2011).

RESULT AND DISCUSSION

Absolute maximum error and non-linearity were the factors that most significantly affected sensor accuracy (Figure 1). Brendan *et al.* (2024) focus on developing an operational farm-scale soil monitoring system that generates highly detailed daily soil maps; notably, their research emphasizes iterative improvements—particularly regarding sensor recalibration and spatiotemporal modeling—aligning with the importance of continuous refinement and validation in soil monitoring systems.

Figure 1. Determination of the precision of pH (A), temperature (B), electrical conductivity (C), and soil moisture (D) sensors.



Source: Prepared by the authors.

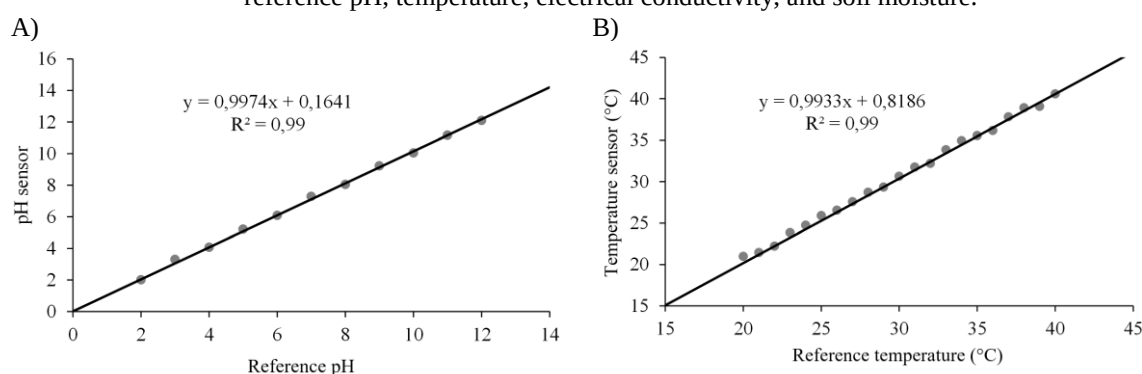
After absolute maximum error and non-linearity, the factors that most influenced the equipment's precision were hysteresis and repeatability, with mean errors of 4.8% and 6.7%, respectively. Faria *et al.* (2006) found excellent linearity between mass and voltage variations; they observed no hysteresis and recorded low absolute error values, thereby demonstrating high precision in determining water mass variations.

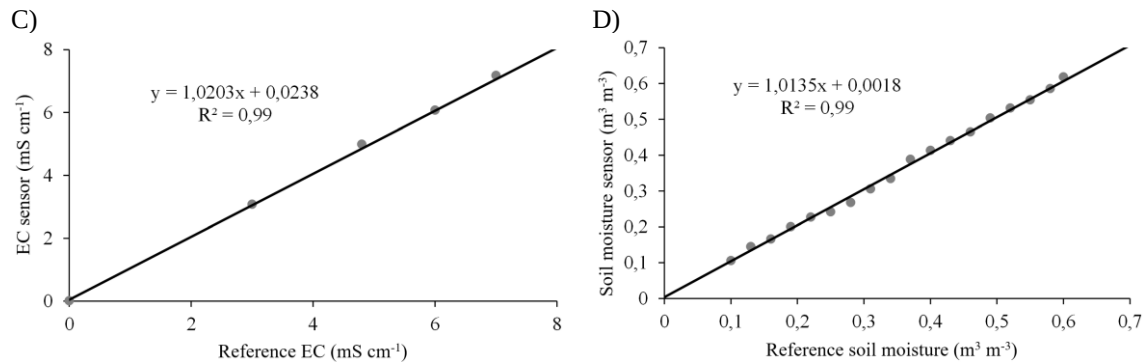
The variations observed in absolute maximum error, hysteresis, repeatability (95% uncertainty), repeatability (maximum deviation), and non-linearity during the calibration process—across pH, temperature, electrical conductivity, and soil moisture sensors—were generally low. Maximum differences in error values between sensors were 3.2% for absolute maximum error, 1.5% for hysteresis, 0.8% for repeatability (95% uncertainty), 1.3% for repeatability (maximum deviation), and 4.8% for non-linearity. Vilela *et al.* (2015) found that errors related to hysteresis, non-linearity, repeatability, and absolute maximum error arising from the calibration process cannot be disregarded, particularly regarding deviations.

The agricultural sector is undergoing transformations driven by new technologies; consequently, farmers are using sensors and computer software to optimize cultivation. These sensors are installed in the field to monitor key factors and assess soil conditions, enabling farmers to make smarter decisions regarding their crops (Misra *et al.*, 2025; Ivanova, 2025).

Figure 2 shows the calibration of the pH, temperature, electrical conductivity, and soil moisture sensors.

Figure 2. Calibration of pH (A), temperature (B), electrical conductivity (C), and soil moisture (D) sensors against reference pH, temperature, electrical conductivity, and soil moisture.





Source: Prepared by the authors.

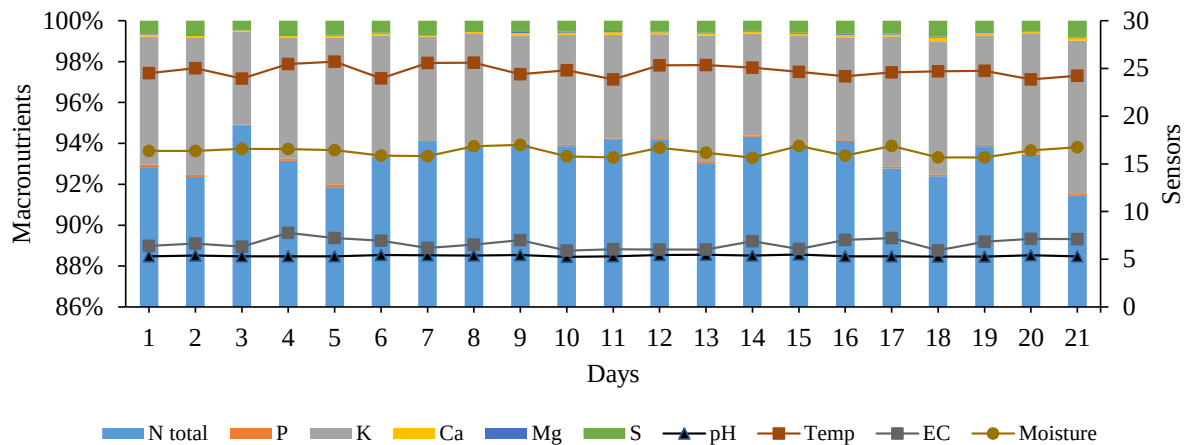
During the calibration process for the pH, temperature, electrical conductivity, and soil moisture sensors, it was observed that all of them fit a linear model with an R^2 of 99%, indicating that only 1% of the observed values for these parameters remains unexplained by the variation in the estimated values.

Soil monitoring equipment benefits significantly from the integration of soil sensors with actual soil samples for validation and calibration purposes. Field-based data assimilation approaches generally demonstrate how observations can improve predictions by providing reference data to validate measurements from sensor networks; consequently, data records enable long-term trend analyses that support the adaptive management of sensor networks (Crow *et al.*, 2017; Gruber *et al.*, 2019).

Studies involving sensor calibration through the comparison of reference parameters to evaluate equipment performance are essential (Al-Yaari *et al.*, 2019). Refining sensor-derived data yields field-scale estimates of pH, temperature, electrical conductivity, and soil moisture, which can serve to validate and calibrate local sensor networks (Zeng *et al.*, 2016). Validation studies have established protocols for comparing field measurements, while comprehensive evaluation frameworks guide the optimal integration of multi-scale monitoring systems, thereby enhancing overall system efficiency (Beck *et al.*, 2021).

Figure 3 presents macronutrient levels plotted against the days of data collection from the sensors (pH, temperature, electrical conductivity, and soil moisture).

Figure 3. Macronutrients plotted against the days of data collection from the automated soil monitoring equipment sensors (pH, temperature, electrical conductivity, and soil moisture).



Source: Prepared by the authors.

The continuous data flow provides immediate information on essential conditions, including nutrient levels, enhancing the clarity and applicability of automated monitoring (Priya; Kaur *et al.*, 2021).

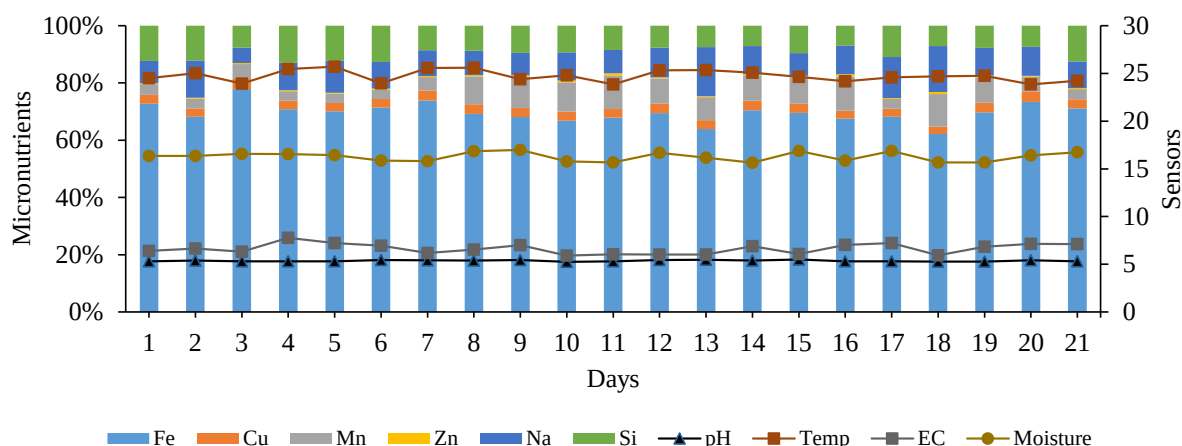
Soil nitrogen values ranged from 952 to 1743 mg kg⁻¹, indicating a mean N level of 1335 mg kg⁻¹. Soil phosphorus values ranged from 0.90 to 1.80 mg dm⁻³, indicating a mean P level of 1.10 mg dm⁻³. Soil potassium values ranged from 63 to 93 mg dm⁻³, indicating a mean K level of 81.05 mg dm⁻³.

By integrating traditional sensors with advanced processing and communication capabilities, smart sensors transform agriculture from manual practices into dynamic operations that increase production and reduce human effort (Shafi *et al.*, 2019; Munteanu *et al.*, 2024).

Soil calcium values ranged from 0.80 to 2.00 cmol_c dm⁻³, indicating a mean Ca level of 1.46 cmol_c dm⁻³. Soil magnesium values ranged from 0.40 to 0.80 cmol_c dm⁻³, indicating a mean Mg level of 0.54 cmol_c dm⁻³. Soil sulfur values ranged from 7.70 to 11.70 mg dm⁻³, indicating a mean S level of 8.56 mg dm⁻³.

Figure 4 presents the micronutrients plotted against the days of data collection from the sensors (pH, temperature, electrical conductivity, and soil moisture).

Figure 4. Micronutrients plotted against the days of sensor data collection (pH, temperature, electrical conductivity, and soil moisture) from the automated soil monitoring equipment.



Source: Prepared by the authors.

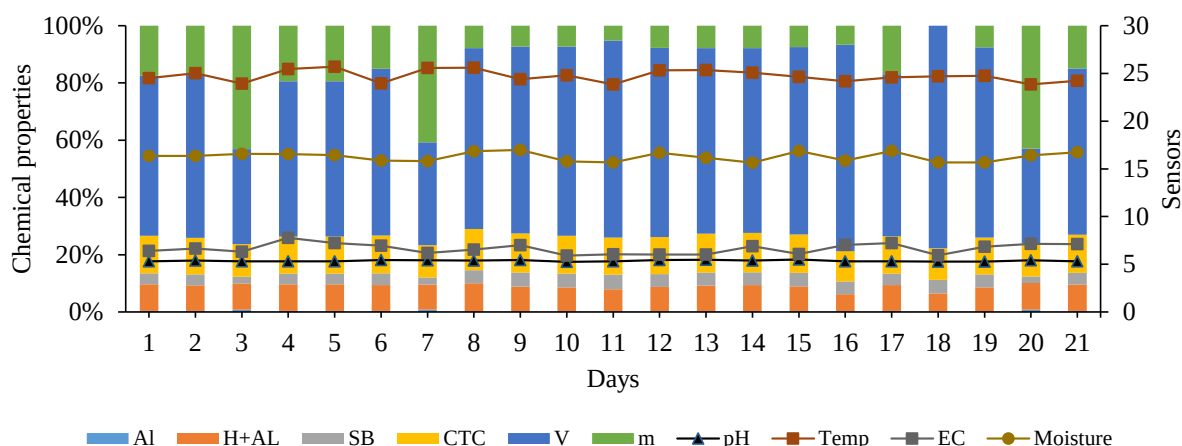
Soil iron values ranged from 27.00 to 43.50 mg dm⁻³, indicating a mean Fe content of 35.87 mg dm⁻³. Soil copper values ranged from 1.10 to 2.20 mg dm⁻³, indicating a mean Cu content of 1.63 mg dm⁻³. Soil manganese values ranged from 1.70 to 5.80 mg dm⁻³, indicating a mean Mn content of 3.53 mg dm⁻³.

In agriculture, sensors optimize cultivation by providing real-time data through integration with automated equipment, enabling more informed decision-making (Gupta *et al.*, 2021).

Soil zinc values ranged from 0.20 to 0.40 mg dm⁻³, indicating a mean Zn content of 0.24 mg dm⁻³. Soil sodium values ranged from 3.00 to 9.00 mg dm⁻³, indicating a mean Na content of 5.24 mg dm⁻³. Soil silicon values ranged from 2.80 to 6.80 mg kg⁻¹, indicating a mean Si content of 4.90 mg kg⁻¹.

Figure 5 presents the chemical properties plotted against the days of sensor data collection (pH, temperature, electrical conductivity, and soil moisture).

Figure 5. Chemical properties (pH, temperature, electrical conductivity, and soil moisture) over the course of the data collection period using automated soil monitoring equipment.



Source: Prepared by the authors.

Soil aluminum values ranged from 0.10 to 0.50 $\text{cmol}_c \text{ dm}^{-3}$, with a mean Al value of 0.19 $\text{cmol}_c \text{ dm}^{-3}$. Soil H+Al values ranged from 3.50 to 5.60 $\text{cmol}_c \text{ dm}^{-3}$, with a mean H+Al value of 4.71 $\text{cmol}_c \text{ dm}^{-3}$. Soil SB values ranged from 1.40 to 3.00 $\text{cmol}_c \text{ dm}^{-3}$, with a mean SB value of 2.20 $\text{cmol}_c \text{ dm}^{-3}$.

Automated equipment is designed to collect continuous, real-time data on various soil parameters (Shafi *et al.*, 2021).

Soil CEC values ranged from 6.10 to 7.50 $\text{cmol}_c \text{ dm}^{-3}$, with a mean CEC value of 6.91 $\text{cmol}_c \text{ dm}^{-3}$. Soil base saturation (V) values ranged from 20% to 43%, with a mean V value of 31.86%. Soil aluminum saturation (m) values ranged from 3.00% to 26.00%, with a mean m value of 8.52%.

To ensure optimal performance of automated soil monitoring equipment, it is essential to conduct comprehensive performance tests that categorize equipment effectiveness based on actual field verification (Oladipupo *et al.*, 2024).

Soil pH values ranged from 5.25 to 5.49, with a mean pH of 5.36 and a coefficient of variation of 1.39%. Soil temperature values ranged from 23.80 to 25.70°C, indicating a mean temperature of 24.70°C and a coefficient of variation of 2.47%. Conducting standardized tests in diverse agricultural environments, implementing long-term monitoring studies, and developing frameworks for comparing equipment performance with real-world implementation results have been crucial for verifying actual soil conditions (Adla *et al.*, 2024).

Soil electrical conductivity values ranged from 5.92 to 7.76 mS cm^{-1} , indicating a mean electrical conductivity of 6.63 mS cm^{-1} and a coefficient of variation of 4.06%. Soil moisture

values ranged from 15.64 to 16.98 m³ m⁻³, indicating a mean moisture content of 16.27 m³ m⁻³ and a coefficient of variation of 2.90%. Equipment performance can vary depending on soil texture, permeability levels, and salinity conditions; therefore, field calibration is also essential (Emami *et al.*, 2025).

CONCLUSION

Soil parameter monitoring equipment automates precision agriculture, transforming farming from manual practices into dynamic operations that boost crop productivity, enhance agricultural sustainability, and reduce manual labor.

Automated soil parameter collection enables a deeper understanding of soil conditions, which is crucial for characterizing relationships between variables and identifying spatiotemporal patterns.

To better understand the complex relationships among soil parameters, it is essential to use calibrated and validated equipment and sensors that provide valuable insights into soil quality.

The autonomous system collects and analyzes soil data by measuring pH, temperature, electrical conductivity, and moisture; this comprehensive data collection allows for real-time soil assessment, serving as a valuable tool for spatiotemporal mapping.

Future efforts should focus on robust models and standardized protocols involving the deployment of autonomous multi-parameter soil monitoring systems across diverse geographical areas.

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