Mobile Robotic Soil Moisture Sensing and Mapping for Precision Agriculture in Small-Scale Farming

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Abstract.

The spatial variability of soil moisture is a key factor for efficient irrigation management and agricultural productivity, particularly in small-scale farming systems where access to Precision Agriculture technologies remains limited due to cost and operational complexity. This study presents the development and preliminary evaluation of a robotic sensing system for georeferenced soil moisture data acquisition, focusing on spatial mapping in small agricultural areas.

The proposed system consists of roboFAM 1.0, a reduced-scale multifunctional robotic prototype equipped with four independently driven wheels, controlled by an embedded central unit based on an ESP32 microcontroller and developed as an experimental platform for applications in small-scale agriculture. For this study, the platform includes a linear actuator designed for controlled insertion of a soil probe, as well as a u-blox NEO-6M GNSS receiver, which provides positioning accuracy of approximately 2.5 m under open-sky conditions, enabling georeferencing of sampling points. Soil moisture measurements are obtained using a HaliSense Soil TH-EC-PH-NPK sensor, a low-cost multi-parameter probe designed for integrated characterization of soil properties. The sensor operates within a typical measurement range of 0–100% volumetric water content, with an accuracy of approximately ±3% under standard conditions, as specified by the manufacturer.

The robot is controlled via a dedicated mobile application responsible for motion control and real-time acquisition of soil moisture data. Each collected sample is associated with its respective latitude and longitude coordinates, forming a spatial dataset representing the distribution of soil moisture within the study area.

The experimental trials were conducted in a 10 m × 10 m area characterized as Planosol, located in an experimental field representative of small-scale agricultural environments. The soil surface was covered with crop residue from a previous maize crop. Data collection was performed at 36 regularly distributed sampling points, arranged in a 2 m × 2 m grid. Soil

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moisture measurements were obtained at a depth of 0–10 cm. A preliminary calibration of the sensor was performed using the gravimetric method as a reference, based on six samples collected across the study area. A linear calibration model was applied to the dataset, improving agreement with reference measurements.

Spatial interpolation was performed using the IDW method, with data processing and map generation carried out offline using custom-developed Python scripts. The interpolation results were evaluated using LOOCV, yielding an RMSE of 1.38%, MAE of 1.17%, and R^2 of 0.09, indicating the model's ability to capture soil moisture spatial variability patterns. Additionally, the interpolated surface generated from GNSS coordinates was compared with a reference surface generated from the ideal sampling grid, allowing the assessment of positioning errors on the spatial representation of soil moisture.

The results demonstrate the feasibility of integrating low-cost robotic platforms and proximal sensing for spatial soil moisture assessment in small-scale agricultural systems. Despite limitations associated with sensor accuracy and sampling density, the proposed approach effectively supports spatial analysis and decision-making for irrigation management. This work contributes to advancing accessible robotic and proximal sensing solutions, supporting the adoption of Precision Agriculture in small-scale farming systems.

Keywords.

Precision Agriculture, Soil moisture mapping, Small-scale farming, Agricultural robotics, Spatial interpolation.

Introduction

Efficient water management is one of the major challenges facing modern agriculture, being directly associated with crop productivity and the sustainability of agricultural systems. Soil moisture plays a fundamental role in regulating water availability for plants and directly influences irrigation planning and management. In this context, acquiring soil moisture data with adequate spatial and temporal resolution is essential for optimizing water use, maintaining crop productivity, and supporting Precision Agriculture practices. Furthermore, increasing concerns regarding water scarcity have stimulated research aimed at developing solutions that improve the efficiency and resilience of agricultural production systems (Ingrao et al. 2023).

The spatial variability of soil moisture is a critical factor for efficient irrigation management, as it limits the adoption of uniform management practices and may result in both water deficit and excessive irrigation. Consequently, Precision Agriculture has emerged as a promising approach by enabling site-specific management based on the spatial and temporal variability of soil attributes (Pusch et al. 2021).

However, the adoption of these technologies remains limited in small-scale farming systems, mainly due to the high cost of equipment, operational complexity, and the need for technical expertise (Castro 2022). Despite these constraints, Precision Agriculture has significant potential to improve resource use efficiency, increase competitiveness, and promote productive inclusion in rural areas (Abreu and Junior 2025; Bassoi et al. 2019).

In recent years, advances in proximal sensing and embedded systems have enabled the development of cost-effective solutions for monitoring soil properties (Manono et al. 2026; Yu et al. 2021). The integration of soil moisture sensors with Global Navigation Satellite System (GNSS) technologies enables the acquisition of georeferenced data and the generation of spatial maps (Reghini and Cavichioli 2020). Nevertheless, many of these systems still rely on manual data collection, making the process labor-intensive, time-consuming, and susceptible to operational inconsistencies, particularly in applications requiring high sampling density (Vasques et al. 2020; Zhang et al. 2024).

Despite recent advances in soil moisture sensing and positioning technologies, there remains a need for automated, low-cost solutions tailored to the conditions of small-scale farming. In particular, the integration of robotic mobility, georeferenced data acquisition, and standardized sampling procedures remains limited.

More recently, different studies have explored the use of robotic platforms to automate data acquisition and improve soil moisture mapping. Nguyen (2025) proposed a multimodal sensing system based on data fusion and Gaussian process regression, while Rose et al. (2025) employed a mobile robotic platform with adaptive sampling to increase mapping efficiency and reduce spatial uncertainty. Although promising, these approaches still present limitations related to system complexity, georeferencing accuracy, and implementation cost, reinforcing the need for more accessible and robust alternatives.

In this context, this study proposes and evaluates a robotic sensing system for the georeferenced acquisition of soil moisture data for mapping the spatial variability of this soil attribute. The proposed system consists of a low-cost multifunctional robotic platform equipped with a soil moisture sensor, a GNSS positioning system, and a mechanism for controlled probe insertion into the soil. Soil moisture measurements are associated with their respective geographic coordinates and subsequently processed using spatial interpolation techniques, allowing the representation of soil moisture variability within the study area.

Materials and Methods

Robotic platform and data acquisition system

The developed system, roboFAM 1.0, consists of a reduced-scale multifunctional robotic prototype designed for applications in small agricultural areas, as shown in Fig. 1. The platform was developed with emphasis on low cost, modularity, and ease of operation.

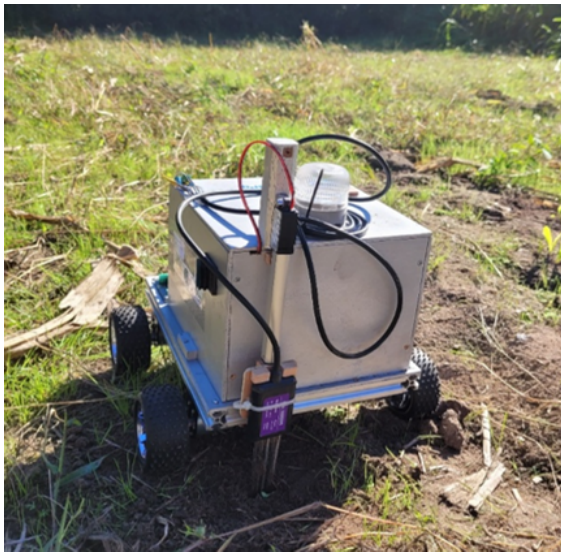

Fig. 1 Multifunctional robotic prototype developed for soil moisture data acquisition during field experiments

The platform is equipped with four wheels, each driven by an independent motor, enabling differential-drive mobility. System control is performed by a central embedded unit based on an ESP32 microcontroller, which handles motor and actuator control, sensor data acquisition, and communication with external devices.

For this study, the prototype was equipped with a data acquisition system integrating a HaliSense Soil TH-EC-PH-NPK soil sensor, capable of measuring volumetric water content within a range of 0–100%, with a nominal accuracy of ±3%, according to the manufacturer's specifications. To ensure measurement standardization, a linear actuator mechanism was developed to provide controlled insertion of the probe into the soil.

The robot is operated through a dedicated mobile application responsible for motion control and real-time acquisition of soil moisture data. Communication between the robot and the application is established via Wi-Fi, with the ESP32 operating in Access Point (AP) mode and using the WebSocket protocol for bidirectional communication. Each measurement is automatically associated with its corresponding geographic coordinates obtained from a u-blox NEO-6M GNSS receiver, providing an approximate positioning accuracy of 2.5 m under open-sky conditions and enabling the construction of a georeferenced spatial dataset.

The collected data are stored by the mobile application as a CSV file, generating a structured dataset containing latitude, longitude, and soil moisture measurements.

Study area and experimental procedure

The experiment was conducted in March 2026 within a 10 m × 10 m experimental area classified as a Planosol, located at the experimental field of the Federal University of Pelotas (Capão do Leão Campus), representative of small-scale agricultural environments, with approximate central coordinates of 31.801205° S and 52.412028° W. The soil surface was covered with crop residues from a previous maize cultivation.

Data collection was performed at 36 sampling points regularly distributed on a 2 m × 2 m sampling grid, covering the entire experimental area. At each sampling location, soil moisture measurements were obtained at a depth of 0–10 cm using the controlled probe insertion mechanism.

A stabilization time of 10 s was adopted before data acquisition, and eight consecutive readings were collected at each sampling point. The average value was subsequently calculated to reduce measurement noise and improve data stability.

Sensor calibration

The soil moisture sensor was calibrated using the gravimetric method as the reference standard. Six soil samples were selected from the 36 sampling locations across the experimental area. Gravimetric soil moisture was determined under laboratory conditions and compared with the corresponding measurements obtained by the robotic acquisition system.

Based on these data, a linear calibration model was fitted to correct the sensor readings and improve their agreement with the reference measurements.

Spatial analysis and model evaluation

The collected data were processed and analyzed using custom-developed Python scripts. Spatial interpolation of soil moisture was performed using the inverse distance weighting (IDW) method, enabling the generation of spatial distribution maps of the analyzed soil attribute.

To evaluate the influence of GNSS positioning errors on the spatial representation of soil moisture, two interpolated surfaces were generated using the same set of soil moisture measurements. The first surface was constructed using the georeferenced coordinates provided by the GNSS receiver, whereas the second employed the coordinates corresponding to the predefined regular sampling grid, considered as the ideal reference. The two interpolated surfaces were compared point by point over the same interpolation grid using the root mean square error (RMSE) and the mean absolute error (MAE) to quantify the differences between the maps and assess the impact of positioning errors on the spatial representation of the analyzed variable.

Additionally, the quality of the interpolation was assessed through leave-one-out cross-validation (LOOCV). The RMSE, MAE, and the coefficient of determination (R^2) were adopted as performance metrics to evaluate the ability of the interpolation model to represent the spatial variability of soil moisture.

Results

Sensor calibration

The sensor calibration exhibited an approximately linear relationship between the sensor readings and the reference values obtained using the gravimetric method, as shown in Fig. 2. The fitted linear regression model resulted in $y = 1.11x - 0.32$, with an R^2 of 0.38, indicating limited to moderate predictive performance.

The observed performance may be associated with the limited number of samples used for calibration ($n = 6$) as well as the inherent limitations of the low-cost sensor employed. Nevertheless, the calibration model improved the agreement between the sensor readings and the reference measurements, proving suitable for exploratory field applications.

Similar results have been reported in studies employing low-cost soil moisture sensors under field conditions, where soil heterogeneity and environmental interference can significantly affect calibration performance (Zhang et al. 2024).

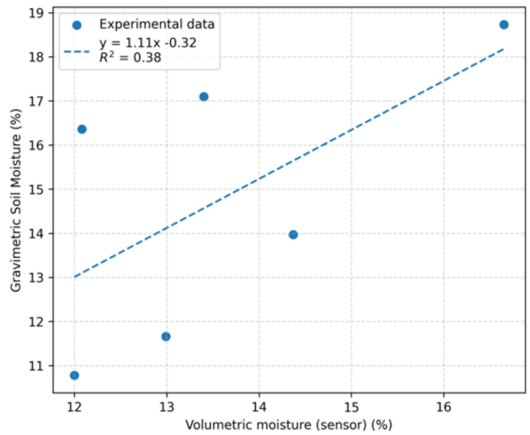

Fig. 2 Relationship between volumetric soil moisture measured by the sensor and gravimetric soil moisture, with a linear regression fitted to the experimental data

Spatial distribution of the samples

Fig. 3 presents the soil moisture surfaces interpolated using the IDW method, with the sampling locations superimposed on the maps. Fig. 3a was generated using the regular sampling grid, considered as the ideal reference, whereas Fig. 3b was generated using the georeferenced coordinates obtained from the GNSS receiver.

The ideal sampling grid exhibits a regular spatial distribution, while the georeferenced sampling points show positional dispersion resulting from GNSS positioning uncertainty. For spatial analysis purposes, the geographic coordinates were converted into planar coordinates expressed in meters using a local Cartesian projection based on the equirectangular approximation, adopting the first sampling point as reference.

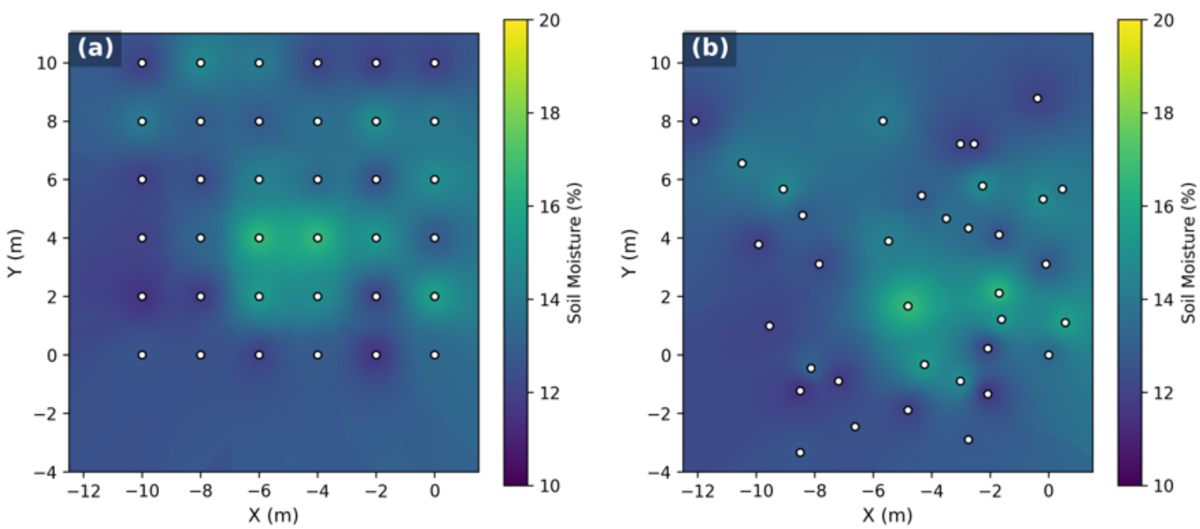

Fig. 3 Spatial distribution maps of soil moisture generated using IDW interpolation: (a) based on the regular sampling grid (ideal reference) and (b) based on the georeferenced coordinates obtained from the GNSS receiver. The points indicate the sampling locations used for interpolation

Evaluation of GNSS positioning error

The comparison between the coordinates obtained from the GNSS receiver and the corresponding coordinates of the ideal sampling grid resulted in a mean positioning error of 2.49 m, with a maximum error of 4.46 m and a standard deviation of 0.97 m. These values are consistent with the nominal positioning accuracy specified by the GNSS receiver manufacturer, approximately 2.5 m under open-sky conditions.

Considering that the sampling grid spacing was 2 m, the magnitude of the positioning error is comparable to the distance between adjacent sampling points, potentially affecting the spatial representation of the analyzed variable.

Spatial mapping and interpolation assessment

The comparison between the interpolated maps yielded RMSE and MAE values of 0.98% and 0.72%, respectively, indicating relatively small differences between the interpolated surfaces. These results demonstrate good overall agreement between the maps, suggesting that the use of georeferenced coordinates provides an adequate representation of the spatial distribution of soil moisture.

Visual comparison of the interpolated maps further supports these findings, indicating that the main spatial patterns of soil moisture were preserved, with regions of higher and lower moisture exhibiting similar spatial distributions in both approaches.

Additionally, the interpolation based on the georeferenced sampling positions was evaluated using LOOCV, resulting in RMSE = 1.38%, MAE = 1.17%, and a $R^2 = 0.09$. Although these results indicate limited ability of the interpolation model to explain the total variability of the data, they demonstrate that the method successfully captured the overall spatial trends of soil moisture across the experimental area, despite the limitations imposed by sensor accuracy, sampling density, and GNSS positioning uncertainty.

Conclusion

The results demonstrate the feasibility of the proposed robotic platform for the georeferenced acquisition of soil moisture data in small-scale agricultural areas. The system proved capable of performing field measurements and generating spatial maps that adequately represent soil moisture variability, highlighting its applicability to small-scale farming systems.

Although limitations associated with the performance of the low-cost sensor and GNSS positioning uncertainty were observed, the main spatial patterns of soil moisture were successfully preserved. The comparison between the maps generated from the ideal sampling grid and those obtained using the georeferenced coordinates showed low discrepancies, with reduced RMSE and MAE values, indicating good agreement between the interpolated surfaces.

The results further demonstrate that, even when using a low-cost system equipped with a meter-level accuracy GNSS receiver, the main spatial patterns of soil moisture can be reliably preserved after IDW interpolation. Therefore, the proposed approach represents a promising alternative for supporting Precision Agriculture practices in small-scale farming, contributing to irrigation management, more efficient water use, and field decision-making.

Future work should focus on the use of higher-accuracy sensors, improvements in positioning quality, increased sampling density, and the incorporation of more advanced interpolation methods and sampling strategies to enhance the accuracy of the maps generated and expand the applicability of the proposed system under different agricultural conditions.

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