PREDICTION OF SOIL POTASSIUM CONCENTRATION USING ELECTRICAL IMPEDANCE SPECTROSCOPY

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Abstract.
The increasing global dependence on potassium fertilizers, combined with instability in international trade driven by recent geopolitical tensions, has raised concerns regarding potassium (K) availability and cost in 2026. In this context, variable-rate fertilizer application enables more efficient input use, making the delineation of management zones based on the spatial variability of soil potassium concentration essential. This study evaluated the use of electrical impedance spectroscopy (EIS) for rapid prediction of soil potassium content. Measurements were performed using a LiteVNA64 portable vector network analyzer over a frequency range from 50 kHz to 6.3 GHz. A total of 71 soil samples collected from different Brazilian states, with distinct physicochemical properties, were analyzed. Each sample was measured at three points under two moisture conditions: dry (0% volumetric water content) and moist (10% volumetric water content, dry basis). For each frequency, mean values of the real and imaginary impedance components were computed. The spectral data were divided into five frequency bands, from 5.0×10^4 to 6.0×10^9 Hz. For each band, mean spectral amplitude and spectral energy (defined as the integral of the squared resultant amplitude over frequency) were extracted as features. A Random Forest regression model with 100 trees and unrestricted maximum depth was used for prediction. The best performance was obtained under moist soil conditions, achieving $R^2 = 0.60$, RMSE = 71.93 mg dm^{-3}, and MAE = 60.72 mg dm^{-3}. The results demonstrate the potential of EIS as a rapid and non-destructive approach for estimating soil potassium variability and supporting the generation of management zone maps. However, further studies with larger and more diverse datasets are required to improve model generalization and accuracy.

Keywords.
Soil fertility, real-time soil sensing, machine learning.

Introduction

Agricultural producers face the ongoing challenge of increasing productivity in a sustainable manner, balancing the growing global demand for food with the responsible use of natural resources. In this context, Precision and Digital Agriculture has emerged as a tool for optimizing farm management through the integration of sensors, computational systems, and data analysis applied to monitoring soil and crop conditions (Liakos et al., 2018; Abraham et al., 2020). These technologies enable more accurate decision-making, supporting site-specific input application and improving production efficiency.

Among precision agriculture strategies, the definition of management zones stands out. This approach consists of dividing agricultural fields into homogeneous areas based on the physical, chemical, and productive properties of the soil. Such zoning enables site-specific management, reducing fertilizer waste and minimizing environmental impacts (Moral et al., 2020). The development of these zones relies on understanding the spatial variability of soil nutrients, especially those directly related to soil fertility such as potassium. Potassium is an essential macronutrient for crop development, playing a key role in physiological processes such as photosynthesis, osmotic regulation, sugar transport, and resistance to both biotic and abiotic stresses. However, its distribution in soil can exhibit high spatial variability, requiring efficient monitoring methods to support more precise management practices.

Conventional soil analysis methods rely on point sampling and laboratory testing, which, despite their high reliability, present limitations related to operational cost, processing time, and low spatial resolution (Ladha et al., 2005). In this context, soil sensing technologies have been investigated as alternatives capable of providing real-time information with higher sampling density (Shah et al., 2022).

Among the promising techniques, electrical impedance spectroscopy (EIS) has gained attention. This method analyzes the electrical response of soil across different excitation frequencies. It enables the inference of soil physicochemical properties based on the interaction between the applied electrical signal and ionic conduction and interfacial polarization phenomena within the soil matrix (Kanoun, 2019). Additionally, the use of low-cost sensors increases the potential for applying this technique in commercial agricultural systems (Kondaveeti et al., 2021).

Therefore, the objective of this study was to evaluate the potential of EIS, using a low-cost sensor developed from a portable vector network analyzer, to estimate soil potassium content and support the delineation of management zones in agricultural systems.

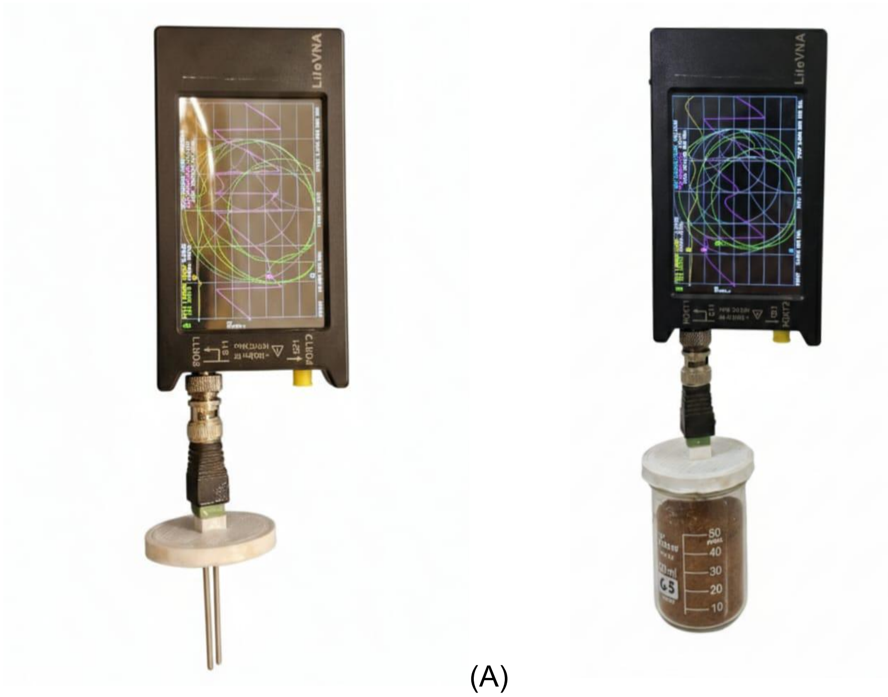
Materials and Methods

Soil Sample Preparation and Characterization

The study was conducted using 71 soil samples collected from various Brazilian municipalities, capturing a wide range of physical and chemical soil properties. The reference potassium content of the samples was determined using the standard Mehlich-1 extraction method. For the Electrical Impedance Spectroscopy (EIS) analysis, the soil samples were first oven-dried at 105 °C for 24 hours. Measurements were then performed under two distinct moisture conditions: i) dry condition with 0% volumetric water content and ii) moist condition prepared by adding distilled water to achieve a 10% volumetric water content.

EIS Data Acquisition and Experimental Setup

EIS data acquisition was performed using a LiteVNA 64, a low-cost, portable vector network analyzer operating within a frequency range of 50 kHz to 6.3 GHz. To conduct the measurements, a custom two-rod metallic electrode (2 mm diameter) was developed and connected to the device using SMA-to-BNC and BNC-to-binding post adapters (Fig. 1A). For each measurement, the soil sample was placed in a 50 mL beaker. Impedance spectra were collected at three distinct points within the container to minimize local heterogeneity and ensure a representative spectral response for each sample (Fig. 1B).



(A) (B)

Fig 1. LiteVNA 64 vector network analyzer equipped with a two-rod electrode and SMA-to-BNC and BNC-to-binding post adapters (A); measurement of the electrical impedance spectrum in soil samples (B).

The LiteVNA 64 recorded the electrical response of the soil samples across 4,501 frequency points ranging from 50 kHz to 6 GHz. For each frequency, the real and imaginary components of the average electrical impedance were calculated from the three replicate measurements.

Impedance Spectrum Processing and Feature Extraction

The electrical impedance spectra were divided into five fixed frequency bands: i) 5.0×10^4 to 5.0×10^8 Hz; ii) 5.0×10^8 to 1.25×10^9 Hz; iii) 1.25×10^9 to 2.25×10^9 Hz; iv) 2.25×10^9 to 4.0×10^9 Hz) and v) 4.0×10^9 to 6.0×10^9 Hz. Within each band, two spectral metrics were extracted: mean amplitude and spectral energy (defined as the integral of the squared magnitude over the frequency range). Since these metrics were computed for both the real and imaginary components, each soil sample was characterized by a total of 20 spectral features, which served as inputs for the predictive models.

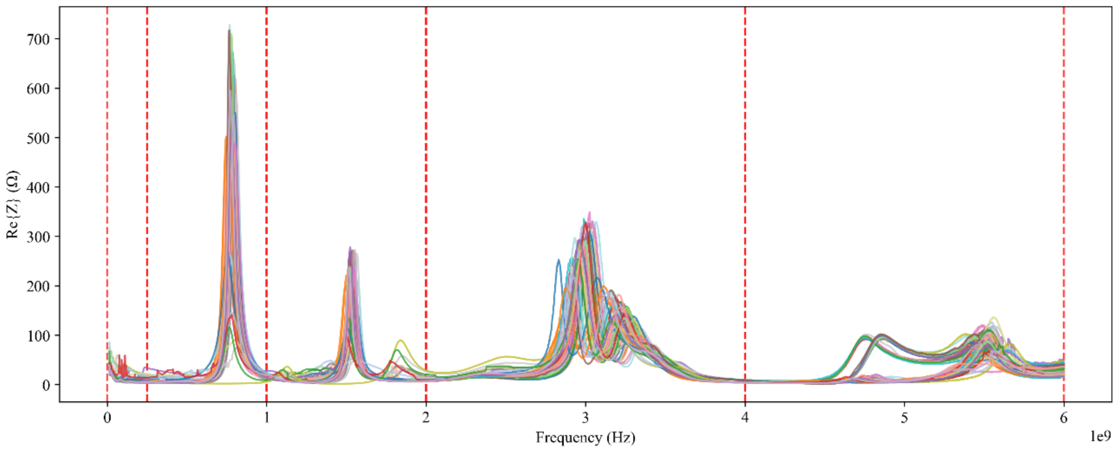
Predictive Modeling

A Random Forest regression algorithm was then trained to estimate soil potassium content based on the 20 spectral features. The Random Forest model was configured with 100 decision trees, unlimited maximum depth, and the mean squared error (MSE) splitting criterion. The dataset was split using 80% of the data for training and 20% for testing. Model performance was evaluated using the coefficient of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE).

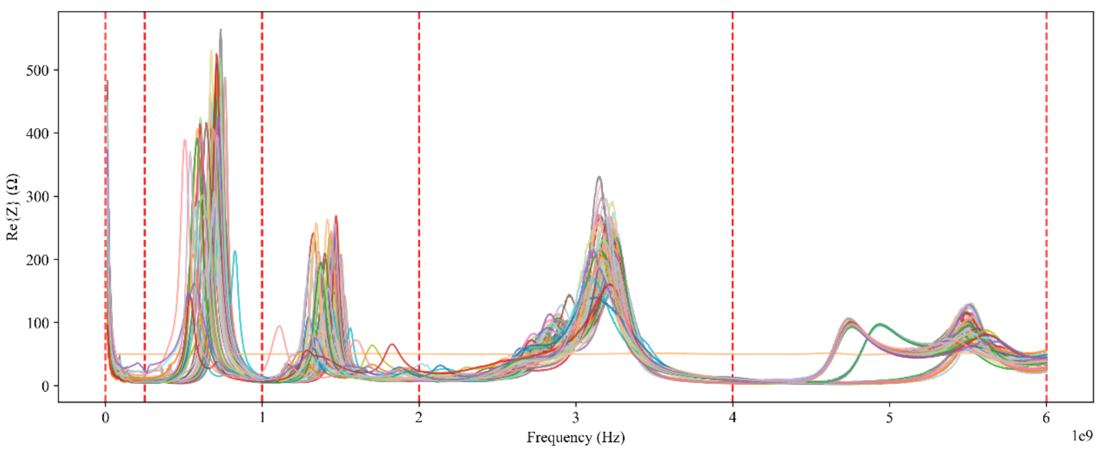
Results and Discussion

Impedance Spectra and Correlation Analysis

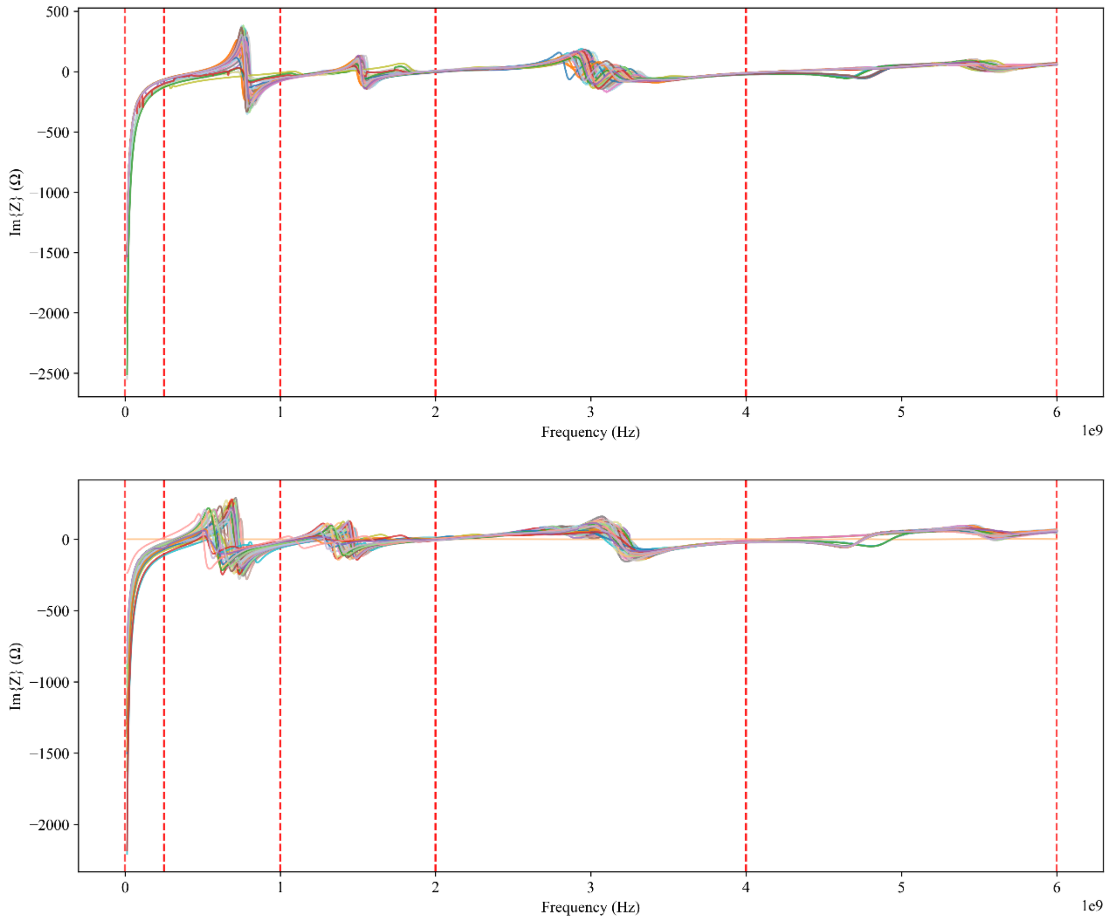
The electrical impedance spectra exhibited distinct behaviors among the 71 analyzed soil samples, demonstrating that this technique can effectively capture variations related to soil chemical properties (Fig. 2). These spectral differences were notably more pronounced under moist soil conditions for both the real and imaginary components. While both impedance components displayed recurring spectral peaks within specific frequency ranges, the variations in intensity and spectral distribution across the samples became significantly more evident in the moist state.



(a)



(b)



(c)

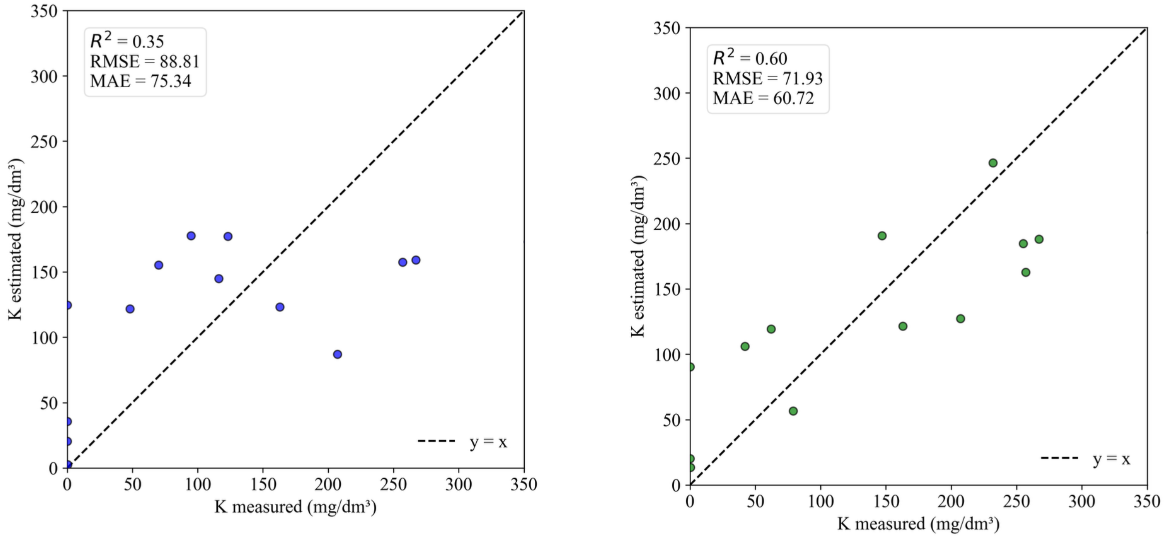
(d)

Fig 2. Electrical impedance spectra for the 71 soil samples: (a) real component (Re {Z}) under dry conditions, (b) real component (Re {Z}) under moist conditions, (c) imaginary component (Im {Z}) under dry conditions, and (d) imaginary component (Im {Z}) under moist conditions. Vertical red line indicates the frequencies bounding of the five frequency bands.

This behavior can be attributed to water acting as a conductive medium, which enhances the mobility of ions present in the soil solution. Since potassium is a highly mobile cation, its presence directly influences electrical conduction and interfacial polarization mechanisms, making its response more pronounced in the electrical impedance spectrum under moist conditions.

Model Performance

The machine learning model achieved its best performance for predicting exchangeable potassium under moist soil conditions, yielding a R^2 = 0.60, RMSE = 71.93 mg/dm³ and MAE=60.72 mg/dm³ (Fig. 3).



(a) (b)

Fig 3. Measured versus predicted values for soil potassium under (a) dry and (b) moist conditions.

These results demonstrate the potential of electrical impedance spectroscopy (EIS) as a tool for soil fertility monitoring and the delineation of management zones. However, further studies encompassing larger datasets and evaluating alternative machine learning algorithms are required to reduce estimation errors and improve model generalization. Nevertheless, the ability to estimate potassium content rapidly using low-cost sensors represents a promising alternative for precision agriculture applications, particularly in production systems that demand high spatial data resolution.

Conclusions

Electrical impedance spectroscopy (EIS) demonstrated potential for estimating soil potassium content, showing high sensitivity to chemical variations among the analyzed samples. Moist soil conditions significantly enhanced the spectral response, providing a higher number of significant correlations and superior predictive model performance.

The Random Forest model achieved satisfactory performance in estimating exchangeable potassium, indicating that features extracted from the electrical impedance spectrum can serve as reliable predictor variables for this nutrient. Overall, the findings indicate that this technique is a viable candidate for application in delineating management zones, contributing to efficient soil fertility monitoring in precision agriculture systems.

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