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PREDIÇÃO ESPECTRAL DA CONDUTIVIDADE ELÉTRICA DO SOLO COM ESPECTROSCOPIA VISÍVEL E INFRAVERMELHO PRÓXIMO

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RESUMO: A salinização é uma das principais causas de degradação do solo no mundo, todavia, esse fenômeno ocorre com maior frequência em regiões áridas e semiáridas. Nesse contexto, este estudo tem como objetivo prever a condutividade elétrica de solos do Ceará, usando informações espectrais na faixa de 350 a 2500 nm associadas à regressão por mínimos quadrados parciais. Além disso, busca-se avaliar se o pré-processamento espectral melhora os modelos de regressão. Foram analisadas 114 amostras de solo oriundas de municípios do Ceará. As amostras foram avaliadas com método tradicional para determinar a condutividade elétrica (CE), e com método espectral na faixa do visível ao infravermelho de ondas curtas (350 – 2500 nm). Os resultados da CE foram analisados com estatística descritiva. Os dados espectrais foram submetidos a técnicas de pré-processamentos, e para a modelagem da CE os espectros brutos e processados foram usados juntamente com o algoritmo de regressão por mínimos quadrados parciais. A estatística descritiva dos solos evidenciou a presença de caráter salino e/ou sálico. O modelo preditivo com os dados transformados em absorbância obteve o melhor desempenho ($R^2 = 0,74$ e RPD = 2,0).

Palavras-chaves: espectroscopia de reflectância, salinidade, regressão.

SPECTRAL PREDICTION OF SOIL ELECTRICAL CONDUCTIVITY USING VISIBLE AND NEAR-INFRARED SPECTROSCOPY

ABSTRACT: Salinization is among the main causes of soil degradation worldwide, but this phenomenon occurs more frequently in arid and semiarid regions. In this context, this study aims to predict the electrical conductivity of soils in Ceará using spectral information in the range of 350 to 2500 nm associated with partial least squares regression. In addition, we seek to evaluate whether spectral preprocessing improves regression models. A total of 114 soil samples from municipalities in Ceará were analyzed. The samples were evaluated using the traditional method to determine electrical conductivity (EC) and the spectral method in the visible to shortwave infrared range (350–2500 nm). The EC results were analyzed using descriptive statistics. The spectral data were subjected to preprocessing techniques, and for EC modeling, the raw and processed spectra were used together with the partial least squares regression algorithm. Descriptive statistics of the soils revealed the presence of saline and/or saline characteristics. The predictive model with the data transformed into absorbance obtained the best performance ($R^2 = 0.74$ and RPD = 2.0).

Keywords: reflectance spectroscopy, salinity, regression.

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1 INTRODUCTION

Salinization is among the main causes of land degradation and is characterized by the progressive accumulation of soluble salts on the soil surface (Wang *et al.*, 2023) . Excess salt in the soil severely affects plant development, compromising global food security. (Sun *et al.,* 2024). Salinization is generated by both natural processes and inadequate anthropogenic practices, such as the use of low-quality water for irrigation and inadequate soil management (Muhammad *et al.,* 2024) .

Salinization occurs more frequently in arid and semiarid regions, where climatic conditions with high evapotranspiration rates associated with low precipitation intensify the concentration of salts on the soil surface (Hailu; Mehari, 2021). Currently, approximately 1.4 billion hectares of land worldwide are affected by salt (FAO, 2024) . In Brazil, this phenomenon manifests itself in a worrying way, especially in irrigated areas.

Traditionally, salinity is assessed in the laboratory by determining the electrical conductivity (EC) of the soil (Barreto *et al.*, 2023) . However, this methodology requires specific sample preparation and longer analysis times, in addition to being costly, limiting the scope of mapping saline areas. Considering these aspects, alternative methodologies, such as remote sensing, are being studied to assess salinity and monitor these areas in a faster and more economically viable way.

From this perspective, multispectral remote sensors have been successively employed to map and monitor salinity. However, aspects such as image resolution and vegetation canopies can limit the remote determination of salts (Barreto *et al.*, 2023) . Therefore, the use of near-hyperspectral sensors, associated with reflectance spectroscopy, has emerged as a promising technique for salinity assessment (Pessoa *et al.* , 2016) .

Reflectance spectroscopy stands out for its rapid analysis capabilities, requiring minimal sample preparation (Lotfollahi *et al.*, 2023) . Soil analysis using this technique is performed in the visible (Vis: 350–750 nm), near-infrared (NIR: 750–1100 nm), shortwave infrared (SWIR: 1100–2500 nm), and mid-infrared (MIR: 2500–25000 nm or 4000–400 cm$^{-1)}$ ranges (Mendes *et al.*, 2022) . The spectral data generated in these ranges are associated with statistical methods to obtain predictive models.

Spectroscopy has stood out for its great potential in soil characterization; however, its use in identifying salinization is still incipient, especially in arid and semiarid regions. In this context, this study aims to predict the electrical conductivity of soils in Ceará using spectral information in the 350 to 2500 nm range associated with partial least squares regression (PLSR). Furthermore, it seeks to evaluate whether spectral preprocessing improves regression models.

2 MATERIALS AND METHODS

In this study, soil samples deposited in the collection of the Soil, Water, Tissue and Fertilizer Analysis Laboratory, located in the Department of Soil Science at the Federal University of Ceará (UFC), were used. The soils evaluated came from 13 municipalities in Ceará, which are located in the Northwest Ceará, North Ceará and Metropolitan Fortaleza mesoregions, and are part of the data from the Medium-Intensity Reconnaissance Survey of the Soils of the State of Ceará, published in 2024.

One hundred and fourteen soil samples were analyzed, comprising 24 pedological profiles classified into 9 soil orders. Analyses using traditional (wet chemistry) and spectral methods were performed on air-dried fine earth samples. For this purpose, the soils were placed in the shade, air-dried, ground and sieved through a sieve with a 2 mm mesh opening.

In the analysis using the traditional method, the electrical conductivity (EC) of the soil was evaluated according to the Embrapa Soil Analysis Methods Manual (Teixeira *et al.*, 2017). For the spectral analyses, the TFSA samples were subjected to a drying process in a forced-air oven at a temperature of 45 °C for

24 hours to homogenize the effects of soil moisture (Epiphanio *et al.* . 1992).

Spectral reflectance data were obtained using a contact probe (*Hi-Brite Contact Probe*) and a FieldSpec Pro FR 3 spectroradiometer (Analytical Spectral Devices, Boulder, Colorado, USA). This instrument performs readings in the visible to shortwave infrared range (350–2500 nm) and has spectral resolutions of 3 nm and 10 nm, respectively. resampled to 1 nm, yielding 2151 features.

To read spectral data in the Vis-NIR-SWIR range, the equipment sensor was calibrated every 20 minutes. Calibration is performed by reading a blank plate (Spectralon), which is considered a 100% reflectance reference standard. Three spectral readings were performed on the surface of each sample to perform a complete scan of the sample and obtain good representativeness.

Savitzky–Golay smoothing preprocessing and conversion of values to absorbances are performed, with the goal of suppressing noise and irrelevant information and improving the quality of the spectral data for subsequent modeling processes. Spectral data preprocessing and statistical analyses were performed using R software (R Core Team, 2024) .

Descriptive statistical analyses were applied to the electrical conductivity results. The normality of the data was also assessed using the Kolmogorov–Smirnov normality hypothesis test at 5%. Given the nonnormality of the data, the base-10 logarithm transformation was applied to obtain normally distributed values and improve the performance of the models.

To construct the predictive models, the data were separated into 75% of the samples for calibration and 25% for model testing with unpublished data. For this purpose, a random selection was performed on the basis of the soil profiles to encompass all the profiles and avoid bias. During the calibration phase, *k-fold cross-validation was performed.* 10 times. CE modeling was performed using the partial least squares regression (PLSR) algorithm associated with raw reflectance spectra and preprocessed spectra.

The performance of the predictive models was evaluated on the basis of the coefficient of determination (Equation 1), root mean square error (Equation 2), and performance-to-deviation ratio (Equation 3). Before these metrics were computed, the CE values were converted back to their original units.

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}-\bar{y})^2}{\sum_{i=1}^{n}(y-\bar{y})^2} \qquad (1)$$

where R² = coefficient of determination; Ŷ = predicted value; Ȳ = mean of observed values; Y = observed value; and n = number of samples.

$$RMSE = \sqrt{\sum_{i=1}^{n-m}\frac{\mathrm{yi'}-\mathrm{yi}}{n-m}} \qquad (2)$$

where RMSE = root mean square error; n = number of samples; m = number of samples used for prediction; and yi'- yi = predicted and observed values.

$$RPD = \frac{\sigma_{YO}}{RMSE} \qquad (3)$$

where RPD is the ratio of deviation performance and σ is the standard deviation of the observed values.

The performance of the models was divided into classes on the basis of the values obtained from the metrics. With respect to the R² results, Terra *et al* . (2015) suggest the following classes: $R^2 > 0.75$ - models well fitted to accurately predict soil attributes; $0.50 \leq R^2 \leq 0.75$ - models that are fair but could be improved; and $R^2 < 0.50$ - unreliable models with no predictive capacity. On the basis of the RPD values, Sun *et al. (2024)* suggest the following classes: RPD > 2 - excellent models; $1.4 \leq RPD \leq 2$ - models with moderate performance; RPD < 1.4 – models without predictive capability.

3 RESULTS AND DISCUSSION

Descriptive statistical analysis (Table 1) revealed that the average electrical conductivity of the soil samples was 0.65

dS/m, which is considered low. However, the standard deviation (1.68 dS/m) was high relative to the average, and the maximum EC value observed (10.15 dS/m) indicated that some of the evaluated soils presented saline and/or saline characteristics, which are conditions potentially detrimental to soil quality and agricultural productivity (Santos *et al.,* 2018).

Table 1. Descriptive statistics for electrical conductivity values. (dS/m) of the soil.

Average	Median	Minimum	Maximum	Q1	Q3	SD	p value
0.65	0.14	0.01	10.15	0.08	0.28	1.68	7.34E-20

Note: Q1 = first quartile; Q3 = thirty quartile; SD = standard deviation; p value = Kolmogorov–Smirnov normality test.
Source: Authors (2025)

The Kolmogorov–Smirnov normality test indicated that the EC data do not follow a normal distribution, a behavior that is quite common in soil attributes (Bellon-Maurel *et al.*, 2010) . The high standard deviation and nonnormality of the data reflect the heterogeneity of the soils studied, which present contrasting characteristics. These results suggest that predictive models for EC should consider robust approaches geared toward heterogeneous data.

CE modeling with spectral data (Table 2) revealed, on the basis of the metric values obtained in the validation with unpublished data, that all the developed models showed moderate reliability and performance, with $R^2 \geq 0.50$. Nevertheless, adjustments are needed to improve the prediction accuracy.

Table 2. Results of the calibration and testing of the PLSR model for estimating the electrical conductivity (dS/m) of the soil in the spectral range 350–2500 nm.

Treatment - spectral data	No. C	R² cal.	RMSE	R² val	RMSE	RPD	DP
Gross	13	0.52	1.31	0.60	0.29	1.60	0.46
Abs	12	0.59	1.21	0.74	0.23	2.00	0.46
SG	13	0.48	1.36	0.58	0.29	1.57	0.46

Note: Abs = Absorbance; SG = Savitzky–Golay smoothing; No. C = Number of model components; R^2 cal. = Coefficient of determination for calibration; RMSE = root mean square error; R^2 val = Coefficient of determination for validation; RPD = ratio of performance deviation; DP = standard deviation.
Source: Authors (2025)

Among the models developed, the best performance was achieved with the PLSR regression applied to spectral data transformed into absorbance, whose metrics approached the values classified as excellent accuracy. In contrast, preprocessing with the SG filter resulted in the lowest performance, with R^2 and RPD values close to the minimum reliability limit for the predictive models.

The conversion of spectral data to absorbance was the most efficient preprocessing technique for improving EC prediction, demonstrating that not all preprocessing methods produce the same effect on model performance. These results corroborate previous work showing that spectral processing can efficiently highlight small differences in the data, increasing the sensitivity of the regression to variations in soil salinity (Sun *et al.,* 2024) .

The performance of the models obtained was superior to that reported by Lotfollahi *et al.* (2023) for the spectral prediction of soil salinity in the visible to near-infrared region; however, the results were inferior to those reported by Sun *et al.* (2024) . The lower predictive performance of the EC may be related to the absence of specific signatures of this attribute; thus, greater accuracy is obtained for attributes with active spectral characteristics or when there is a high concentration of the element in the soil and when there is a high correlation with spectrally active elements (Ng). *et al.,* 2022) .

4 CONCLUSIONS

The use of the partial least squares regression algorithm in conjunction with spectral data in the 350–2500 nm range made it possible to generate reliable soil EC prediction models. Transforming reflectance data into absorbance data was an efficient strategy for improving the accuracy of the prediction models.

The results obtained reinforce the potential of reflectance spectroscopy as a promising method for evaluating salinity on a large scale and as an alternative technique to conventional analyses. However, it is important to highlight that broader studies addressing this technique are necessary to further improve the accuracy of spectral prediction.

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