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Use of a multisensor platform for characterizing soil spatial variability in precision agriculture

Uso de uma plataforma multissensor para caracterização da variabilidade espacial do solo em agricultura de precisão

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ABSTRACT

The use of precision agriculture techniques can contribute to increased productivity efficiency, as management decisions are based on the spatial variability of soil attributes that influence the productive performance of crops. This study aimed to evaluate the use of a multisensor platform in mapping the apparent soil electrical conductivity (EC), soil temperature, and soil moisture. Measurements were taken at 75 georeferenced sample points spaced 35 meters apart in an 8.6-hectare area. Statistical and geostatistical techniques were employed in the analysis and mapping of the measured variables. The EC readings from the multisensor platform were compared with those obtained using a commercial sensor, based on the analysis and calculation of the Pearson correlation coefficient (r). All measured variables showed spatial variability in the study area. The use of the multisensor platform allowed for mapping the spatial variability of EC, temperature, and soil moisture, and thematic maps indicating these variations throughout the studied area were generated. The EC measured by the multisensor platform was similar to the EC measured by the commercial sensor, with r = 0.8, indicating reliability in the field readings.

Keywords: Apparent soil electrical conductivity; Soil temperature; Soil moisture

RESUMO

O emprego de técnicas de agricultura de precisão pode contribuir com o aumento da eficiência produtiva, pois as decisões de manejo são pautadas com base na variabilidade espacial dos atributos do solo que influenciam o desempenho produtivo das culturas. Este estudo teve como objetivo avaliar o uso de uma plataforma multissensor no mapeamento da condutividade elétrica aparente do solo

(CE), temperatura do solo e umidade do solo. Foram realizadas mensurações em 75 pontos amostrais georreferenciados, espaçados em 35 metros, em uma área de 8,6 hectares. Técnicas estatísticas e geoestatística foram empregadas na análise e mapeamento das variáveis medidas. As leituras de CE da plataforma multissensor foram comparadas com aquelas obtidas utilizando um sensor comercial, a partir da análise e cálculo do coeficiente de correlação de Pearson (r). Todas as vaiáveis mensuradas apresentaram variabilidade espacial na área de estudo. Com o uso da plataforma multissensor foi possível mapear a variabilidade espacial da CE, temperatura e umidade do solo, sendo confeccionados mapas temáticos indicativos d tais variações ao longo da área estudada. A CE mensurada pela plataforma multissensor foi similar à CE mensurada pelo sensor comercial, apresentando r = 0,8, indicando confiabilidade nas leituras realizadas no campo.

Palavras-chave: Condutividade elétrica aparente do solo; Temperatura do solo; Umidade do solo

1 INTRODUCTION

To increasing the economic income by reaching higher yields in the same area without harming the environment is the main goal of the farmers nowadays. Precision agriculture can help them to achieve this goal by providing tools for choosing the right decisions in different regions of the same field, that are necessary due to the soil spatial variability (Inamasu & Bernardi, 2014).

One way to characterize the soil variations is by measuring the apparent electrical conductivity (EC), which can be related to clay, water, organic matter, and nutrient contents. The EC can be used to create management zones by reducing the number of samples to be collected, resulting in cost reduction and making the activity more profitable (Kitchen et al., 2003; Serrano *et al*., 2010).

Considering the cheapness and fastness of collecting EC data, the generated maps can result in better spatial resolution in comparison with maps generated by grid soil sampling followed by laboratory analysis. The use of soil EC data can delimit management zones to guide the location where soil samples should be collected to have a better characterization of each zone (Queiroz *et al*., 2020).

Many sensors have been used to characterize the soil spatial variability by the EC. Those with the electrical resistivity method, in which a current is applied in a pair of electrodes and the electrical potential difference is measured in other pair electrodes, are the most used (Queiroz et al., 2020). This method is simple, and it can be easily applied. As the soil apparent electrical conductivity depends on the temperature and moisture of the soil and considering that these two variables also present spatial variability, it is expected that a sensor that measures EC, temperature, and moisture of the soil has a better chance of success in soil variability characterization.

The objective of this work was to evaluate a multisensor platform designed to analyze spatial variations in soil within an agricultural production field. This platform measures the soil temperature and moisture, and the apparent soil electrical conductivity for the 0-30 cm layer.

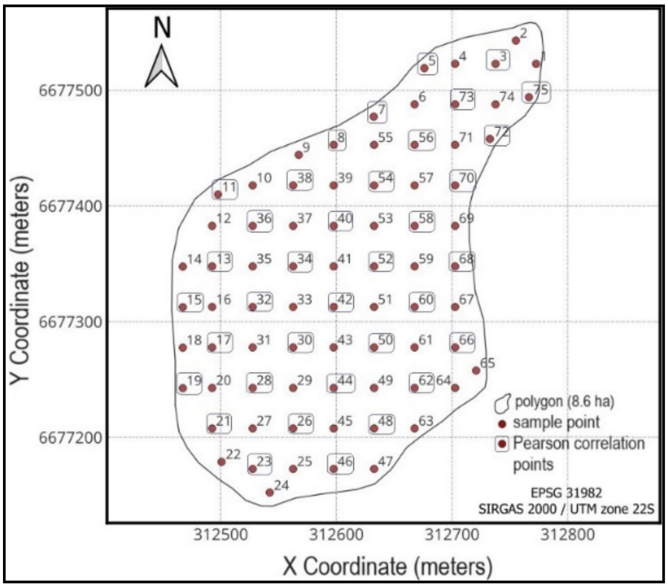
2 MATERIAL AND METHODS

The present study was conducted in the agricultural area of the Federal University of Santa Maria (UFSM) campus in Cachoeira do Sul (UFSM-CS). The field had an area of 8.6 hectares, with central coordinates at 30°01'23" South latitude and 52°56'59" West longitude. The soil has been classified as Red Argisol, according to the soil classification system developed by EMBRAPA (2013).

In the experimental field, a sample grid was established. It consisted of 75 points, regularly spaced at 35 meters. Of these, 36 points were included in the database used for Pearson correlation analysis ($p<0.05$). At each of the 75 sample points, measurements were taken for soil apparent soil electrical conductivity (EC, mS m^{-1}), soil moisture (UMD, %), and soil temperature (T, °C). The EC was measured using two different sensors, a commercial (standard) and a new soil sensor platform (under testing).

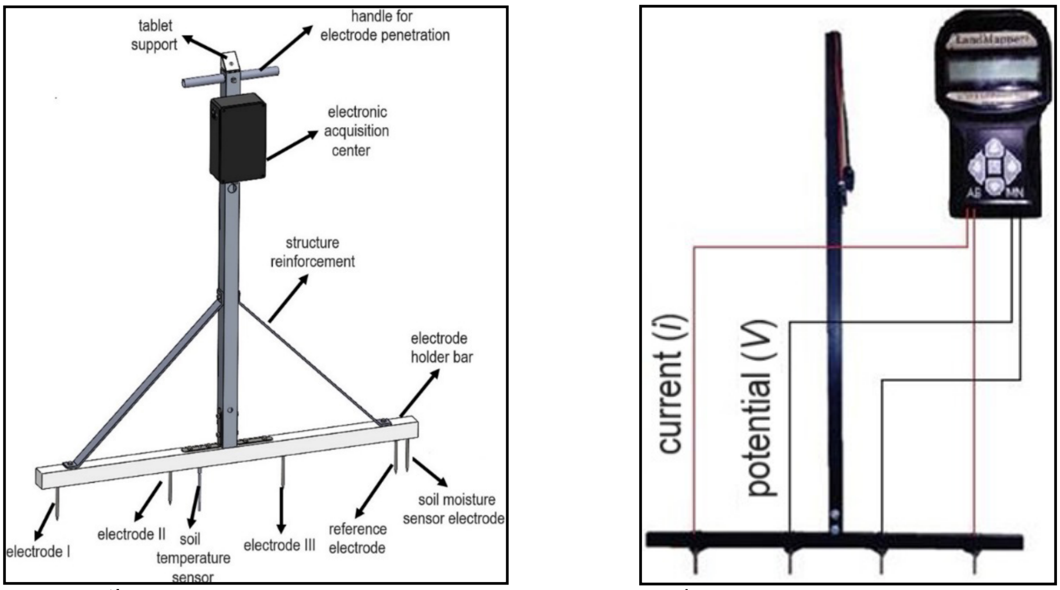
The commercial sensor used in this experiment was the LandMapper® ERM-02, produced by the Landviser® company. The new soil sensor platform was the Smart Soil Sensor, developed by researchers from the Department of Agricultural Engineering (DEA) at the Federal University of Viçosa (UFV). This sensor is characterized as a multisensor platform, as it not only measures EC but also measures soil moisture and temperature. Figure 1 shows the area delimitation polygon and the sampling points grid and Figure 2 presents the sensors used in the measurements.

Figure 1 – Grid of sample points used as a basis for field data collection and for calculating the Pearson correlation coefficient



Source: Authors (2024)

Figure 2 – Smart Soil Sensor multisensor platform and commercial LandMapper® ERM-02 sensor



Smart Soil Sensor
Source: Authors (2024)

LandMapper ERM-02
Source: Adapted from Bottega et al. (2022)

Both sensors are based on the electrical resistivity method to obtain EC measurements. In this method, electrical conductivity is obtained by introducing four equally spaced electrodes into the soil surface. An electric current is applied to the outer electrodes, and the electrical potential difference is measured at the inner electrodes. The electrode arrangement is denominated the Wenner array. In the used sensor, electrodes were spaced 30 centimeters apart, to obtain EC readings representative of the 0-0.3 meters soil layer (Corwin & Hedrickx, 2002; Corwin & Lesh, 2003).

The resistivity obtained using the Werner array was calculated using Equation 1.

$$\rho = \frac{2 \cdot \pi \cdot a \cdot \Delta V}{i} \quad (1)$$

where:

ρ = Resistivity, Ohm m^{-1};

a = Electrode spacing, m;

ΔV = Measured electrical potential difference, V; and

i = Applied electric currrent, A.

The apparent soil electrical conductivity is the inverse of resistivity. EC was calculated using Equation 2.

$$EC = \frac{1}{\rho} \quad (2)$$

where:

EC = Apparent soil electrical conductivity, S m^{-1}.

The soil moisture and temperature measurements, along with the EC obtained by both sensors at the 75 sample points, formed the database used for subsequent analyses. Firstly, a descriptive statistical analysis was conducted, identifying the minimum and maximum values, and calculating the mean, variance, standard deviation, and coefficient of variation.

Subsequently, spatial dependence modeling was performed to characterize the spatial variability of the measured variables in the study area. Spatial dependence was assessed through semivariogram fitting, assuming the stationarity of the intrinsic hypothesis, as defined by Equation 3.

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(xi) - Z(xi+h)]^2 \quad (3)$$

where:

$\hat{\gamma}(h)$ = Semivariance as a function of the separation distance (h) between pairs of points;

h = Separation distance between pairs of points, m;

N(h) = Number of experimental pairs of observations Z(xi) and Z(xi + h) separated by a distance h.

The tested semivariogram models included Gaussian, Linear with a sill, Spherical, and Exponential. The model that exhibited the lowest Root Mean Square Error (RMSE) and the highest coefficient of determination (R^2) was selected. Once the model was adjusted and validated, the experimental values of the EC were interpolated for prediction at unsampled locations. The adopted validation method of the interpolation process was cross-validation, and the interpolation of values was carried out using ordinary kriging, which, according to Oliver and Webster (2014), provides the best unbiased linear predictions.

The analysis of spatial variability was conducted in the Quantum GIS (QGIS) Geographic Information System, version 3.28 Firenze, using the Smart-Map plugin developed by Pereira *et al*. (2022). Smart-Map enables the prediction of values at unsampled locations and the mapping of soil attributes through data interpolation using ordinary kriging.

For descriptive statistical analysis and the calculation of the Pearson correlation coefficient, the statistical software Statistica, version 7, was used. In this same software, Pearson correlation graphs ($p<0.05$) were also generated for the values of apparent soil electrical conductivity, measured by the multisensor platform and the commercial ERM-02 sensor.

3 RESULTS AND DISCUSSION

The mapped area showed variation in the values of the measured variables based on the location of the sample points where readings were taken with the two sensors. The sensors used here indicated that soil attributes had spatial variability. The results of the descriptive statistical analysis are presented in Table 1.

Table 1 – Descriptive statistics of soil variables measured by the sensors

Measured variables	Minimum	Mean	Maximum	Variance	Standard deviation	VC (%)
T (°C)[1]	19.30	21.29	25.10	1.86	1.36	6.4
SM (%)[2]	20.60	31.47	40.80	14.57	3.82	12.1
EC[3] Smart Soil	2.10	5.51	11.00	2.52	1.59	28.9
EC ERM-02	2.93	5.76	12.73	2.19	1.48	25.7

Source: Authors (2024)

[1]Soil temperature. [2]Soil moisture. [3]Apparent soil electrical conductivity

Variations in soil moisture can be explained by differences in clay content and vegetative cover (mulch) in the soil. Locations with higher levels of these attributes tend to have a higher holding water capacity and, consequently, higher moisture levels. This is because clay has a smaller particle size than sand and silt, resulting in fewer macropores in the soil and, consequently, more efficient water retention (Molin et al., 2011). On the other hand, mulch acts as a physical barrier, reducing soil water evaporation and increasing water retention capacity, thus keeping the soil with higher moisture content for a longer period (Salomão *et al*., 2020).

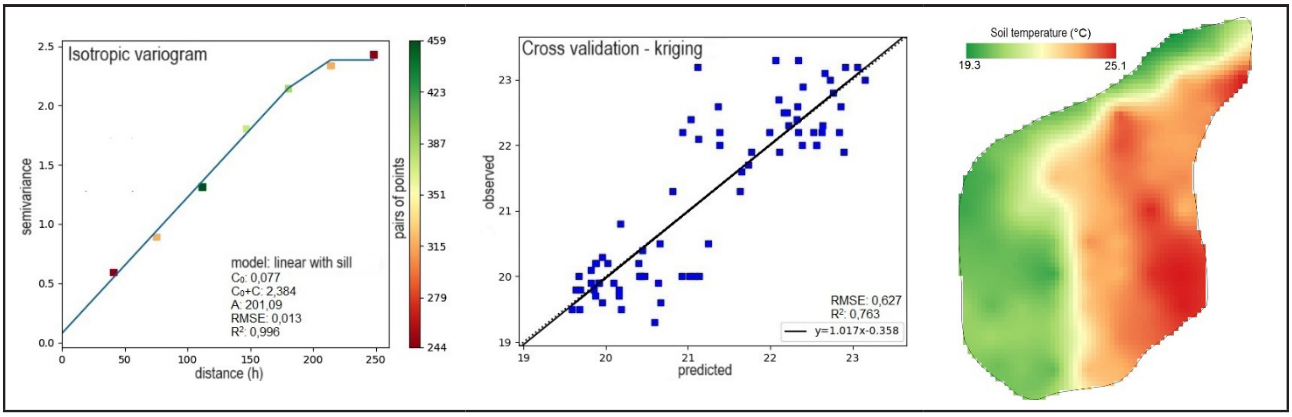
According to Table 1, the coefficient of variation of the soil temperature was only 6.4%, which is the lowest value among the variables measured. This behavior is probably associated with the quantity and type of vegetative cover in the field. According to Gasparim *et al*. (2005), the reduction in soil temperature is caused by the existing mulch cover, which, because of its thermal properties, acts as a physical barrier, therefore preventing direct exposure to solar radiation and reducing soil temperature fluctuations. A study conducted by Vieira *et al*. (2020) demonstrated that soil temperature was reduced with the use of soil cover. According to the authors, soil cover led to a reduction in soil temperature amplitude of up to 5.8°C.

Variations observed in the apparent electrical conductivity of the soil are directly related to variations in soil moisture, organic matter content, clay content, and chemical attributes of the soil (Kitchen *et al*., 2003 and Serrano et al., 2010). This variation is indicative of differences in soil attributes in the studied area, demonstrating that, even in a small field (8.6 hectares), the uniform application of fertilizers and amendments may not be the most suitable.

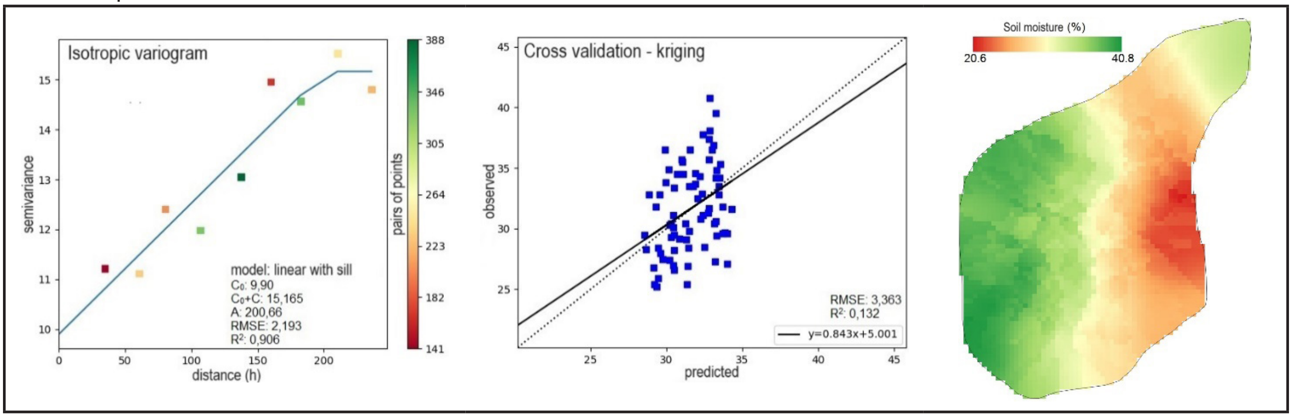
Comparing the EC values measured by the two devices highlights the precision of the data, with low standard deviation and coefficient of variation values indicating the ability of the sensors in replicate the collection at the same point. The minimum, mean, and maximum values of electrical conductivity show similarity with other studies that used resistivity as the data collection method, such as those conducted by Bernardi et al. (2017), Sousa et al. (2021), Bottega *et al.* (2022a), and Bottega *et al*. (2022b).

In Figure 3, presents the results of the geostatistical analysis and the spatial variability maps. Isotropic variograms, cross-validation graphs, and thematic maps representing the spatial variability of soil temperature, soil moisture, apparent soil electrical conductivity measured by the multisensor platform, and the commercial ERM-02 sensor are presented.

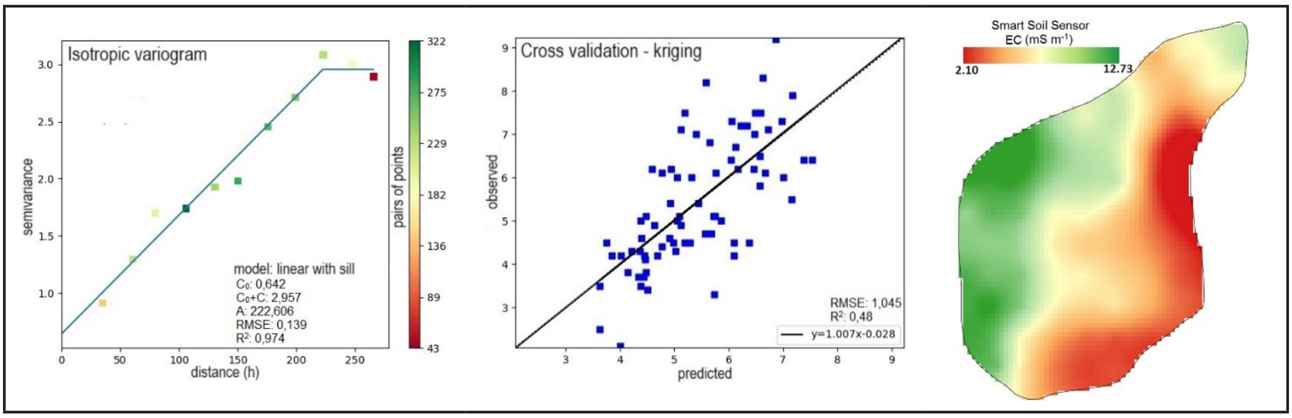
Figure 3 – Results of the geostatistical analysis and the spatial variability maps



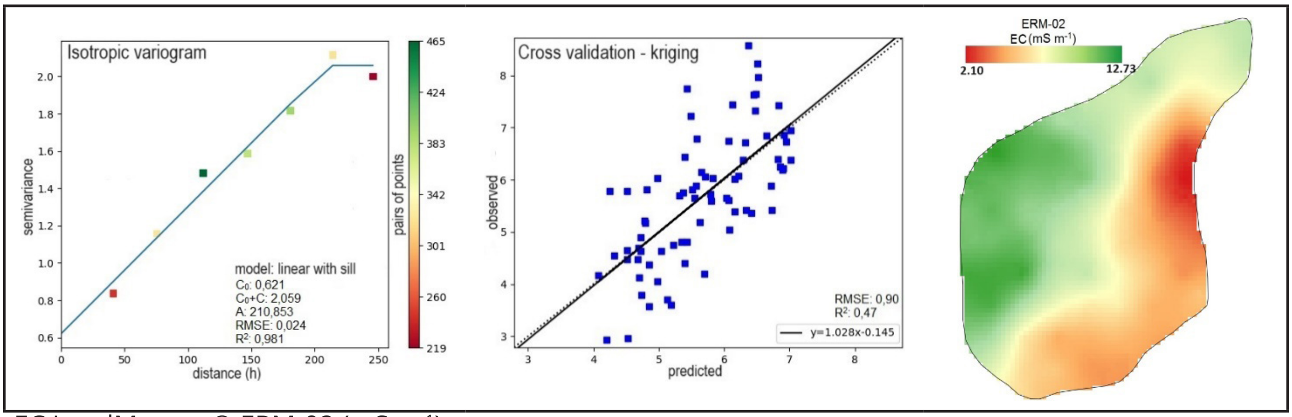
Soil temperature (°C)



Soil moisture (%)



EC Smart Soil Sensor (mS m^{-1})



EC LandMapper® ERM-02 (mS m^{-1})

Source: Authors (202

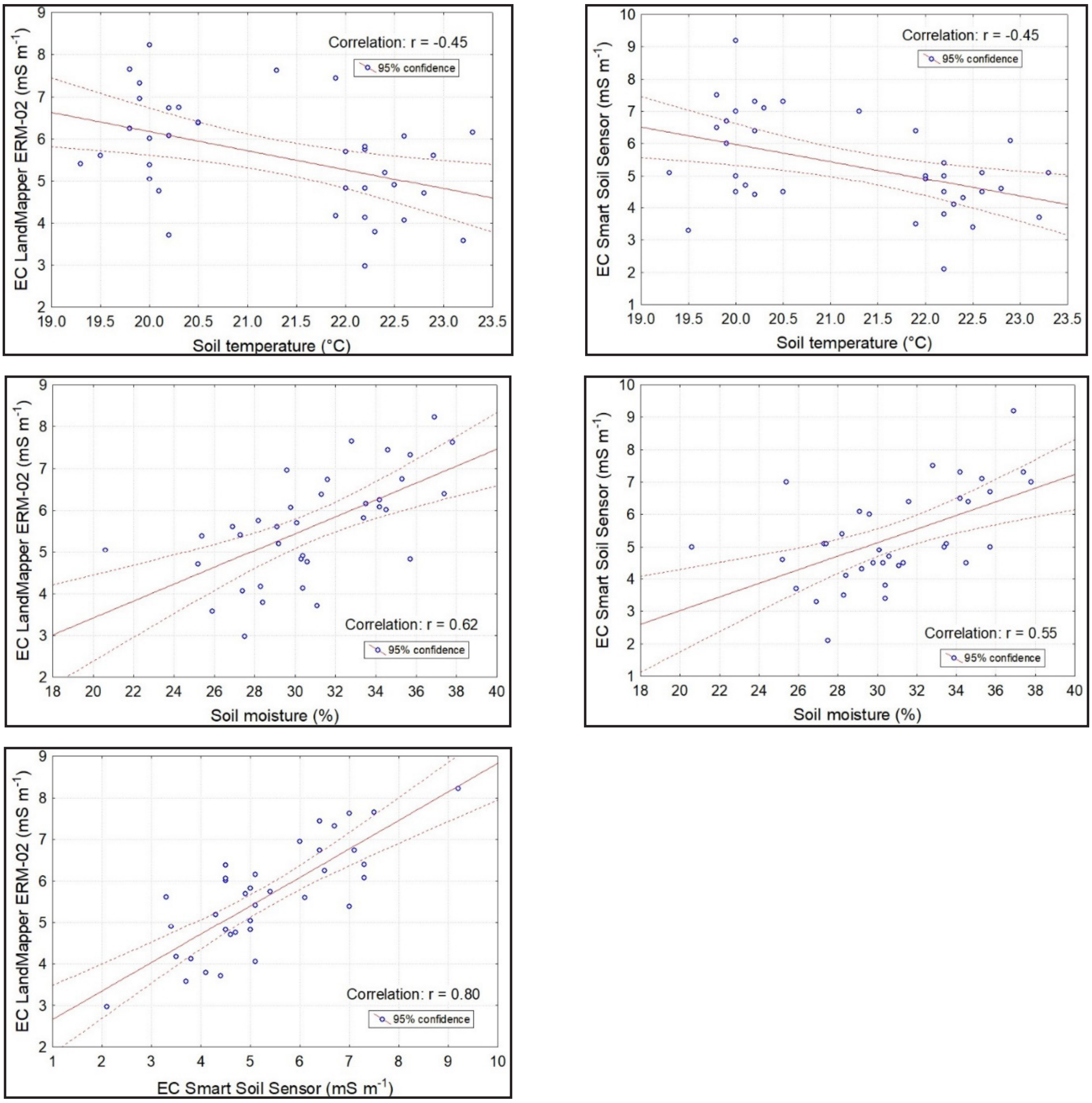
All the mapped variables exhibited spatial dependence, allowing for the fitting of theoretical models of semivariance to the empirical semivariance of the measured variables. Thus, the prediction of values at unsampled locations and the creation of maps representing variations in the area were possible.

The geostatistical modeling that showed the best spatial behavior for all measured variables was the linear model with a sill. In general, the range values obtained in fitting the semivariograms were five times greater than the distance between sampled points, ensuring reliability in estimating values at unsampled locations. According to Mello *et al*. (2006), the range parameter is indicative of the magnitude of spatial continuity. Therefore, the larger this value, the greater the spatial continuity, and consequently, the more accurate the estimation of values at unsampled locations.

After the maps were created, it was possible to observe that the variables EC (measured by both sensors) and soil moisture showed high similarity. Locations with higher EC values also had higher moisture levels. Conversely, the opposite behavior was observed between these maps (EC and soil moisture) and the soil temperature map, with the causes of these variations previously discussed.

In Figure 4, graphs and Pearson correlation coefficients (r, $p<0.05$) between the values of temperature, soil moisture, and apparent soil electrical conductivity are shown. Galarça *et al*. (2010) emphasize that the Pearson correlation coefficient (r) takes values from -1 to 1. A perfect positive correlation between two variables is observed for $r = 1$. A perfect negative correlation between two variables, meaning that as one increases, the other decreases, is obtained when $r = -1$. The authors also highlight that the correlation between two characteristics measures the association between them; however, it does not determine the cause-and-effect relationship between them.

Figure 4 – Graphs of Pearson correlation ($p<0.05$) between the values of temperature, soil moisture, and apparent soil electrical conductivity



Source: Authors (2024)

All correlations were significant at the 5% probability level. A negative correlation was observed between soil temperature and EC measured by both devices, with r = -0.45 for both. Soil moisture showed a positive correlation with EC, regardless of the sensor used for EC measurement. The highest correlation coefficient (r) was observed for the correlation between EC values measured by the two sensors (r = 0.8).

Locations with higher soil temperatures typically have less vegetative cover, favoring solar radiation incidence on the soil, causing an increase in temperature, and consequently, water loss through evaporation, reducing soil moisture. This behavior justifies the observed negative correlation coefficient, as water in the soil has a direct influence on electrical conductivity, as evidenced by the significant positive correlation between EC and soil moisture, as discussed earlier.

4 FINAL CONSIDERATIONS

All measured variables showed spatial dependence in the experimental area. The use of a multisensor platform enabled the mapping of the spatial variability of apparent soil electrical conductivity (EC), temperature, and soil moisture, resulting in thematic maps indicating these variations across the experimental area. The EC measured by using the multisensor platform was similar to the EC measured by the commercial sensor, with r = 0.8, indicating reliability in the field readings.

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