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Use of geostatistical analyses for wheat production areas throung the variables NDVI, surface temperature and yield

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Abstract. Geostatistics is a crucial tool for data analysis in the field of precision agriculture, allowing the characterization of spatial variability magnitude, optimizing profitability and yield in agricultural areas. In this context, the present study aimed to evaluate the spatial dependence of the variables yield, Normalized Difference Vegetation Index (NDVI), and surface temperature in winter wheat plants. This was achieved through fitting semivariograms with different statistical models and interpolating the study variables using Ordinary kriging. The experiment was conducted at Fazenda Santa Helena, located in the municipality of Lavras in the state of Minas Gerais, Brazil, with a 12-hectare winter wheat crop of the TBIO Calibre variety. Data were collected using a grid sampling method at different stages of wheat plant growth (tillering and elongation). The analyzed variables included yield, NDVI, and surface temperature. Statistical analyses were performed using the R software. Initially, the spatial dependence of the study variables was analyzed by fitting semivariograms using the Restricted Maximum Likelihood (REML) method and considering spherical, exponential, and gaussian models. The evaluation of errors was carried out through cross-validation, and subsequently, the data interpolation was performed using ordinary kriging with the best-fitted semivariogram model. The results demonstrated a proper fit of semivariograms for the study models, with the spherical model standing out for surface temperature variables (elongation and tillering), NDVI (tillering), and the exponential model for NDVI (elongation) and yield. Therefore, the use of geostatistics is emphasized as an important tool to assist in precision agriculture management in winter wheat crops.

Key words: spatial analyses, winter wheat, cross-validation, active sensor, vegetation index.

INTRODUCTION

Wheat (*Triticum aestivum* L.) is a cereal of great economic importance that has been cultivated by humans for centuries. According to CONAB (2023), Brazil had an estimated planted area of wheat for the 2023 crop of 223.9 million hectares, showing an increase of 1.36% compared to the previous year's crop. It is worth noting that Brazil has the potential for further growth in wheat cultivation, as it currently ranks 14th in global production, with an estimated forecast of 10.3 million tons of wheat in the 2023/24 crop, thus enabling the development of various sectors (CONAB, 2023).

Alongside agricultural advancements, one can observe the growth of precision agriculture (PA) and statistical methods, as obtaining more accurate information is crucial in the agricultural context. A more in-depth study of new techniques aimed at analyses for increased yield, cost reduction, and inferences of variables in the field is of fundamental importance to ensure profitability in the sector.

In this context, as highlighted by Oliveira et al. (2007), Silva et al. (2008), Carvalho et al. (2009), Pomortsev (2019), and Kuznetsov et al. (2020), precision agriculture (PA) stands out as a set of techniques and technologies that utilize data collection, processing, and analysis to enhance the management of agricultural activities. It involves the development of innovative technologies to ensure environmentally safe products and improved production efficiencies. One of the techniques and technologies within precision agriculture is the acquisition of data through various sensors. According to Yumashev et al. (2020), Jayashree et al. (2021), Muangmee et al. (2022), and Schirmbeck et al. (2022), information generated from sensor-derived data, at different spatial scales, can serve as a foundation for studies, addressing both yield gaps and risk management in the agricultural sector, thus promoting environmental sustainability.

Information obtained through statistical methods allows the assessment of agricultural variables based on their spatial variability, also known as a precision agriculture practice, enabling greater accuracy and cost reduction in agricultural fields (IPEA, 2022). The use of analytical techniques is steadily rising due to the need for methodologies that optimize the analysis of information for rural producers, contributing to the development of this important economic sector.

Among these methods, geostatistical analyses are mentioned, which allow the identification of spatial variability in different study attributes. Their broad applications in agriculture mainly encompass analyses of physical-chemical components of soils (Alves et al., 2014; Corrêa et al., 2009; Ferraz et al., 2019a), analyses of environmental attributes (Medeiros et al., 2014), analysis of animal facility environments (Damasceno et al., 2019; Ferraz et al., 2019b; Ferraz et al., 2020; Saraz et al., 2021), as well as analyses of agricultural equipment and its relationship with crops (Marasca et al., 2017) and agricultural equipment and worker health (Martins et al., 2022; Gomes et al., 2021).

The geostatistical method involves unbiased interpolation based on a semivariance function that considers the spatial characteristics of the variables (Madenoglu et al., 2020). Ordinary kriging is used for creating representative maps of agricultural variables (Ma et al., 2022). Vieira (2000) and Hilal et al. (2024) emphasize that the objective of geostatistics applied to precision agriculture is to characterize the magnitude of spatial variability in soil and plant attributes, and to make estimates using the principle of spatial variability to identify interrelationships of attributes in space and time, allowing the study of appropriate sampling patterns.

In wheat plants, the variable of surface temperature serves as an indicator of their development and yield. Wheat is susceptible to thermal stress at critical growth stages (Gupta et al., 2013; Tian et al., 2020), leading to yield losses (Goher & Akmal, 2021). Surface temperature can be measured using proximal, remote sensors, satellite images, or remotely piloted aircraft (Galvincio, 2019). These measurements can be employed to monitor agricultural crops during their development, playing a crucial role in site-specific management decisions (Jelínek et al., 2020).

With the advancement of affordable devices equipped with specialized applications, new information can be obtained from agricultural fields (Żelazny, 2020). A good example of this is the sensors that measure radiation in the red and near-infrared ranges, as they provide data for calculating the Normalized Difference Vegetation Index (NDVI). This index has been used to estimate crop yield, as highlighted by Barbosa et al. (2019), enabling the conduct of various studies. Such investigations have revealed a positive correlation between NDVI values and wheat yield, as discussed by Reznick et al. (2021). The magnitude of NDVI values is directly related to differences between infrared and red reflectance, indicating a higher presence of chlorophyll and, consequently, a greater plant yield potential, as observed by Rissini et al. (2015). Additionally, NDVI can be employed to identify areas susceptible to water or nutritional stress, as evidenced by Pallottino et al. (2019). Under water or nutritional stress conditions, wheat crops typically exhibit lower NDVI values.

In this context, the objective of this study was to employ precision agriculture techniques combined with geostatistical tools to investigate the spatial variability of yield, surface temperature, and NDVI attributes in a winter wheat field. This was achieved by fitting semivariograms to different statistical models and interpolating the data for the creation of maps using ordinary kriging. The research problem is that information from unsampled sample points can be studied through data interpolation via geostatistics, facilitating and optimizing correct decision-making in agricultural areas.

MATERIALS AND METHODS

The experimentwas developed at Fazenda Santa Helena, located in the municipality of Lavras, Minas Gerais, Brazil. The average altitude of the area corresponds to 930 m above sea level and the average slope of the terrain is 5%. According to the classification established by the Köppen method, the climate is characterized as subtropical with dry winter (Cwb) (Sá Junior et al., 2012).

The experimental area consists of a wheat crop, planted with a spacing of 0.50 m between rows and 0.17 m between plants in a total area of 12 hectares. The variety planted was TBIO Caliber. A rate of 270 plants per hectare was adopted for the planting process, crop nutrition was based on the nutritional needs of the wheat crop, where 300 kg per hectare of (21-00-21) was adopted before planting and in the planting process. planting 100 kg per hectare of Map.

Wheat, along with barley, rye and oats, are examples of winter crops, those that are, regardless of the zoning of the region, as is characteristic of Brazilian regions, these are planted between April and August, when the coldest periods begin. of the year.

To obtain data on surface temperature, NDVI and wheat productivity, two periods were defined, for both data collections, they were carried out under favorable environmental conditions, without the presence of rain. Collection in the tillering phase took place on May 19, 2023 and the elongation collection took place on June 5, 2023. The tillering phase comprises the period in which tillers appear on the plant and the crop elongation phase is the one in that the first stem node appears.

After the culture was established, point distributions were carried out for data collection in the field, developing a 10 m × 10 m sampling grid (Fig. 1), totaling 77 points. The creation of this sampling grid was carried out using the QGIS software version 3.28. The georeferencing of the sampling points in the field was obtained using the Garmin eTrex 10 portable GPS with an accuracy of approximately 2 m.

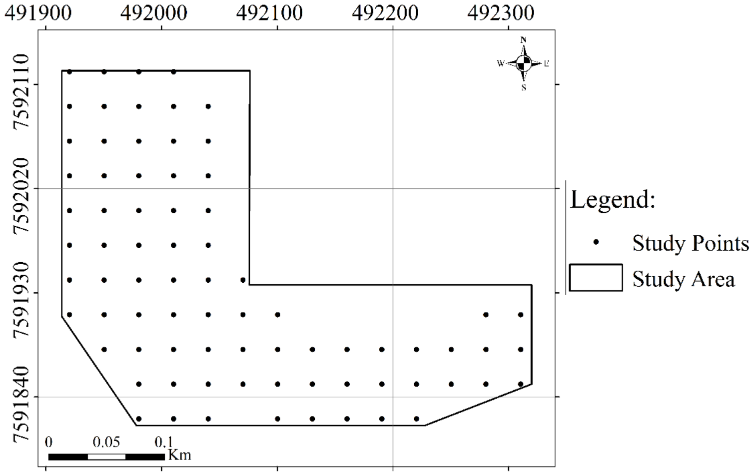

Figure 1. Sampling mesh and details of the sampling scheme.

Surface temperature and NDVI data were collected in both phases (tilling and elongation) in the morning, between 07:00 and 09:00 on May 19, 2023 (tiller) and June 5, 2023 (elongation). Surface temperature data was collected using the Texto 830-T1 equipment, which is a laser thermometer, and NDVI data was collected using the GreenSeeker ® active sensor. For both equipment, information was obtained 0.5 m away from the plant.

The climatic conditions in the period referring to the months of activities were, in April, accumulated precipitation 3.4 mm and average temperature 21.29 °C; month of May, accumulated precipitation 0.025 mm and average temperature 18.6 °C; June, accumulated precipitation 0.29 mm and average temperature 17.16 °C; July, accumulated precipitation 0.2193 mm and average temperature 17.97 °C; month of August, accumulated precipitation 1.01 mm and average temperature 19.95 °C.

After 130 days of sowing, the crop harvesting process was carried out, enabling the collection of productivity data. To this end, the data was collected manually in the area in the relevant georeferenced locations, in a space of 1m², covered with tarpaulin, so that no loss would occur. The extracted plants were subjected to the threshing and weighing process. The grains were weighed and the yield calculated with moisture corrected to 16%.

After this process, geostatistical models were applied to the NDVI data, average surface temperature of the crop and productivity, and semivariograms adjusted by the Matheron (1962) estimator (Eq. 1) were produced to evaluate the spatial dependence of the variables collected in the field, since currently there is a gap in science due to these variables related to wheat cultivation.

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

where $\hat{\gamma}(h)$ is the semivariance; N(h) is the number of experimental pairs of observations *Z*(*X i*) e *Z*(*X i*+ *h* at locations *Xi e Xi*+*h*, separated by distance *h*.

The first model worked on was the spherical model (Eq. 2), due to its recommendation for use in cases where phenomena that exhibit transition in the study region, that is, some areas (patches) present large values and others small ones. The average diameter of the patches is represented by the model range.

$$\gamma(h) = \left\{ C_O + C\left[\frac{3}{2}\left(\frac{h}{a}\right) - \frac{1}{2}\left(\frac{h}{a}\right)^3\right]\right| (0 \leq h \leq a) \tag{2}$$

$$\gamma(h) = C_O + C \text{ (h > a)}$$

The second model worked was the Gaussian model (Eq. 3), and the function with reverse curvature near the origin is continuously repeated in geostatistical texts and software packages. The c is the limit and r is a distance parameter. The function approaches its limit asymptotically and can be considered to have an effective range of approximately $\sqrt{3}r$.Where it reaches 95% of its sill variance.

$$\gamma(h) = C_0 + C\left[1 - e^{\left[-3\left(\frac{h}{a}\right)^2\right]}\right] \quad (0 \leq h \leq a) \tag{3}$$

The third model tested was the exponential model (Eq. 4), however for practical purposes, it is convenient to attribute a practical range to it, and this is generally considered as a distance in which γ is equal to approximately 95% of the variation of the sill variance.

$$\gamma(h) = C_0 + C\left[1 - e^{\left[-3\left(\frac{h}{a}\right)\right]}\right] \quad (0 < h < a) \tag{4}$$

One of the objectives of geostatistical analysis is not only to obtain a model of spatial dependence, but also to predict values at unsampled points (Hussain et al., 2022). The interest may be in one or more specific points in the area or in obtaining a grid of interpolated points that allow viewing the behavior of the variable through a map.

To analyze the degree of spatial dependence of the variable, a quantitative assessment of spatial variability called degree of spatial dependence was used (DSD), which is the percentage relationship between the nugget effect (C_0) and the sill variance (C = C_1+C_0), that is, the higher this coefficient, the lower the spatial variability.

According to Cambardella et al. (1994) and Souza et al. (1999), the nugget effect coefficient with a value up to 25% is classified as having strong spatial dependence, values between 25% and 75% as moderate and above 75% as having weak spatial dependence.

The restricted maximum likelihood (REML) method was used to adjust a mathematical model. Spherical, exponential and Gaussian models were tested for each variable under study (surface temperature, NDVI and wheat yield). As described by Diggle & Ribeiro Junior (2007), the principle of REML is to estimate the semivariogram parameters by the maximum likelihood applied to the data using linear transformation to maximize the probability of the profile of the semivariogram parameters based on the transformation of the variables.

To choose the best semivariogram adjustment model, cross-validation of the data was considered (Faraco et al., 2008; Johann et al., 2010). According to Isaaks &

Srivastava (1989), cross-validation is the technique for evaluating estimation errors that allows comparing predicted values with those sampled. This made it possible to analyze the choice of the best adjustment method based on the Average Error (ME) (Eq. 5), which must be closest to zero.

$$\mathrm{ME}=\frac{1}{n}\sum_{i=1}^{1}\left(Z(s_i)-\hat{Z}(s_{(i)})\right) \qquad (5)$$

where n is the number of data; $Z(s_{(i)})$ is the value observed at the points $s_{(i)}$, $\hat{Z}(s_{(i)})$ refers to the value predicted by ordinary kriging at the point $(s_{(i)})$, without considering the observation $Z(s_{(i)})$ (Faraco et al., 2008).

After adjusting the best semivariograms, data interpolation was performed using ordinary kriging to enable the creation of isocolor maps to visualize the spatial distribution patterns of variables in the field.

For the analysis of statistical and geostatistical parameters, the R Development Core Team software was used, through the geoR library (Ribeiro Junior & Diggle, 2001) and Qgis software version 3.28. The interpolated maps were generated in the Universal Transverse Mercator (UTM) coordinate in zone 23S, in which the Lavras region is located. Finally, Pearson's correlation was verified between the study variables with the aid of the Orange Canvas software (Demsar et al., 2013).

RESULTS AND DISCUSSION

In Table 1, the results of the descriptive statistics of the variables surface temperature, NDVI and yield of the wheat crop in the tillering and elongation phases are presented.

Table 1. Descriptive statistics in the tillering and elongation phase of the wheat crop

Variable	Mean	Standard Deviation	Median	Minimum	Maximum	Variance	Coefficient of variance
STT	16.31	3.5820	16.70	8.40	22.30	12.8307	21.9597
STE	16.37	3.6271	16.70	8.40	22.30	13.1563	22.1572
NDVI-T	0.3945	0.0563	0.3800	0.3000	0.5000	0.0031	14.2818
NDVI-E	0.4964	0.1038	0.4800	0.3100	0.7000	0.0107	20.9187
Yield	0.2915	0.0079	0.2900	0.2800	0.3100	6.2571e-05	2.71387

Legend: STT – Surface temperature in the tillering phase; STE – Surface temperature int the elongation phase; NDVI-T – Vegetation index in the tillering phase; and NDVI-E – Vegetation index in the elongation phase.

The variable surface temperature of wheat plants is an indicator of the plant's well-being and yield, as the plant's surface temperature is interrelated with plant functions, such as evapotranspiration, which is controlled by stomatal conductance (Abdullah et al., 2019). It can be seen in Table 1 that the average surface temperatures of the crop were 16.31 °C and 16.37 °C respectively for the tillering and elongation phases, while the coefficient of variation was 21.9597 and 22.1572 respectively for the tillering and elongation phase. It can be stated through descriptive analysis that the variable surface temperature of the plant in the elongation phase presented higher average values than those in the tillering phase, even when the same conditions were presented.In general, wheat plants prefer surface temperatures between 15 and 20 degrees Celsius, as discussed by Doorenbos & Kassam (1979). Surface temperatures between

9 and 12 degrees Celsius can retard plant growth and development, while temperatures between 25 and 31 degrees Celsius can cause thermal stress and a reduction in grain weight and yield, with no differences between cultivars (Asana & Williams, 1965).

However, the NDVI variable becomes another strong indicator, presenting a coefficient of variation in the tillering and elongation phases respectively 14.2818 and 20.9187. Values above 10% may indicate heterogeneity of the collected variable, according to Gomes & Garcia (2002). The NDVI average value was 0.3945 in tillering and 0.4964 in the elongation phase.

The wheat yield of the studied area, observed in Table 1, presented an average value of 0.2915 g ha^{-1}, indicating a yield slightly below the average for the 2023 harvest, in relation to the national average, which was 0.2931 g ha^{-1}, according to the bulletin from the National Supply Company (CONAB 2023). These average yield values can be explained by unfavorable weather conditions between the months of April and August, a period affected by low levels of rainfall in the Minas Gerais regions, as can be seen in Fig. 2. Water stress threatens wheat growth and yield and risks possible crop losses (Joshi et al., 2020, Ansari et al., 2023).

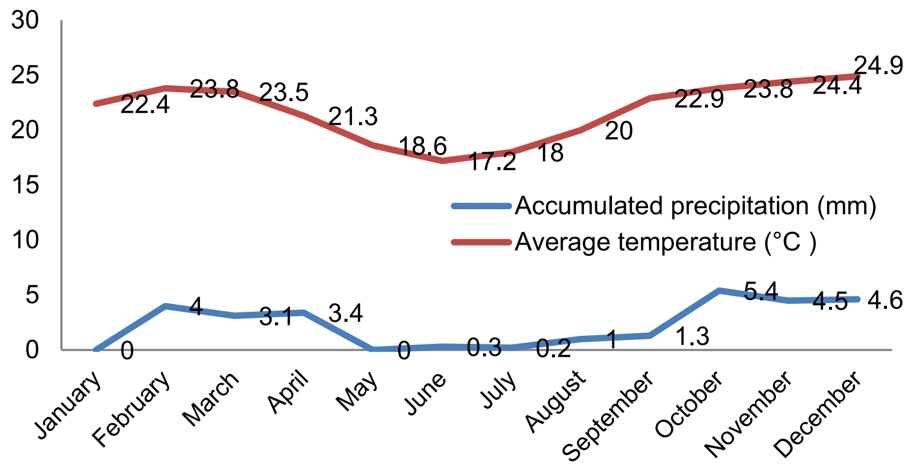

Figure 2. Meteorological information for the Lavras region for the year 2023 of average temperature and accumulated precipitation.

It is noteworthy that wheat cultivation in relation to the climate requires colder temperatures, generally between 10 °C and 19 °C, essentially to promote tillering and minimize the emergence of some diseases in the ears. Regarding precipitation, water stress prevents some tillers from producing ears, therefore, excess rain or irrigation and high relative humidity favor the incidence of various diseases. And which can become a limiting factor for wheat cultivation, with generally high production losses (Manfron et al., 1993).

In Brazil, it allows the development of the crop, due to wheat, along with barley, rye and oats, being examples of winter crops, those that, regardless of the region's zoning, as is characteristic of Brazilian regions, are planted between April and August, when the coldest periods begin and the cultivars are most adapted.

Fig. 3 shows the boxplots for the variables under study. The data described in the descriptive statistics are also evidenced according to the boxplots, with surface temperature values for both elongation and profiling varying from 14 to 18 °C, NDVI varying from 0.4 to 0.6 and yield varying from 0.28 to 0.30 g ha^{-1}, making it possible to detect discrepant values (outliers) for the yield variable.

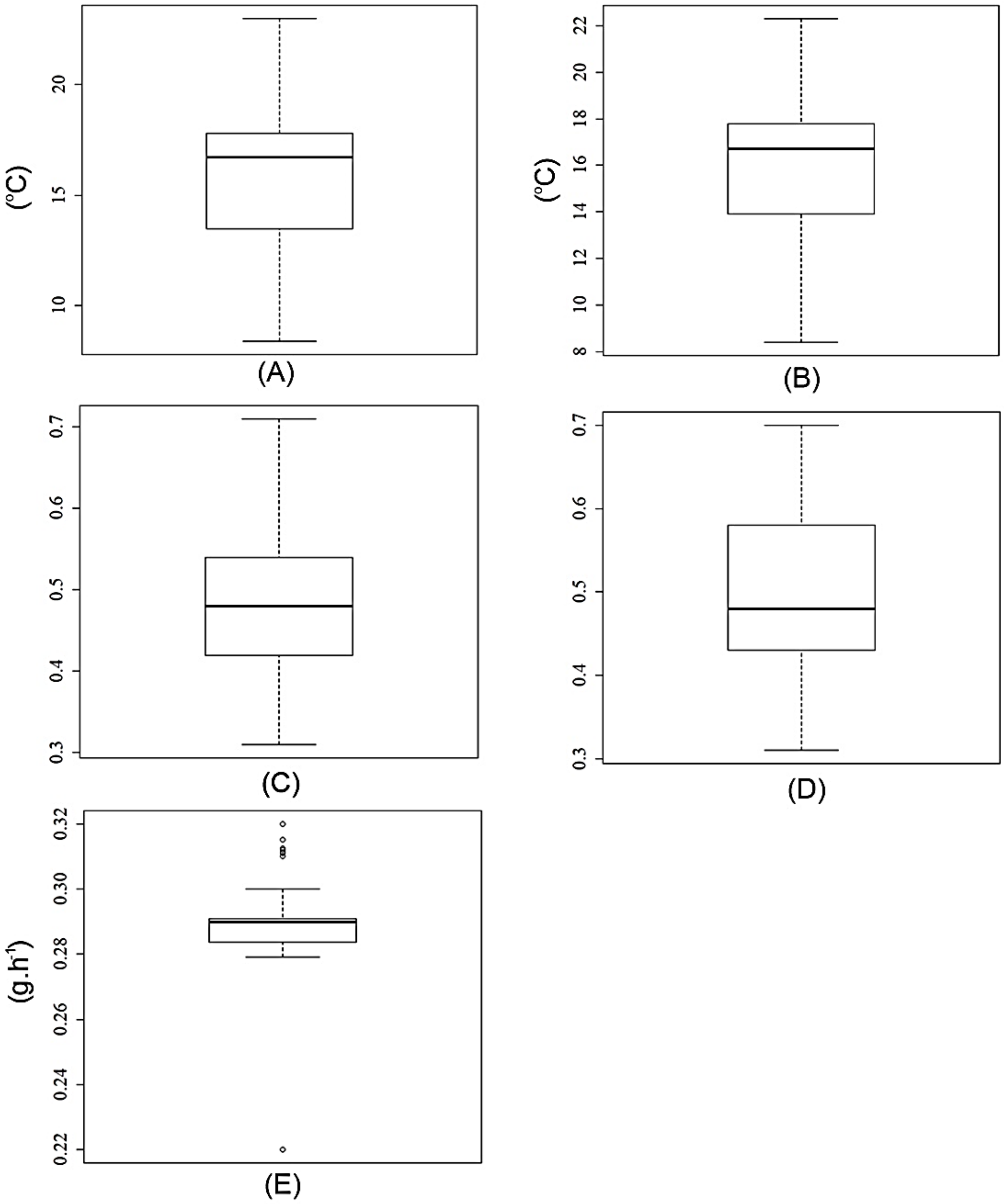

Figure 3. Boxplot of study variables: A) surface temperature tillering; B) surface temperature elongation; C) NDVI tillering; D) NDVI elongation; E) yield.

It can be observed that, with just the use of descriptive statistics analyses, it is not possible to identify the spatial variability of the data. Therefore, it is necessary to search for other tools, such as geostatistical methods, so that it is possible to identify the spatial variability of the data and the development of isocolor maps for the observation of areas that present low, medium, and high values of variables studied.

Based on the geostatistical analysis methodology, it was possible to quantify the magnitude and spatial dependence of the study variables. Through the validation presented in Table 2, it is observed that the semivariogram adjustments were well executed as highlighted by the criteria for best adjustment based on validation according to the Average Error (ME) values close to zero.

Based on geostatistical analyses, the nugget effect is an important parameter of the semivariogram, indicating the unexplained variability of the sample data (Mcbratney & Webster, 1986; Silva et al., 2010). The nugget effect can be expressed as a percentage of the sill variance for the purpose of comparing the degree of spatial dependence of the variables under study (Trangmar et al., 1985) (Table 2). Therefore, variation at distances smaller than the sampling interval is also measurement error.

According to Cressie (1993), the interval determines the space under which the variable is correlated. The largest range was 149 m for the spherical model of the yield variable and the smallest range of 2 m was for the NDVI tillering variable for the exponential model. For the practical range, which is defined as the distance at which the model value is 95% of the threshold (Isaaks & Srivastava, 1989), the highest practical range values of 149 m were for the spherical and exponential models of the yield variable, and the lowest value of 5 m was the exponential model of the NDVI tillering variable.

The estimation of the variables presented in this study by the maximum residual likelihood method (REML) were adjusted by the spherical, exponential and Gaussian models. According to Cambardella et al. (1994), the variables studied showed a moderate and strong degree of spatial dependence for the spherical, exponential and Gaussian models, only the variable NDVI tillering presented a weak degree of dependence for the exponential and Gaussian models.

In this study, the model that exhibited the best fit to the data for the variables surface temperature in the tillering and elongation phase was the spherical model. For the vegetation index in the tillering phase the spherical model demonstrated superior fit, whereas for the vegetation index in the elongation phase, the exponential model emerged as the most suitable. For the yield, the exponential model proved to be the best-fitting.

All variables underwent cross-validation criteria, facilitating the selection of the semivariogram model fitting method that best suited each variable, as highlighted in Fig. 4.

The semivariogram is a comprehensive tool, and its conclusions are derived from the results obtained through its analysis, in accordance with the study parameters. Cross-validation, in turn, serves as additional support in the decision-making process based on the best-fitted model. In this study, semivariograms for all variables were adjusted using the REML method for the spherical statistical model, except for the NDVI elongation and yield variables, which were fitted to the exponential statistical model. According to Webster & Oliver (2007) and Silva et al. (2010), the spherical mathematical model is the most employed in geostatistics, however, the exponential model is also widely used.

Table 2. Method, models and estimated parameters of the experimental semivariograms for the variables: surface temperature, NDVI, yield in the tillering and crop elongation phases

	Model	Nugget effect (C_0)	Contribuition (C_1)	Sill variance ($C_0 + C_1$)	Range (a)	Practical range (a`)	DSD	ME
	Sph.	**0**	**12.27**	**12.27**	**60**	**60**	**0.00 strong**	**-8.61e-09**
REML	Exp.	0	13.75	13.75	30	91	0.00 strong	6.11e-06
	Gau.	0	13.61	13.61	31	54	0.00 strong	2.73e-07
Elongation temperature								
	Model	Nugget effect (C_0)	Contribuition (C_1)	Sill variance ($C_0 + C_1$)	Range (a)	Practical range (a`)	DSD	ME
	Sph.	**0**	**12.75**	**12.75**	**52**	**52**	**0.00 strong**	**-8.61e-09**
REML	Exp.	0	13.5	13.5	20	59	0.00 strong	6.96e-05
	Gau.	0	13.83	13.83	28	48	0.00 strong	2.92e-06
NDVI tillering								
	Model	Nugget effect (C_0)	Contribuition (C_1)	Sill variance ($C_0 + C_1$)	Range (a)	Practical range (a`)	DSD	ME
	Sph.	**0.0079**	**0.0032**	**0.0111**	**30**	**30**	**71.17 moderate**	**3.06e-10**
REML	Exp.	0.0100	0.0011	0.0111	2	5	90.09 weak	1.12e-07
	Gau.	0.0109	0.0002	0.0111	43	74	98.20 weak	4.54e+00
NDVI elongation								
	Model	Nugget effect (C_0)	Contribuition (C_1)	Sill variance ($C_0 + C_1$)	Range (a)	Practical range (a`)	DSD	ME
	Sph.	0.0067	0.0047	0.0114	107	107	57.77 moderate	3.09e-10
REML	**Exp**.	**0.0000**	**0.0112**	**0.0112**	**21**	**62**	**0.00 strong**	**1.28e-06**
	Gau.	0.0081	0.0032	0.0113	56	97	71.68 moderate	5.60e-08
Yield								
	Model	Nugget effect (C_0)	Contribuition (C_1)	Sill variance ($C_0 + C_1$)	Range (a)	Practical range (a`)	DSD	ME
	Sph.	0.0001	0.0003	0.0004	149	149	**25.00 moderate**	-1.86e-10
REML	**Exp**.	**0**	**0.0003**	**0.0003**	**50**	**149**	0.00 strong	**3.95e-07**
	Gau.	0.0001	0.0002	0.0003	40	68	33.33 moderate	1.73e-08

Legend: REML – Restricted Maximum Likelihood; Sph. - Spherical; Exp. – Exponential; Gau. – Gausian; DSD – Degree of Spatial Dependence; ME - Medium Error.

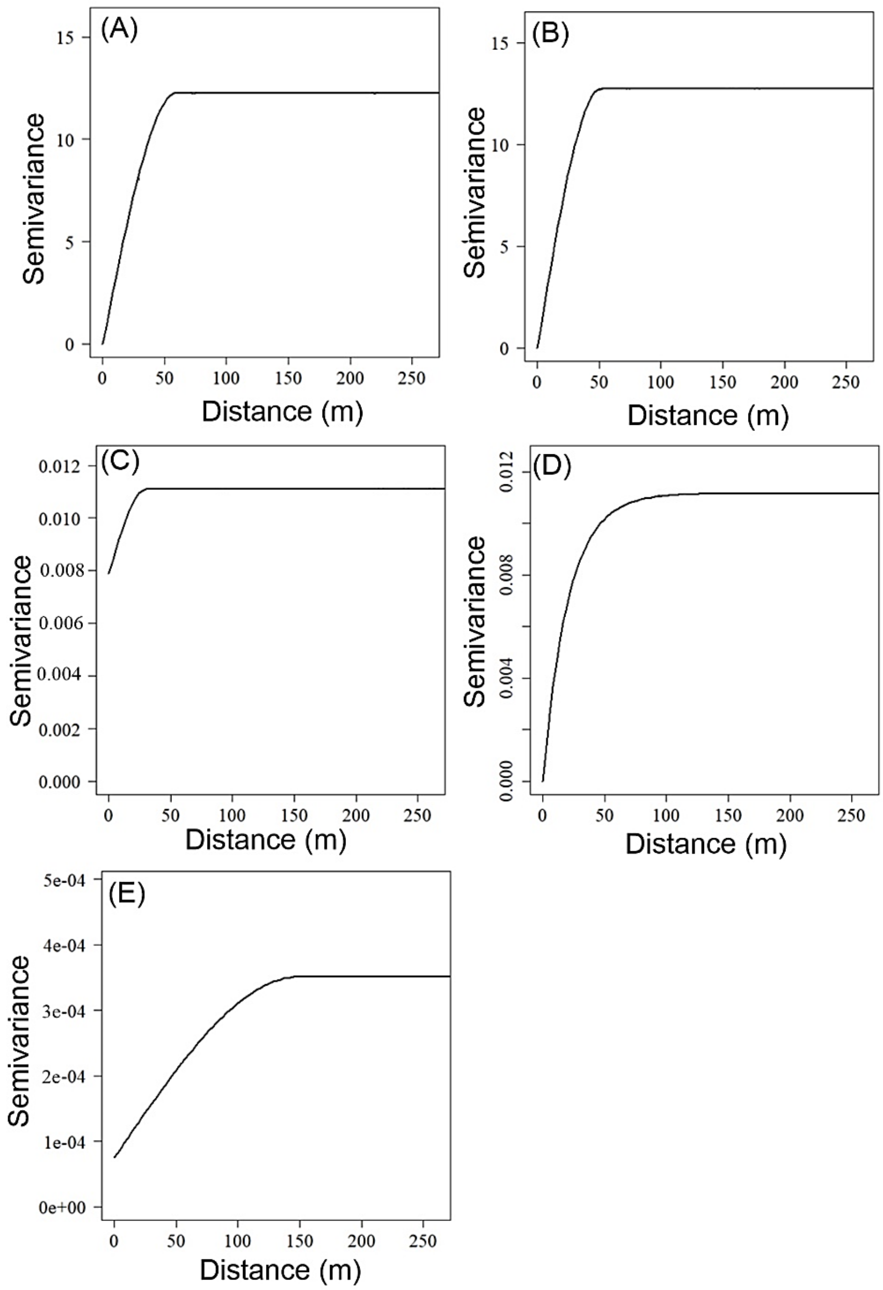

Figure 4. Semivariograms chosen depending on the method and model for the variables: A) surface temperature tillering; B) surface temperature elongation; C) NDVI tillering; D) NDVI elongation; E) yield.

Subsequently, values for surface temperature, NDVI, and yield were estimated through ordinary kriging, relying on the spatial dependence of the semivariogram models. Thus, spatial distribution maps for all variables in this study were developed, as presented in Fig. 5, where the irregular polygon outlines the perimeter of the experimental area.

It can be observed that the interpolation via kriging demonstrated effective performance in estimating unsampled values for the study variables, attributed to the optimal fitting of semivariograms. Through visual analysis of the interpolated maps, it is evident that each variable exhibits a distinct distribution.

For the elongation and tillering temperature variable (Fig. 5, A and 5, B), a wide temperature distribution ranging from 14 to 22 °C is observed, with a notable lower-western and upper-eastern area featuring lower temperatures of 10 to 14 °C. However, this variation does not become a limit to the development of culture.

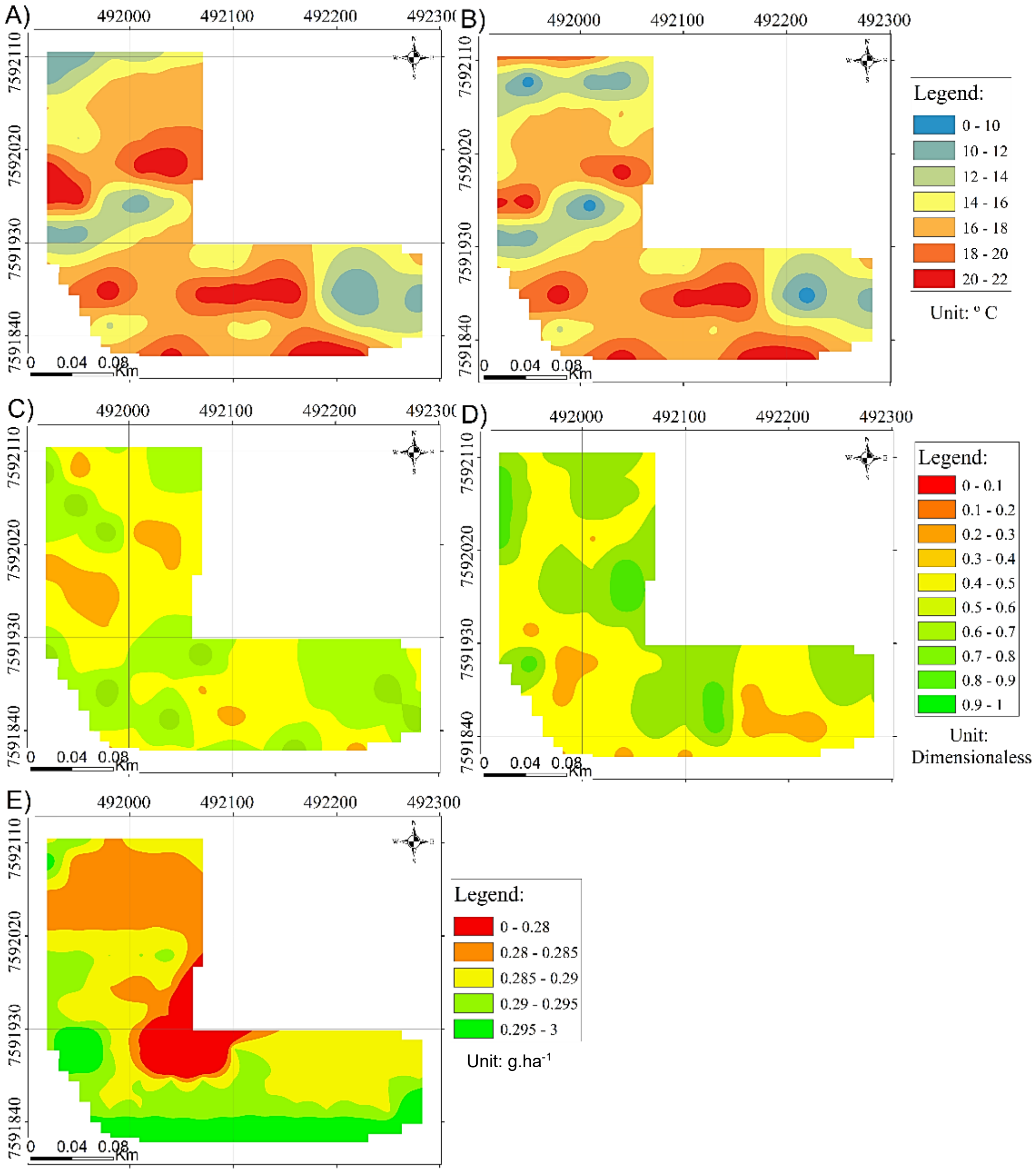

Figure 5. Spatial distribution of the variable: A) surface temperature tillering; B) surface temperature elongation; C) NDVI tillering; D) NDVI elongation; E) yield.

Regarding the NDVI variable for the elongation and tillering phases (Fig. 5, C and 5, D), values are predominantly concentrated in the range of 0.4 to 0.5 across the majority of the area. Additionally, there is a distributed presence of higher values up to 0.7 and values ranging from 0.2 to 0.3 in the upper-eastern part for the tillering phase (Fig. 5, C), as well as a distributed presence of higher values up to 0.8 and values ranging from 0.2 to 0.3 in the lower-western part for the elongation phase (Fig. 5, D). As for the yield variable, lower values are observed in the central part of the study area, approximately around 0.28 g ha^{-1}. While higher values are evident in the lower part of the study area, reaching around 0.30 g ha^{-1} (Fig. 5, E).

Correlating the variables of tillering temperature with elongation temperature reveals a correlation of 0.639. It is evident that as the tillering temperature increases, the elongation temperature proportionally increases, as indicated by the data behavior. Meanwhile, the correlation between the NDVI tillering variable and other variables, including tillering temperature, elongation temperature, NDVI elongation, and yield, showed negative correlations with values of -0.133, -0.126, -0.027, and -0.026, respectively. In this case, an increase in the NDVI tillering value corresponds to a proportional decrease in the correlated variables. For the NDVI elongation variable, its correlations with tillering temperature, elongation temperature, and yield also displayed negative correlation values of -0.142, -0.077, and -0.097, respectively. In this specific case, the NDVI tillering and NDVI elongation values exhibited the same behavior concerning the other variables. In contrast to the data related to NDVI tillering and NDVI elongation, yield showed positive correlations of 0.188 and 0.127 with elongation temperature and tillering temperature, respectively.

According to the analysis of Fig. 5, for the temperature variable, the same pattern of special variability between the study periods can be seen, both for tillering and elongation, and the correlation between periods being notable. However, the same was not observed for the NDVI variable. As there was an increase in the values during the tillering period for elongation with low correlation between data. The yield variable in turn shows low correlation between data with the study variables temperature and NDVI.

Based on the analysis of the interpolated maps, it is evident that using an average value for the study variables does not adequately represent the entire area. Thus, it is highlighted that studies employing geostatistics for understanding the spatial variability of different agricultural areas are crucial. This approach is essential for identifying demands and guiding intelligent and informed decision-making regarding the adoption of management techniques and economic returns in wheat fields. It is further emphasized that the selection of the best-fitting semivariogram model ensures an improved interpolation process of data through ordinary kriging, facilitating the creation of maps that accurately describe the spatial variability of the studied variable.

It is noteworthy that, in addition to the application described in this work for winter wheat, geostatistics can be applied to other agricultural crops if it meets the precept of spatial dependence between data. Therefore, it is possible to organize available data spatially according to the similarity between georeferenced neighbors. It is worth highlighting that the massive number of observations allows for a more detailed view of the spatial and temporal relationships of agronomic processes, enabling more accurate decision-making in different agricultural areas and crops.

Farmers, through mapping of areas, can apply the results of this research in decision-making and identifying application demands at variable rates of inputs and correctives according to the area's needs, potentially increasing the. productivity of wheat crops in areas with greater nutrient deficiency.

CONCLUSIONS

The semivariograms enabled the characterization of the magnitude of spatial variability in the study variables: surface temperature, NDVI, and yield in winter wheat cultivation. Testing different semivariogram fitting models facilitated the identification of the most suitable model for each variable. Consequently, this allowed for interpolation via kriging, enabling the creation of maps that effectively characterized the spatial variability of the variables under consideration in winter wheat fields. This underscores the potential of geostatistical analysis in the monitoring and assessment of winter wheat agricultural areas in Brazil.

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