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# Spatial Variability of the Organic Matter in the Soil in Cassava Cultivation Under Differentiated Management

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**Abstract**

The management of soil organic matter (SOM) is fundamental in agriculture for soil conservation and crop yields. However, in addition the soil being dynamics, it is heterogeneous, therefore, understanding the spatial variability of SOM is essential. The main objective of this study was to evaluate the spatial variability of SOM in a cassava cultivation under different management, seeking to classify its spatial dependence by geostatistics. A filed experiment was conducted out on soil classified as oxisol with four different management systems: irrigation (micro sprinkler, drip and no irrigation), spacing (1.0 × 0.8 m, 1.0 × 1.0 m and 1.0 × 1.5 m), weed control (manual control and no control) and acidity correction (limestone and withouth limestone), totaling 36 experimental plots. To determine the SOM, the wet oxidation method was used, and the semivariograms were generated by the GS$^{+®}$ software. The effect of the different management systems on the spatial variability of the SOM was evaluated at a depth of 0.0-0.2 m. The theoretical semivariogram model that best fitted the study was the Gaussian model, with a well-defined level, also expressing the condition of data stationarity. The spatial dependence was classified as strong and, through the thematic map generated from the kriging, it was possible to observe the variability in the SOM content for different management zones. The use of geostatistics techniques provided important information for understanding the spatial distribution of soil organic matter.

**Keywords:** organic carbon, geostatistics, kriging, soil management

## 1. Introduction

Cassava (*Manihot esculenta* Crantz), originally from South America (Okudoh et al., 2014), is a crop that forms starchy tuberous roots (Thanni et al., 2022), and is a staple food in Latin America, Africa and Asia (Howeler, 2014). It is one of the most important crops in the world, serving as food for more than 800 million people, mainly for the population with lower purchasing power (Maxmen, 2019). Although cassava is labeled “food of the poor” or “bread of the tropics” (Oghenejoboh et al., 2021), it is central to the United Nations’ goals for sustainable development and food security.

In Brazil, cassava is produced mostly by family farmers, having economic, agronomic and sociocultural relevance, mainly in the Amazon region (Lins et al., 2021; Pimentel et al., 2021). The northern region accounts for 35.1% of all national cassava production, with the state of Pará as the largest producer, accounting for 22.1% of the total produced in the country. Pará has 17 municipalities among the 20 largest producers, and the municipality of Santarém is considered the second largest producer of cassava in Brazil (IBGE, 2021).

The processes that control the development of field crops can vary both in space and time, and soil properties have greater influence on the expected results, due to the relationships between source material, relief and time that generate the natural variability of the system (Maestrini & Basso, 2018). Among the soil attributes, organic matter (SOM) is one of the most sensitive to management systems and has relevant importance in relation to the physical, chemical and biological characteristics of the soil (Hoffland et al., 2020).

In agricultural systems, several practices are adopted for crop management, and may interfere with the organic carbon content and consequently in SOM. This can vary in small or large distances, depending on the intrinsic characteristics of the soil and the management practices used.

For many years, univariate statistics were the main statistical methodology used in soil study, however, this method considers only random or medium values, disregarding the position in space. Therefore, it is not recommended in the study of environments, since it evaluates the behavior of variables two to two (Karydis, 2022). Today the technique that presents results closer to the reality of the soil system, is geostatistics, because it takes into account the variability existing in space, enabling the more accurate management of agricultural production systems (Oliveira et al., 2022).

The study of spatial variability of soil properties can help in the development of more efficient and sustainable management systems, in this sense, making it an important study to assist farmers in better soil management and more comprehensively agroecosystems.

In this context, this study aimed to evaluate the spatial variability of SOM in an area cultivated with cassava under differentiated management, seeking to classify the spatial dependence of this variable using the techniques of the geostatistics.

## 2. Material and Methods

The experiment was carried in the community of Boa Esperança, at Km 43 of the Santarém (2°44′S 54°31′W, 145 m elevation), Pará State, Brazil. According to the Köppen classification, the region has climatic type Ami (Humid Tropical Climate), characterized by high annual rainfall (> 1800 mm) and moderate dry season, with an average annual temperature between 25 ºC and 28 ºC. The soil was classified as a "Latossolo Amarelo", according to Brazilian Soil Classification System (Santos et al., 2018), this is, "oxisol", according to Soil taxonomy (Soil Survey Staff, 2014).

Before the implementation of the experiment, soil sampling was performed for initial characterization purposes regarding chemical and physical attributes (Table 1). The preparation and fertilization of the area was according to Brasil et al. (2020), and on March 15, 2017 the cassava crop of the Bem-te-vi variety was implemented under the practices of differentiated management: control of infesting plants, distinct irrigation systems, correction of soil acidity and population density.

Table 1. Results of the chemical and physical analysis of soil in the studied area, before the implementation of the experiment

| pH | | P | K | Ca + Mg | Ca | Mg | Al | H | SOM | Sand | Silt | Clay | SB | T | V |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $H_2O$ | $CaCl^2$ | -- mg/dm$^{-3}$ -- | | ------------ cmol$_c$/dm$^{-3}$ ------------ | | | | | g/kg | ----------- g/kg ---------- | | | -- cmol$_c$/dm$^{-3}$ -- | | % |
| 6.1 | 5.4 | 4.0 | 43.9 | 4.7 | 3.4 | 1.2 | 0.0 | 4.0 | 37.8 | 173.0 | 168.0 | 659.0 | 4.8 | 8.7 | 54.5 |

*Note*. Soil Organic Matter (SOM), Sum of Bases (SB), Cation Exchange Capacity (T), Base Saturation (V).

The area has three distinct irrigation managements (Microaspersion-MI; Drip-GT; Without Irrigation-SI) spacing (1.0 × 0.8; 1.0 × 1.0; 1.0 × 1.5 m), and two weed management (Manual Control; No Control) and acidity correction (limestone and withouth limestone), with dimensions of 75 × 32 m, totaling 2,400 m².

The soil samples were collected with the aid of dutch auger at the depth of 0.0-0.2 m, in the central region of each plot, with the location of known through pre-established metric scale, between February and March 2018 to determine SOM. In each plot, two samples were collected, totaling 72 samples for the entire area (Figure 1). After collection, disturbed samples were air-dried, passed into the 2.0 mm sieve, then crushed in gral and passed in the 0.177 mm sieve.

After the preparation of the samples, soil organic carbon (SOC) analyses were performed at the Soil Laboratory of the Federal University of Western Pará (UFOPA), following the methodology proposed by Walkley-Black and described by Donagema (2011), which was adapted, using 2.5 mL of $H_3PO_4$ p.a. per sample, titration with Fe solution $(NH_4)_2(SO_4)_2 \cdot 6H_2O$ 0.2 mol $L^{-1}$ (Mohr salt). The result obtained from organic carbon analysis was multiplied by 1.724, considering that approximately 58% of SOM consists of SOC (Donagema, 2011).

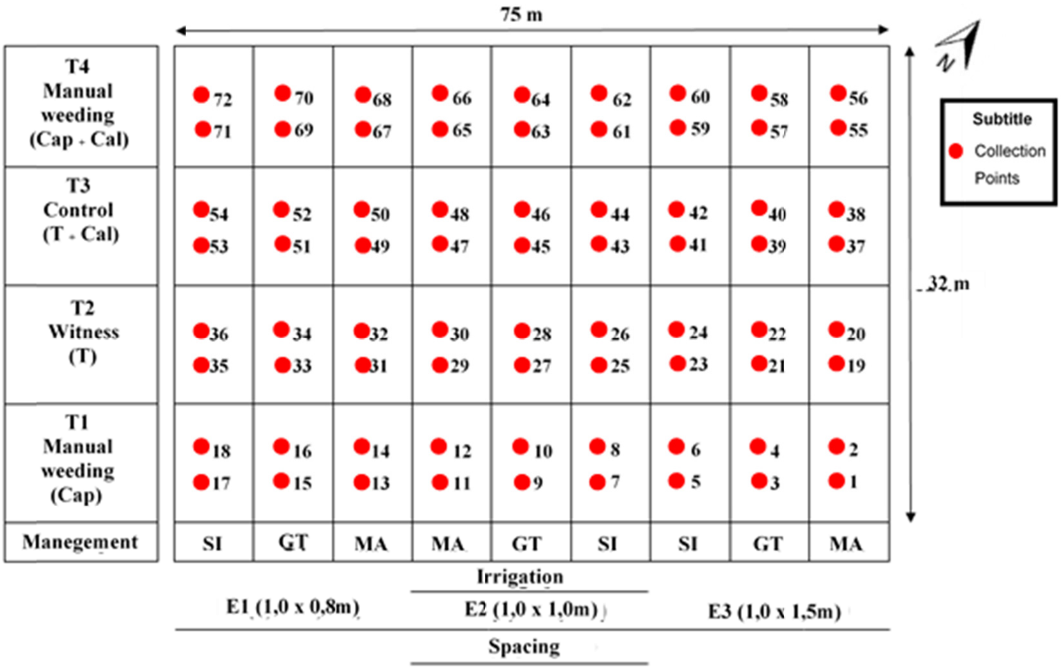


Figure 1. Sketch of the experimental area, illustrating the sampling mesh. without irrigation (SI), drip (GT), micro sprinkler (MA)

The analysis of descriptive and exploratory statistics of the data, together with the Kolmogorov-Smirnov normality test were performed using Minitab 18.1® software, obtaining the location measures (mean, median, minimum and maximum), variability (standard deviation and coefficient of variation (CV)) and central tendency (skewness and kurtosis).

To evaluate the coefficient of variation obtained by descriptive statistics, the Warrick & Nielsen (1980) classification was used, which considers low variability for CV below 12%, mean for CV between 12-62% and high for CV above 62%.

In the characterization of the frequency distribution, the classification Lopes (2003) was used, in which he considers skewness negative distribution when skewness coefficient (As) < 0, positive skewness when As > 0 and symmetry distribution if As = 0. While its classification for kurtosis says that the coefficient of kurtosis (K) > 0.263 the distribution will be platicurtica, or if K < 0.263 the curve is considered leptocurtic, and finally, it will be mesocutic when K = 0.263.

The normality of the data and the conditions of stationarity, the semivariogram was generated using the GS+® Software, where spatial dependence of the samples was determined, by means of an experimental semivariogram:

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

Where, $\gamma(h)$ is the estimated semivariance; n represents the number of measured values pairs Z(x), Z (x + h) separated by a vector (h).

The choice of the best model of the theoretical semivariogram was observed by observing the smallest sum of the waste square (SQR), the highest coefficient of determination ($r^2$), and then the regression coefficient closest to the ideal (1) obtained by the cross-validation technique (Lima et al., 2010).

After the validation of the modeled semivariogram, the calculation was made to know the Degree of Spatial Dependence (GDE) that was obtained by the relationship $[C_0/(C_0 + C)] \times 100$, and classified as recommended by Cambardella et al. (1994), which considers strong spatial dependence when < 25%, moderate between 25 and 75% and weak when > 75%.

Then, the technique of interpolation by krigagem was used to determine values in unsampled points.

$$Z^*(x_0) = \sum_{i=1}^{N} \lambda_i \times Z(x_i) \quad (2)$$

Through the kriging interpolation technique, the map of isolines representative of the spatial distribution of SOM was constructed with the aid of the same software used in the construction of the semivariogram.

## 3. Results

To determine if the CV of the variable SOM presented low variability, we adopted the classification of the coefficient of variation proposed by Warrick and Nielsen (1980). And we observed that SOM presented low variability (< 12%) with CV of 9.79% (Table 2).

For the variable SOM in the results of the median (42.29), minimum (33.81) and maximum (52.02), we observed that the median is close to the average (42.24) this indicates that the central measures are not represented by users when distributed.

In the kurtosis value (-0.33), we observed that the SOM values are more clustered close to the mode (43.94 m).

To determine the normality of the variable SOM, we applied the Kolmogorov-Smirnov test and observed that the data distribution can be considered normal.

Table 2. Descriptive statistics for SOM after installation of the experimental area under study, in March 2018

| Variable | Average | Median | Minimum | Maximum | Standard Deviation | CV (%) | Skewness | Kurtosis | Test K-S |
|---|---|---|---|---|---|---|---|---|---|
| | ---------------------- g/kg ---------------------- | | | | | | | | |
| SOM | 42.24 | 42.29 | 33.81 | 52.02 | 4.13 | 9.79 | 0.11 | -0.33 | $p > 0.15^{ns}$ |

*Note*. $^{ns}$ normal distribution by the 5% Kolmogorov-Smirnov test. Coefficient of variation (CV).

The scope observed in this study, obtained by the semivariogram was 4.83 m representing the maximum distance that a sampling point is correlated with its neighbors (Table 3).

The degree of spatial dependence (GDE) obtained by the ratio between the nugget effect ($C_0$) and the landing ($C_0 + C$) was 0.07% in the three models.

The adjustment of the semivariogram models showed better results to the Gaussian model (Table 3).

Table 3. Geostatistical analysis performed showing the values obtained: Nugget effect ($C_0$), threshold ($C_0 + C$), range (A), coefficient of determination ($R^2$), degree of spatial dependence (GDE), and regression coefficient of cross-validation (CRVC) for the semivariogram models of SOM data in cassava cultivation in the experimental area under study

| Parameter | Model | $C_0$ | $C_0 + C$ | A (m) | SQR | $R^2$ | GDE (%) | CRVC |
|---|---|---|---|---|---|---|---|---|
| SOM (g/kg) | Spherical | 0.01000 | 13.040 | 5.890 | 32.7 | 0.721 | 0.07 | 1.088 |
| | Gaussian | 0.01000 | 13.110 | 4.832 | 29.2 | 0.720 | 0.07 | 1.007 |
| | Exponential | 0.01000 | 13.200 | 7.830 | 45.1 | 0.580 | 0.07 | 1.105 |

In relation the theoretical semivariogram model that obtained better adjustment to SOM data in the area under study. The modeled semivariogram presented a well-defined level which indicates a low degree of randomness present in the samples, with influence of spatial dependence, which expresses the stationarity of the data, and supports the use of the technique of interpolation by ordinary krigagem to assign values to unsampled locations (Figure 2A).

The attribute under study presented regression coefficient of the cross-validation test close to 1.00, indicating that the model adjusted to the semivariogram of organic matter is coherent (Figure 2B).

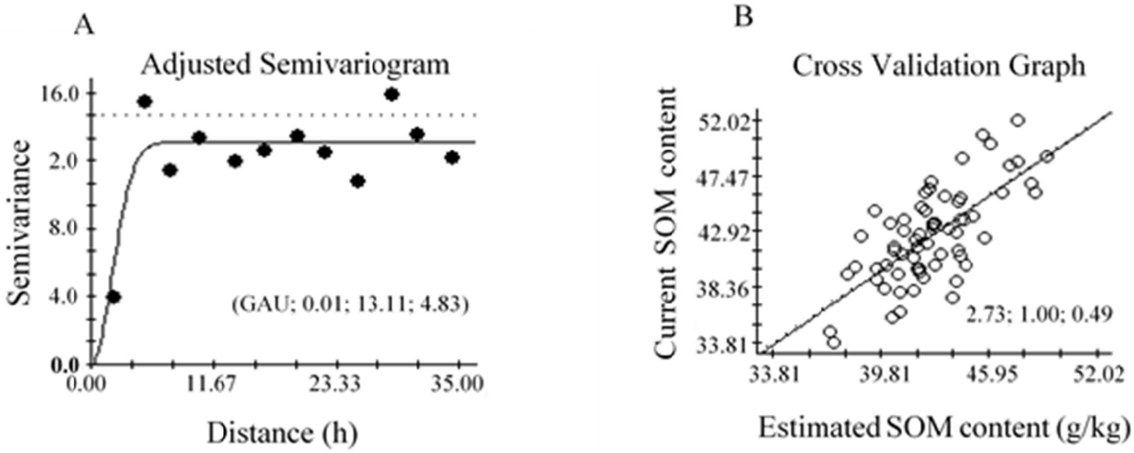


Figure 2. Theoretical semivariogram (Model; $C_0$; $C_0$ + C; A) of SOM (A). Cross-validation graph and adjustment parameters: quadratic prediction error (SE); regression coefficient and determination coefficient ($r^2$) (B)

## 4. Discussion

The application of the Kolmogorov-Smirnov test shows that SOM contents present normal distribution (Lima et al., 2013; Yao et al., 2020; Addise et al., 2022).

Silva et al. (2021) evaluating soil attributes in a alfisol under integrated farming systems, found that SOM presented mean CV between 9.0-12.8%, due the variation of sampled depth. Thus, different CVs can be obtained depending on the management system adopted in the area and soil characteristics and can be high or low. For example, CV values between 47-52% are obtained in the literature for SOM due to spatial variability (Chikere-Njoku, 2019; John et al., 2020). Assumpção and Hadlich (2017) conducting a study of environmental geochemical variables, showed coefficients of medium and high variation, 49% and 77% respectively.

It was also verified that the mean and median values were very close, a similar situation was obtained by Aquino et al. (2014), which according to Cambardella et al. (1994) indicates that central trend measurements are not dominated by outliers in distributions.

Using the Lopes (2003) classification, we found that the value of skewness demonstrates a slight positive skewness of the data, since the result of the kurtosis (-0.33) indicates a leptocurtic characteristic curve, indicating that the values of the variable under study are more grouped around mode (43.94 m).

Mao et al. (2014) evaluating soil variability, verified for SOM a log-normal distribution, while Keshavarzi et al. (2021) seeking to understand the spatial variability in Northeast Iran, observed that SOM in a savanna system did not present normality in the data.

However, if the data has a non-normal distribution, it is possible to perform a transformation of the data to achieve normality, such as a box-cox transformation (Lisboa et al., 2016; Hosseini et al., 2019). A more important event than normality is the condition of stationarity presented by the data, in which there are no biased values, a condition that was achieved in this study (Assumpção & Hadlich, 2017).

A similar result was obtained by Mondal et al. (2021) studying the spatial variability of SOM under different land uses in India, as well as corroborating the results of Reichert et al. (2008), and Barbieri et al. (2013) evaluating respectively the variability of attribute. This result of semivariogram modeling differs from that found by Lima et al. (2013) and Aquino et al. (2014) that found respectively better adjustment to exponential models in area of natural and spherical vegetation in pasture areas.

The result of the scope of the semivariogram (4.83 m) serves as a subsidy, by providing important information for experimental planning, because it indicates that the determinations made at distances greater than the range become random, independent distribution among themselves, while those carried out at shorter distances than the scope of the spatial characteristics (Reichert et al., 2008; Barbieri et al., 2013; Lima et al., 2013; Aquino et al., 2014).

Souza et al. (1997), and Souza et al. (2010) verified reach values, respectively, 59 m and 77 m, while Cavalcante et al. (2007) observed for the systems of land use and management, savanna, no-tillage and pasture, respectively the values of reach 8.0, 5.3 and 4.7 m.

As prescribed by Robertson (2008), and Cruz et al. (2010) the reach value obtained maintained a behavior appropriate to the theory of regionalized variables, being less than the maximum sampling distance (69.89 m) and maximum Lag (34.94 m) corresponding to 50% of the maximum sampling distance.

The nugget effect is caused by random variance and may be resulting from the variability of the phenomenon, sampling scale or experimental analysis errors (Yanamoto & Landim, 2013). The area under study presented low and satisfactory value of the nugget effect for SOM. The magnitude of this property of the geostatistical analysis of a variable is important, since the lower the proportion between $C_0$ in relation to the level of the semivariogram, the greater its spatial dependence, thus presenting greater continuity of the phenomenon, lower variance and higher reliability in the estimated value (Cambardella et al., 1994; Lima et al., 2006).

The GDE (0.07%) was classified according to Cambardella et al. (1994), in which the variable under study showed strong spatial dependence (< 25%), which coincides with the study by Reichert et al. (2008), Barbieri et al. (2013) and Aquino et al. (2014). While Souza et al. (2010) observed moderate GDE for SOM at the depth of 0.0-0.2 m and strong GDE at a depth of 0.2-0.4 m.

Cambardella et al. (1994) still states that when strong spatial dependence occurs, it means that the variable may be more influenced by the intrinsic properties of the soil. This demonstrates that the semivariograms explain most of the variance of the experimental data (Souza et al., 2010). Alcântara and Ferreira (2000) evaluating the effects of weed control methods on coffee crop on soil quality, observed that the maintenance of invasive plants between planting lines contributed to an increase in SOM in the superficial soil.

In addition, another pertinent observation is about the portion to the right of the central region, which does not have irrigation system and has lower SOM contents compared to its neighborhood with irrigation and expresses sites with higher concentration of SOM. According to Bona et al. (2006) irrigation usually results in the increase in the increase of the addition of plant biomass to the soil, which contributes to our findings.

## 5. Conclusion

The variable analyzed indicated the presence of spatial dependence. The Degree of Spatial Dependence has been classified as strong. The data fit more satisfactorily to the Gaussian model semivariogram.

It was possible to observe the spatial variability of SOM in the extension of the experimental area, presenting higher levels in the more conservationist management zone.

The use of geostatistical techniques provided adequate information for the understanding of spatial distribution in the area under study.

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