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Spatial and multivariate analysis of soybean productivity and soil physical-chemical attributes

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ABSTRACT: The objective of this study was to evaluate the spatial variability of soybean yield, carbon stock, and soil physical attributes using multivariate and geostatistical techniques. The attributes were determined in Oxisols samples with clayey and cohesive textures collected from the municipality of Mata Roma, Maranhão state, Brazil. In the study area, 70 sampling points were demarcated, and soybean yield and soil attributes were evaluated at soil depths of 0-0.20 and 0.20-0.40 m. Data were analysed using multivariate analyses (principal component analysis, PCA) and geostatistical tools. The mean soybean yield was 3,370 kg ha^{-1}. The semivariogram of productivity, organic carbon (OC), and carbon stock (Cst) at the 0-0.20 m layer were adjusted to the spherical model. The PCA explained 73.21% of the variance and covariance structure between productivity and soil attributes at the 0-0.20 m layer [(PCA 1 (26.89%), PCA 2 (24.10%), and PCA 3 (22.22%)] and 68.64% at the 0.20-0.40 m layer [PCA 1 (31.95%), PCA 2 (22.83%), and PCA 3 (13.85%)]. The spatial variability maps of the PCA eigenvalue scores showed that it is possible to determine management zones using PCA 1 in the two studied depths; however, with different management strategies for each of the layers in this study.

Key words: management zones, geostatistics, principal components

Análise espacial e multivariada da produtividade de soja e de atributos físico-químicos do solo

RESUMO: O objetivo deste trabalho foi avaliar a variabilidade espacial da produtividade de soja, do estoque de carbono e de atributos físicos do solo por meio de técnicas multivariadas e de geoestatística. Os atributos foram determinados em um Latossolo Vermelho textura argilosa e coeso no município de Mata Roma (Maranhão, Brasil). Na área de estudo foram demarcados 70 pontos de amostragem, sendo avaliada a produtividade de soja e os atributos do solo nas camadas de 0-0,20 e 0,20-0,40 m de profundidade. Os dados foram analisados por meio de análise multivariada (ACP - Análise de Componentes Principais) e de ferramentas de geoestatística. A produtividade média de soja foi de 3370 kg ha^{-1}. O semivariograma da produtividade, carbono orgânico (OC) e do estoque de carbono (Cst) na camada de 0-0,20 m se ajustaram ao modelo esférico. A ACP explicou 73.21% da estrutura da variância e covariância entre a produtividade e os atributos do solo na camada de 0-0.20 m [ACP 1 (26.89%), ACP 2 (24.10%) e ACP 3 (22.22%)] e 68.64% na camada de 0.20-0.40 m [ACP 1 (31.95%), ACP 2 (22.83%) e ACP 3 (13.85%)]. Os mapas de variabilidade espacial dos scores dos autovalores da ACP demonstraram que é possível a determinação de zonas de manejo utilizando a ACP 1 nas duas profundidades em estudo, todavia, com diferentes estratégias de manejo para cada uma das camadas.

Palavras-chave: zonas de manejo, geoestatística, componentes principais

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Introduction

The implementation and development of precision agriculture requires knowledge about the spatial variability of crops and soil attributes, making it possible to determine specific management zones. However, to delineate specific management areas, it is necessary to conduct joint analyses of the many variables that affect crop productivity (Córdoba et al., 2013; Yao et al., 2014; Haghverdi et al., 2015), which vary vertically and horizontally along the landscape (Zanão Júnior et al., 2010; Siqueira et al., 2015).

Thus, the univariate variability of soil and plant attributes was examined using geostatistics (Warrick & Nielsen, 1980; Siqueira et al., 2008; Andreotti et al., 2010; Leite et al., 2010). The spatial patterns of these attributes can differ each year, making it difficult to determine the patterns homogeneous (Guedes Filho et al., 2010; Haghverdi et al., 2015), justifying the use of multivariate analysis tools for the determination of management zones.

Several studies have used successfully multivariate techniques to evaluate, characterize, and integrate multiple soil and plant attributes (Córdoba et al., 2013; Yao et al., 2014; Gong et al., 2015; Haghverdi et al., 2015; Rojas et al., 2016; Freddi et al., 2017; Carvalho et al., 2018; Silva et al., 2018). The integration of geostatistics tools and multivariate analysis allows the design of management zones with greater accuracy.

The objective of this work was to evaluate the spatial variability of soybean yield and soil physical-chemical attributes under no-tillage management using geostatistical tools and multivariate analyses.

Material and Methods

This study was conducted at Unha de Gato Farm Mata Roma, Maranhão State, Brazil, 3° 70' 80" S, 43° 18' 71" W at a mean altitude of 130 m (Figure 1). The regional climate is tropical sub-humid dry (Aw) and the soil of the study area is an Oxisols, which has a clayey texture and is cohesive (USDA, 2010). Approximately 44.75 ha in this region is cultivated with no-tillage of soybean [*Glycine max* (L.) Merrill] and maize (*Zea mays* L.) that were in crop rotation since 2007. Samples of soybean yield (kg ha^{-1}) and soil attributes were collected on 20/04/2016 from 70 sampling points that were spaced 70 x 35 m apart (Figure 1).

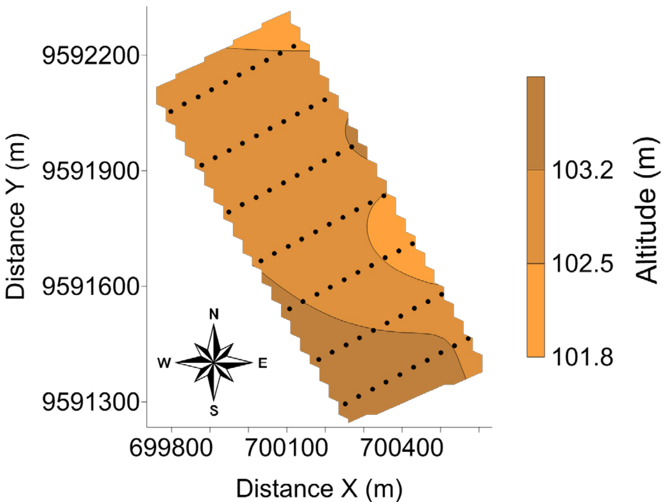

Figure 1. Topographic map and location of the 70 sampling points spaced 70 x 35 m apart in the study area cultivated with soybean

Soybean yield (kg ha^{-1}) was determined from 18 m^2 plots. Soil attributes (organic carbon content, carbon stock, hydraulic conductivity, bulk density, soil macroporosity, soil microporosity, total porosity, total sand, coarse sand, fine sand, silt and clay) were sampled at 0-0.20 and 0.20-0.40 m soil depths.

The hydraulic conductivity of the saturated soil (m d^{-1}) was determined in the field with a Guelph permeameter and a constant hydraulic load of 0.05 m following the assumptions of Reynolds et al. (1983).

Undisturbed soil samples were collected using volumetric rings for the determination of bulk density (Mg m^{-3}), soil macroporosity (m^3 m^{-3}), soil microporosity (m^3 m^{-3}), and total porosity (m^3 m^{-3}) according to EMBRAPA (1997). Disturbed soil samples were collected to determine total sand (g kg^{-1}), coarse sand (g kg^{-1}), fine sand (g kg^{-1}), silt (g kg^{-1}), and clay (g kg^{-1}) contents using the densimeter method (EMBRAPA, 1997). Organic carbon content (OC, g kg^{-1}) was determined by spectrophotometry (Raij et al., 2001), and carbon stock (Cst, Mg ha^{-1}) was calculated as proposed by Veldkamp (1994).

Statistical parameters [mean, variance, standard deviation, coefficient of variation (%), skewness, kurtosis, and D-maximum deviation related to the normal frequency distribution by the Kolmogorov-Smirnov test ($p < 0.001$) were determined for each variable including in depth for the physical-chemical attributes of the soil. Coefficients of variation (CV, %) were used to determine the variability of the data according to the classification of Warrick & Nielsen (1980). The assumptions of the intrinsic hypothesis of geostatistics were considered for modelling and adjusting the experimental semivariogram according to Vieira (2000). The spatial dependence ratio (SDR) among samples were determined as previously described by Cambardella et al. (1994).

Multivariate analysis (principal component analysis, PCA) was used to analyse data for each of the soil layers, and collinearity was calculated from the variable correlation matrix (Jeffers, 1978). For the PCA biplot graph, the set of eigenvectors (PC 1, PC 2,..., PC h) was included, which explained more than 60% of the data variability, and the variance of each main component was calculated according to Eq. 1:

$$CP_h = \frac{\lambda_h}{(C)}100 \tag{1}$$

where:

CP_h - principal component h;
λ_h - eigenvalue h; and,
C - covariance matrix; by trace (C) = $\lambda_1 + \lambda_2 + ... + \lambda_h$.

After validating the PCA, the scores of each eigenvalue were determined to further examine spatial variability using experimental semivariogram adjustment. SURFER 11 software (Golden Software, 2014) was used to construct the isoline maps according to the semivariogram adjustment parameters.

Results and Discussion

The mean soybean yield was 3,370 kg ha^{-1} (Table 1), which was 11.96% higher than the mean productivity in the state of Maranhão (3,010 kg ha^{-1}) and similar to the national mean (3,364 kg ha^{-1}) (CONAB, 2017). Soybean yields for the Cst were 18.27 and 22.46 Mg ha^{-1} at the soil depths of 0-0.20 and 0.20-0.40 m, respectively. Leite et al. (2010) reported a higher Cst in the superficial layer than in the subsurface layer of Oxisols cultivated under no-tillage. However, in this study, the higher carbon content observed in the subsurface layer (0.20-0.40 m) is due to the fact that this layer experiences less anthropic action; thus, the values of Cst in the subsurface layer are more stable.

The bulk density was 1.05 Mg m^{-3} in the superficial layer (0-0.20 m) and 1.29 Mg m^{-3} in the subsurface layer (0.20-0.40 m). Dantas et al. (2014) found bulk density values of 1.45 and 1.56 Mg m^{-3} in 0-0.25 and 0.25-0.50 m depth layers, respectively, when studying the genesis of cohesive soils in Mata Roma. Thus, the cohesive characteristic of soil in depth was shown in this study, as an increase of 22.85% was observed in soil bulk density in depth.

Despite the higher bulk density in the subsurface layer (0.20-0.40 m), hydraulic conductivity was higher in this layer (92.2 m d^{-1}) than in the surface layer. This indicates that there was a greater continuity of the porous system in the subsurface layer, which is supported by the fact that higher macroporosity (0.16 m^3 m^{-3}), microporosity (0.37 m^3 m^{-3}), and total porosity (0.53 m^3 m^{-3}) was also observed for this layer (Table 1). Dantas et al. (2014) also found greater pore continuity in subsurface areas under natural vegetation in Mata Roma with the same pedogenic characteristics as in this study.

The mean values for the granulometric fractions in the two layers were slightly different. The total sand content was 745.26 g kg^{-1} in the 0-0.20 m surface layer and 737.87 g kg^{-1} in the 0.20-0.40 m subsurface layer. The mean clay content also increased with depth from 117.14 g kg^{-1} in the surface layer to 120.63 g kg^{-1} in the subsurface layer.

Coefficient of variation (CV, %) values were low (< 12%) for soybean yield, total sand content, and fine sand, according to the classification by Warrick & Nielsen (1980). The other attributes had mean CV values in both layers (12% < CV < 60%), and only hydraulic conductivity showed high CV (> 60%) at the 0.20-0.40 m layer.

All attributes had a normal frequency distribution (Table 1) according to the Kolmogorov-Smirnov test (D), except for OC (0-0.20 m) and hydraulic conductivity (0.20-0.40 m). Asymmetry and kurtosis values observed in the present study are similar to those reported by Andreotti et al. (2010).

Semivariogram adjustment parameters are presented in Table 2. At the 0-0.20 m soil depth, hydraulic conductivity, bulk density, macroporosity, microporosity, total porosity, total sand, silt and clay data showed a pure nugget effect (PNE). At the 0.20-0.40 m depth layer, bulk density, macroporosity, total sand and fine sand data also showed PNE. The occurrence of a PNE shows that the variability of the data occurs on a smaller scale than the spacing used in this study (70 x 35 m), indicating that in future studies, spacing must be reduced to ensure the detection of the spatial variability of all attributes. The occurrence of PNE for attributes in the 0-0.20 and 0.20-0.40 m soil depth layers can also be attributed to the soil cohesive characteristic, as different attributes presented PNE in different layers. The soil density data showed PNE in the two soil layers in this study, similar to results found by Andretti et al. (2010).

In the surface layer (0-0.20 m), the spherical model best fit the soil attributes (Table 2), while the exponential model was

Table 1. Statistical parameters for physical and chemical attributes of soil cultivated with soybean, at 0-0.20 and 0.20-0.40 m depths

Variables	Mean	Variance	SD	CV (%)	Skew	Kurtosis	D*
Yield (kg ha^{-1})	3370.71	189447	435.25	11.54	0.11	-0.50	0.065n
				0-0.20 m			
OC (g kg^{-1})	7.34	11.912	3.45	47.04	1.15	1.43	0.194Ln
Cst (Mg ha^{-1})	18.27	70.685	8.41	46.02	1.26	1.97	0.176n
Hydraulic conductivity (m d^{-1})	86.86	3254.920	57.05	65.68	0.80	0.28	0.129n
Bulk density (Mg m^{-3})	1.05	1.395	1.27	25.00	0.07	5.39	0.087n
Macroporosity (m^3 m^{-3})	0.09	0.364	0.17	22.00	0.04	23.52	0.121n
Microporosity (m^3 m^{-3})	0.24	0.439	0.38	21.00	0.03	7.96	0.109n
Total porosity (m^3 m^{-3})	0.49	0.610	0.55	21.00	0.03	4.98	0.123n
Total sand (g kg^{-1})	745.26	1826.455	42.74	5.74	-0.02	0.70	0.161n
Coarse sand (g kg^{-1})	190.13	1071.302	32.73	17.22	0.80	2.99	0.175n
Fine sand (g kg^{-1})	555.13	1605.679	40.07	7.22	-0.99	0.57	0.173n
Silt (g kg^{-1})	138.21	1961.185	44.29	32.04	0.16	-0.40	0.064n
Clay (g kg^{-1})	117.14	1640.994	40.51	34.58	0.91	0.54	0.158n
				0.20-0.40 m			
OC (g kg^{-1})	8.70	9.767	3.13	35.906	1.45	1.53	0.189n
Cst (Mg ha^{-1})	22.46	65.069	8.07	35.916	1.40	1.42	0.166n
Hydraulic conductivity (m d^{-1})	92.20	4256.019	65.24	70.000	1.50	1.83	0.203Ln
Bulk density (Mg m^{-3})	1.29	0.004	0.07	51.800	-0.02	0.12	0.067n
Macroporosity (m^3 m^{-3})	0.16	0.001	0.03	16.340	-0.21	-0.02	0.067n
Microporosity (m^3 m^{-3})	0.37	0.001	0.02	23.500	-0.28	0.98	0.079n
Total porosity (m^3 m^{-3})	0.53	0.001	0.03	24.200	-0.02	-0.65	0.068n
Total sand (g kg^{-1})	737.87	1719.157	41.46	5.619	-0.17	-0.22	0.163n
Coarse sand (g kg^{-1})	191.84	1003.671	31.68	16.514	0.46	1.40	0.119n
Fine sand (g kg^{-1})	545.93	2095.343	45.77	8.385	-0.97	-0.11	0.192n
Silt (g kg^{-1})	141.70	1570.387	39.63	27.966	0.25	0.09	0.089n
Clay (g kg^{-1})	120.63	1625.686	40.32	33.425	0.82	0.43	0.149n

SD - Standard deviation; CV - Coefficient of variation; Skew - Skewness; D - Maximum deviation related to the normal frequency distribution by the Kolmogorov-Smirnov test, with a probability of $p \leq 0.01$ error; n - Normal distribution; Ln - Lognormal distribution; OC - Organic carbon; Cst - Carbon stock

Table 2. Semivariogram adjustment parameters for soybean yield and soil physical-chemical attributes at 0-0.20 and 0.20-0.40 m soil depths

Variables	Model	C_0	C_0+C_1	a (m)	R^2	RSS	SDR
Yield (kg ha^{-1})	Spherical	145000	250160	200	0.724	35.6	57.96
				0-0.20 m			
OC (g kg^{-1})	Spherical	2.61	13.27	255	0.843	29.4	19.67
Cst (Mg ha^{-1})	Spherical	17.7	79.5	251	0.792	1380	22.26
Hydraulic conductivity (m d^{-1})				PNE			
Bulk density (Mg m^{-3})				PNE			
Macroporosity (m^3 m^{-3})				PNE			
Microporosity (m^3 m^{-3})				PNE			
Total porosity (m^3 m^{-3})				PNE			
Total sand (g kg^{-1})				PNE			
Coarse sand (g kg^{-1})	Exponential	154	1788	84	0.699	322702	8.61
Fine sand (g kg^{-1})	Exponential	116	1035	52	0.341	234020	11.21
Silt (g kg^{-1})				PNE			
Clay (g kg^{-1})				PNE			
				0.20-0.40 m			
OC (g kg^{-1})	Gaussian	8.42	22.64	166	0.313	628	37.19
Cst (Mg ha^{-1})	Gaussian	59.5	217.66	143	0.337	35338	27.34
Hydraulic conductivity (m d^{-1})	Exponential	470	4490	46	0.37	2322276	10.47
Bulk density (Mg m^{-3})				PNE			
Macroporosity (m^3 m^{-3})				PNE			
Microporosity (m^3 m^{-3})	Exponential	0.00006	0.00057	46	0.553	1.29E-08	10.53
Total porosity (m^3 m^{-3})	Spherical	0.00002	0.00064	52	0.587	1.55E-08	3.13
Total sand (g kg^{-1})				PNE			
Coarse sand (g kg^{-1})	Gaussian	205	1061	58	0.69	248241	19.32
Fine sand (g kg^{-1})				PNE			
Silt (g kg^{-1})	Exponential	278	1728	54	0.589	554948	16.09
Clay (g kg^{-1})	Exponential	454	1717	59	0.726	301392	26.44

C_0 - Nugget effect; C_0+C_1 - Sill; a - Range (m); R^2 - Coefficient of determination; RSS - Residual square sum; SDR - Spatial dependence ratio (%); PNE - Pure nugget effect; OC - Organic carbon; Cst - Carbon stock

the most frequent in the subsurface layer. The soybean yield (kg ha^{-1}) was adjusted to the spherical model.

The range values (a, Table 2) at the 0-0.20 m soil depth ranged from 52 m for fine sand to 255 m for OC. The presence of a greater range value for OC in the study area was expected due to the low variability of the data (mean variance: 11.912, mean standard deviation: 3.45, Table 1). At 0.20-0.40 m soil depth, the lowest range value (a) was 46 m for hydraulic conductivity and microporosity, and the highest value was observed for OC (a = 166 m). In general, range values (a) were lower in the 0.20-0.40 m layer due to greater homogeneity of the attributes, as shown by the smaller variation in variance and standard deviation. The range values (a) indicate the extent of sample autocorrelation, showing the maximum distance for which dependence between samples can be detected by the spacing used.

The SDR (Table 2) of yield was moderate according to Cambardella et al. (1994). Soil attributes showed high SDR (< 25%) in the 0-0.20 m layer, and hydraulic conductivity, microporosity, total porosity, coarse sand and silt had high SDR (< 25%) in the 0.20-0.40 m layer. The other attributes (OC, Cst and clay) had medium SDR values (25-75%). The presence of high and medium SDR values confirms the adequacy of the sample spacing used in this study. However, 12 attributes showed PNE, including eight in the superficial layer (0-0.20 m) and four in the subsurface layer (0.20-0.40 m). Thus, SDR values should be interpreted with caution, because no pattern was identified for the occurrence of PNE in different layers. It should be noted that attributes presented higher values of SDR in the 0.20-0.40 m layer according to the classification of Cambardella et al. (1994). However, the semivariogram of attributes that presented spatial dependence in this layer were adjusted to the exponential, spherical, and gaussian models, whereas in the superficial layer, semivariograms were adjusted to exponential and spherical models. The adjustment of a larger number of models to the experimental semivariograms in the subsurface layer may be due to soil cohesion at depth in the study area. Siqueira et al. (2015) and Zanão Júnior et al. (2010) state that spatial variability patterns of soil attributes tend to be more stable at depth, which is similar to results of this study. This justifies the need for research that integrates soil and plant attributes in order to determine specific management zones. Gong et al. (2015), Rojas et al. (2016) and Carvalho et al. (2018) successfully used the multivariate approach to characterize soil biological, physical, and chemical attributes.

The highest soybean yield was in the upper half of the study area (Figure 2A). Spatial variability maps of the OC and the Cst at the 0-0.20 m depth layer (Figures 2B and C) showed patterns similar to those of soybean yield, indicating that a positive relationship exists between these variables. Management practices that allow for the increase of OC and Cst favor increased productivity, with a view to environmental sustainability. Thus, to effectively determine management zones, it is necessary to evaluate the largest possible number of variables considering the spatial and temporal variation of the attributes.

Soybean yield (Figure 2A) was inversely related to coarse and fine sand content (Figures 2D and E) at the 0-0.20 m soil depth layer. Attributes that had spatial variability at the 0.20-0.40 m depth layer (OC, Cst, hydraulic conductivity, microporosity, total porosity and silt, Figures 2F, G, H, I, J and L, respectively) had positive relationships with soybean yield, while coarse sand content (Figure 2K) had an inverse relationship with productivity (Figure 2A), similar to results of Yao et al. (2014).

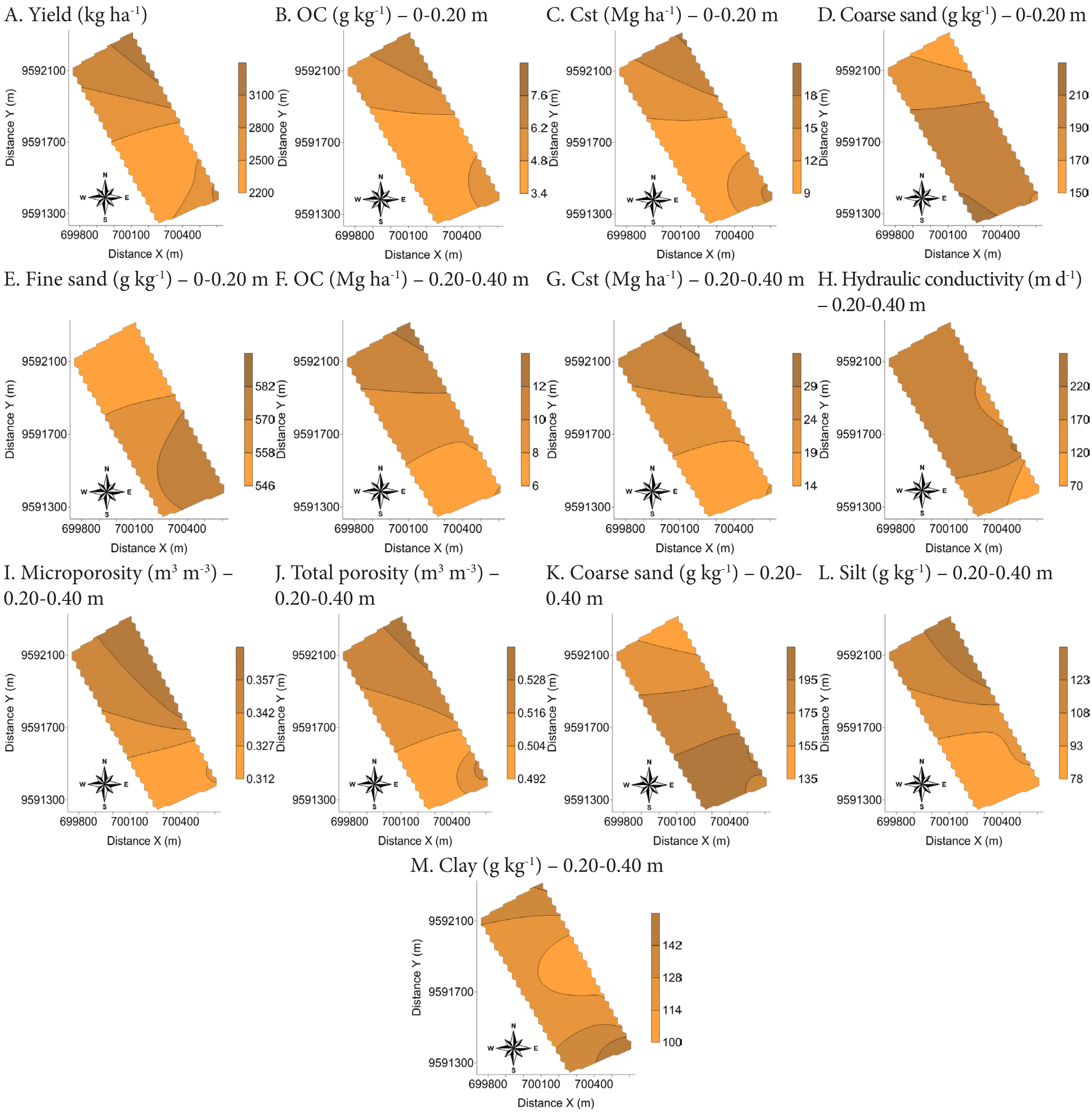

Figure 2. Spatial variability maps of yield of soybean (A) and for attributes of soil cultivated with soybean, at 0-0.20 m (B) OC - Organic carbon; (C) Cst - Carbon stock; (D) Coarse sand; (E) Fine sand and at 0.20-0.40 m depth layers (F) OC - Organic carbon; (G) Cst - Carbon stock; (H) Hydraulic conductivity; (I) Microporosity; (J) Total porosity; (K) Coarse sand; (L) Silt; (M) Clay

PCA (Table 3) explained 73.21 and 68.64% of the variance and covariance structure between soybean yield and soil attributes at the 0-0.20 m depth layer (PCA 1 [26.89%], PCA 2 [24.09%], and PCA 3 [22.22%]) and at the 0.20-0.40 m depth layer (PCA 1 [31.95%], PCA 2 [22.83%], and PCA 3 [13.85%]), respectively. Gong et al. (2015) explained 88.62% of the variance and covariance structure distributed in four components when examining physical-chemical attributes of the 0-0.20 m layer. Córdoba et al. (2013) verified 87.33% of the variance and covariance structure of data distributed in three components when examining soil attributes in three experimental areas in order to determine management areas.

The PCA of the superficial layer (0-0.20 m depth) included seven variables (yield, hydraulic conductivity, total sand, coarse sand, fine sand, silt, and clay), and eight variables contributed to the PCA in the subsurface layer (yield, OC, hydraulic conductivity, total sand, coarse sand, fine sand, silt and clay) (Table 3). Silt and clay in the superficial layer showed PNE (Table 2); however, these were the variables that contributed the most to the PCA, with silt explaining 30.68 and 33.24% of the variation in PCA 1 and PCA 2, respectively, and clay accounting for 34.08% of the variation in PCA 3 (Table 3). In the subsurface layer, fine sand content explained 31.02% of the variation in PCA 1, silt explained 40.91% of the variation in PCA 2, and coarse sand explained 57.22% of the variation in PCA 3 (Table 3). Thus, PCA results showed that the attributes that showed PNE in the univariate geostatistical analysis (Table 2) contributed the most

Table 3. Results of the main component analysis of the soil attributes studied at 0-0.20 and 0.20-0.40 m soil depths

	0-0.20 m			0.20-0.40 m		
	PCA 1	PCA 2	PCA 3	PCA 1	PCA 2	PCA 3
% of variance	26.89	24.09	22.22	31.95	22.83	13.85
Cumulative %	26.89	50.99	73.21	31.95	54.78	68.64
Eigenvalue	18.82	35.69	51.24	22.36	15.98	9.69
			Variable contributions (%) [a]			
Yield	13.17	15.77	11.53	2.59	20.50	1.83
OC	-	-	-	11.24	0.02	14.03
Hydraulic conductivity	0.01	5.20	14.53	1.93	0.95	0.002
Total sand	26.54	4.73	0.20	25.31	6.06	4.89
Coarse sand	0.08	11.83	28.97	2.87	0.09	57.22
Fine sand	28.22	0.07	8.04	31.02	7.38	13.10
Silt	30.68	33.24	2.65	0.70	40.91	7.98
Clay	1.29	29.15	34.08	24.33	24.09	0.95

[a] Variable contributions based on the correlation matrix of the main components (PCA)

to the PCA (Table 3), indicating that multivariate analysis can be used to define specific management areas.

The scores of each eigenvalue for vectors PCA 1, PCA 2, and PCA 3 were analysed using geostatistical tools, allowing for the evaluation of multiple variables in a single semivariogram (Table 4). The exponential model was adjusted for both soil layers (0-0.20 and 0.20-0.40 m). Freddi et al. (2017) also fitted the exponential model for most vectors at 0-0.10 and 0.10-0.20 m soil depths when studying soybean yield and soil physical and chemical attributes.

The semivariogram (PCA 1, PCA 2, and PCA 3, Table 4) shows that all layers had high spatial dependence ratios (SDR < 25%) with low nugget (C_0) and structural variance ($C_0 + C_1$) values, showing that the eigenvalue scores had low variability. Siqueira et al. (2008) reported that low values of C_0 indicate good precision of the experiment. Thus, the combined analysis of variables allows to describe the variability of multiple variables with greater precision than analysing individual variables.

The greater spatial accuracy of the eigenvalue scores (Table 4), shown by the C_0 and $C_0 + C_1$ values, describes a greater spatial dependence of the data, resulting in smaller values of range (a). PCA 1 of the attributes in the two layers have the highest range values (a = 45 m PCA 1 [26.89%] for 0-0.20 m, a = 47 m PCA 1 [31.95%] for 0.20-0.40 m). When less variance and covariance structure is explained by the main components (CP), range values are lower (a).

The maps of spatial variability of eigenvalue scores for vectors at the 0-0.20 m soil depth layer (Figures 3A, B, and C) allow for the description of two specific management zones, one in the upper half and the other in the lower half of the study area. The spatial behavior of isolate maps for PCA 1 (Figure 3A) and PCA 3 (Figure 3C) have spatial distributions similar to contour maps of soybean yield (Figure 2A), OC (Figure 2B), and Cst (Figure 2C). However, Haghverdi et al. (2015), studying the delimitation of management zones in irrigated farming systems, stated that productivity should not be the main factor for the definition of specific management zones. Guedes Filho et al. (2010) conducted a 23-year experiment that failed to determine specific management zones using only the spatial patterns of crop yield under no-tillage. Thus, it is necessary to evaluate multiple soil and plant attributes in different soil layers and analyse the data using tools that group different attributes. Córdoba et al. (2013) found that the main components applied on soil and terrain variables defined management classes with greater differences in yield than spatial unconstrained clustering on the same date, similar to results of this study.

In the 0.20-0.40 m soil depth layer, the maps of spatial variability of eigenvalue scores for vectors PCA 1 (31.95%), PCA 2 (22.83%), and PCA 3 (13.85%) (Figures 3D, E, and F) showed different behaviors in the distribution of isolines for the three vectors. Predominately higher values were observed in the central part of the area, mainly in PCA 1. When the maps of spatial variability of the principal components (PCA 1, PCA 2 and PCA 3, Figures 3D, E and F) are compared with the maps of spatial variability of soil attributes that presented spatial variability at the 0.20-0.40 m layer (Figure 2), it is found that the maps that most closely resembled the spatial representations of the main components were OC (Figure 2F), Cst (Figure 2G) and coarse sand (Figure 2K), showing a positive correlation among these maps and similarity to PCA 1 (31.95%, Figure 3D). PCA 2 (22.83%, Figure 3E) and PCA 3 (13.85%, Figure 3F) had inverse relationships with the distribution of contour lines and clay content (Figure 2M). Yao et al. (2014), when examining soil physical and chemical attributes integrated by geostatistical tools and major components, described visually identifiable spatial patterns similar to results from this study.

Table 4. Parameters for adjustment of the semivariogram for the main components of soil attributes at 0-0.20 and 0.20-0.40 m soil depth layers

	Model	C_0	C_0+C_1	a (m)	R^2	RSS	SDR
			0-0.20 m				
PCA 1	Exponential	0.00007	0.00063	45	0.674	3.003E-08	11.11
PCA 2	Exponential	0.00009	0.00085	38	0.235	5.297E-08	10.59
PCA 3	Exponential	0.00020	0.00153	37	0.590	1.034E-07	13.07
			0.20-0.40 m				
PCA 1	Exponential	0.00006	0.00064	47	0.776	2.599E-08	9.38
PCA 2	Exponential	0.00009	0.00089	34	0.633	6.236E-08	10.11
PCA 3	Exponential	0.00020	0.00151	28	0.420	1.082E-07	13.25

C_0 - Nugget effect; C_0+C_1 - Sill; a - Range (m); R^2 - Coefficient of determination; RSS - Residual square sum; and SDR - Spatial dependence ratio (%)

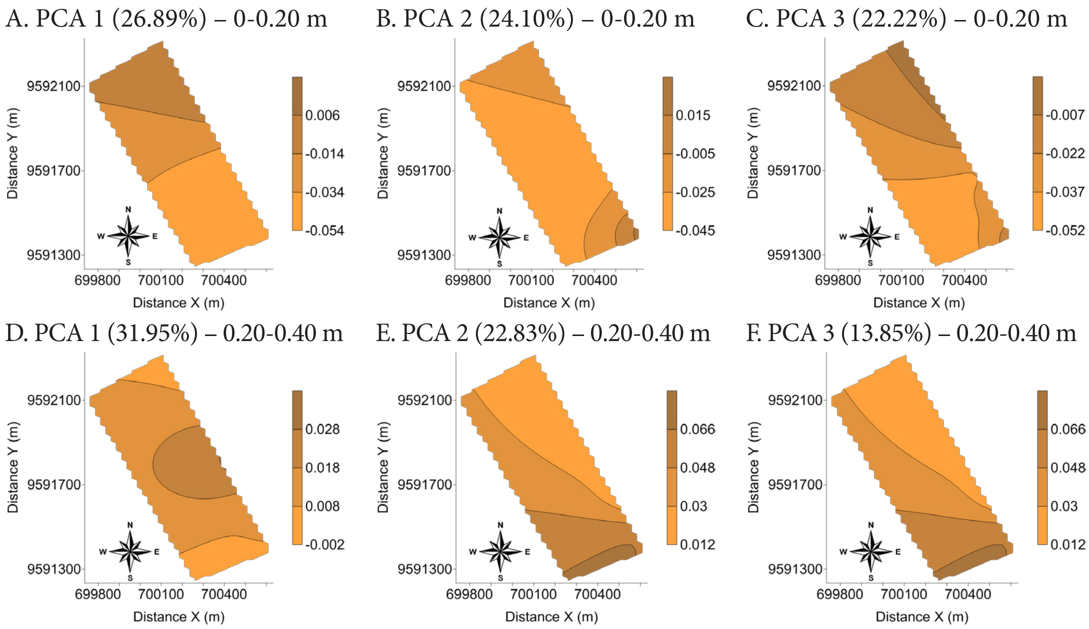

Figure 3. Spatial distribution maps of the principal components (PCA) for the 0-0.20 m (A) PCA 1; (B) PCA 2; and (C) PCA 3) and 0.20-0.40 m (D) PCA 1; (E) PCA 2; and (F) PCA 3) soil depth layers

Conclusions

1. The spatial variability of the physical-chemical attributes of the soil showed differences between the layers examined (0-0.20 and 0.20-0.40 m layer) due to the cohesive characteristic of the soil in the study area.

2. The spatial variability maps of PCA eigenvalue scores allowed for the determination of specific management zones using PCA 1 at both layers (0-0.20 and 0.20-0.40 m), with different strategies for each layer.

3. The combination of geostatistics tools and principal components allowed for the integrative analysis of all attributes in this study, representing an important alternative for determining specific management zones.

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