PHYSICAL ATTRIBUTES OF A PASTURE SOIL IN SOUTHEAST GOIÁS DETERMINED BY GEOSTATISTICS

GABRIEL G. DE G. CARDOSO[1], RILLEY C. WANDERLEY[2], MARA L. C. SOUZA[3]

ABSTRACT: This study aimed to evaluate the spatial dependence of physical attributes in a soil cultivated with Brachiaria grass. A 12-m regular sampling grid was established within an area of 3.500 m^2. Thirty-five soil samples were collected at 0-30 cm depth for particle density, bulk density, texture and total porosity analysis. These data were evaluated using statistical methods of indicator kriging and the GS+ software. The GS+ software was used to develop three-dimensional maps and evaluate semivariograms. The spatial dependence was evaluated using experimental semivariograms. The analyzed attributes indicated the occurrence of spatial dependence when fit to the exponential model. Areas with higher porosity occurred in the regions with lower bulk densities and higher particle densities.

KEYWORDS: spatial variability, management system, kriging.

ATRIBUTOS FÍSICOS DE UM SOLO COM COBERTURA DE PASTAGEM ANALISADOS POR MEIO DA GEOESTATÍSTICA NA REGIÃO SUDESTE DE GOIÁS

RESUMO: O objetivo deste estudo foi avaliar a dependência espacial de alguns atributos físicos de um solo cultivado com Brachiaria, antes da implementação de adubo verde como transição agroecológica para o cultivo de cana-de-açúcar orgânica. Atribuiu-se uma grade de coordenadas para que as amostras pudessem ser georreferenciadas obtendo os valores de variabilidade espacial da densidade das partículas, densidade do solo, teor de areia, argila e da porosidade total em uma área de 3.500 m^2. As amostras do solo foram coletadas em uma malha regular de 12 x 12 m, totalizando 35 pontos, na profundidade de 0-30 cm. Os dados foram avaliados por meio da geoestatística, apoiado no *software* GS+ que possibilita, além do estudo do semivariograma, a elaboração de mapas tridimensionais. A dependência espacial foi avaliada por meio de semivariogramas experimentais. Os atributos analisados apresentaram dependência espacial, ajustando-se ambos ao modelo exponencial. As áreas de maior porosidade ocorreram em regiões com menor densidade do solo e maior densidade de partículas.

PALAVRAS-CHAVE: variabilidade espacial, sistema de gestão, krigagem.

INTRODUCTION

In general, pastures can maintain or increase soil organic matter (SOM) concentrations (in contrast with annual crops). In addition, pastures generally have large amounts of organic residues and extensive root systems that are continuously renewed. According to SPERA et al. (2010), soils under grazing areas can undergo physical changes due to animal trampling. This result is exacerbated when soil humidity is favorable for plastic deformation, which occurs immediately above its friability limit.

Soil bulk density and total porosity can indicate when soil conditions are adequate for root development and exploration and if compaction problems occur (BONFIM-SILVA et al., 2012).

---
[1]Tecgo° em Irrigação e Drenagem, Prof. Doutor, Departamento de Agronomia, IFGoiano/Ceres – GO, Fone: (62) 9275-3638, gabriel.cardoso@ifgoiano.edu.br

[2] Eng° Agrícola, Agrônomo, Departamento de Engenharia Agrícola, IFGoiano/Ceres – GO, rilley.castro@hotmail.com

[3] Eng° Agrícola, Aluna de agronomia, Departamento de Engenharia Agrícola, IFGoiano/Ceres – GO, mara_cruzsouza1@hotmail.com

According to GREGO et al. (2012), understanding the spatial distribution of soil attributes and their relationships with a pasture can help pasture management. Animal management on pastures results in medium- and long-term physical soil changes that vary spatially. According to these authors, by considering that the physical and chemical soil conditions directly affect plant development, investigations of the soil spatial variability and forage biomass production with time can be used to support the planning and management of grazing areas. Therefore, applying geostatistical analysis to these areas may be important for identifying spatial soil and plant patterns that can be used to optimize the system's production.

MIGUEL et al. (2009) indicated the spatial dependence of pasture soil attributes and observed variations in water infiltration as a function of trampling intensity. Several techniques, such as the Geostatistics, could be used to understand the spatial and temporal structures of this variable and to estimate the correlated variables. In addition, Geostatistics can be used to examine experimental data that are often misinterpreted when considering true randomness without the occurrence of spatial dependence.

The interpolation technique is a procedure for estimating the value of an attribute at an unsampled location from points that were sampled in the same area or region. Spatial interpolation converts data from point-based observations to a continuous field, which produces a spatial pattern that can be compared with other continuous spatial entities. Interpolation assumes that attributes that are near each other have values that are more similar than attributes that are far from each other (CARVALHO et al., 2012).

Kriging is a generic name that was adapted by geostatisticians for a family of generalized least squares regression algorithms. Kriging methods rely on the spatial dependence that is expressed in the semivariogram between the neighboring samples to estimate values at any position in the field. Kriging methods do not use trends and have minimum variance, which makes them excellent for estimating the spatial distribution of rainfall. Cross-validation is used to evaluate alternative semivariogram models that will perform kriging. In cross-validation, each point contained within the spatial domain is removed individually. In addition, the value of each point is estimated by kriging as if the point itself did not exist. SILVA et al. (2013) considered several evaluation methods and concluded that cross validation was the most adequate method for choosing the best spatial variability model, which resulted in the most accurate thematic maps.

Geostatistics is an appropriate and essential tool for analyzing spatially variable attributes that have some degree of organization or continuity that is detectable by spatial dependence measures (VIEIRA & DECHEN, 2010).

Given the need to understand the behavior and relationships between physical soil attributes, this study aimed to correlate the total porosity of a pasture soil with the bulk and particle densities by considering spatial variability and using geostatistical analysis.

MATERIAL AND METHODS

The experimental data were obtained in October 2013 in an area that belongs to the Federal Institute of Goiás (Instituto Federal Goiano) - Urutaí Campus (located at 17° 30' 35" S and 48° 12' 03" W). This area has a mean altitude of 800 m, a tropical climate with a dry season during the austral winter and an average rainfall of 1860 mm (IAPAR, 2009). The soil in this region was characterized as a dystroferric Red Latosol with a loamy soil texture containing 43, 41 and 16% sand, silt and clay, respectively. The 3,500 m^2 area had been maintained under pasture for 5 years.

The soil was initially marked by stakes in the area where samples would be collected. A digital theodolite was used to define a rectangular area with sides measuring 48 x 72 m. Thirty-five soil samples were collected from a 12 x 12 m grid by using a volumetric ring in 0-30 cm depth, with three replications. Next, the samples were analyzed for porosity, bulk and particle density and sand and clay content.

The soil density was determined from undisturbed samples using the known volume and particle density methods. With thin dry land to air (TFSA), it was determined particle density, the balloon method volumetric using ethanol for measuring volume. The determination of the total soil porosity was calculated from the ratio of the density particles and bulk density (EMBRAPA, 1997).

Position (mean, median), dispersion (standard deviation) and the distribution shape (coefficient of variation, coefficient of skewness and kurtosis coefficient) were calculated using exploratory data analysis. The coefficients of skewness and kurtosis were compared according to the methods proposed by SILVA & COELHO (2014). The data normality hypothesis was tested using the Anderson-Darling test with a probability of 5%. According to GOMES & GARCIA (2002), the coefficient of variation (CV) was considered low when CV ≤ 10% (homoscedasticity), medium when 10% < CV ≤ 20%, high when 20% < CV ≤ 30% and very high when CV > 30% (heteroscedasticity).

A spatial dependence study was conducted using geostatistical analysis to quantify and examine the existence of spatial dependence among the soil attributes. All models were fit using the GS+ software and by considering the least residual sum of squares, the highest coefficient of determination R^2 and the correlation coefficient that was obtained using the cross validation method. Next, the variograms were scaled according to the data variance.

The experimental semivariograms were obtained using the ordinary least squares (OLS) fitting method and by adopting an isotropic model (unidirectional semivariogram) with a cut-off distance of 50% of the maximum distance in the study area. The best model was selected using cross-validation and the error comparison index (ECI, Equation 1). The ECI provides lower values as the ER (Mean Error, Equation 4) approaches 0 and the RME (Reduced Mean Error, Equation 5) approaches 1 during the selection of j models. Therefore, when choosing among several models, the best model is the model with the lowest *ECI*.

$$ECI_i = A_i + B_i,\tag{1}$$

where,

$$A_i = \begin{cases} \dfrac{\dfrac{ABS(\overline{\overline{ER}})_i}{MAX(ABS(ER))},\ when \quad MAX(ABS(SME)) > 0}{1,\ when \quad MAX(ABS(SME)) = 0} \end{cases}\tag{2}$$

$$B_i = \begin{cases} \dfrac{\dfrac{ABS(SER-1)_i}{MAX(ABS(SER-1))},\ when \quad MAX(ABS(SD\,RME-1)) > 0}{1,\ when \quad MAX(ABS(SD\,RME-1)) = 0} \end{cases}\tag{3}$$

and,

$$\overline{\overline{ER}} = \frac{1}{n}\sum_{i=1}^{n}\frac{Z(s_i)-\hat{Z}(s_{(i)})}{\sigma(\hat{Z}(s_{(i)}))}\tag{4}$$

$$S_{ER} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\frac{\mid Z(s_i)-\hat{Z}(s_{(i)})\mid}{\sigma(\hat{Z}(s_{(i)}))}}\tag{5}$$

where,

n is the number of values,

$Z(s_i)$ is the observed value at the point s_i,

$\hat{Z}(s_{(i)})$ is the value predicted by ordinary kriging at *si* without considering the $Z(s_i)$ observation, and

$o(\hat{Z}(s_{(i)}))$ is the standard deviation of the kriging at s_i without considering the $Z(s_i)$ observation.

The degree of spatial dependence in the semivariograms was assessed by using the nugget effect coefficient (E%, Equation 1) according to the following intervals proposed by CAMBARDELLA et al. (1994): E% ≤ 25 represents a strong spatial dependence, 25 ≤ E% ≤ 75 represents a moderate spatial dependence and E% ≥ 75% represents a poor spatial dependence.

$$E\% = \frac{c_o}{c_1 + c_o} x100 \tag{6}$$

To assess the degree of correlation among the variables, the Pearson correlation coefficient (R) was used and classified according to the interpretations of KOE et al. (2014). Thematic maps were prepared using the parameters of nugget effect, plateau and range and were provided by the GS+ software (Geostatistics for the Environmental Sciences). Cross-validation between the variables was performed using the attributes that presented strong correlations based on Pearson's coefficient.

RESULTS AND DISCUSSION

The descriptive statistics results indicated data normality for all of the studied variables except particle density (Table 1). With the exception of porosity, all variables showed platykurtic kurtosis. Regarding symmetry, only bulk density and clay content followed symmetrical distributions. According to the Anderson-Darling normality test, only particle density did not follow a normal distribution at a probability of 5%.

All variables had CV ≤ 10%, which indicated data homogeneity (CV ≤ 10%) according to GOMES & GARCIA (2002) and agreed with the results of SCHAFFRATH et al. (2008), who studied cultivated and no-tillage systems. The bulk density values varied from 1.17 to 1.60 kg dm^{-3}.

TABLE 1. Descriptive statistics of the total porosity (%), bulk density (kg dm^{-3}), particle density (kg dm^{-3}), sand content (%) and clay content (%).

Variables	Minimum	Mean	Maximum	Median	Standard Deviation (SD)	CV (%)	Asymmetry	Kurtosis
Particle density[NN]	2.44	2.77	2.90	2.82	1.14	5.20	-1.32(c)	0.73(B)
Soil density[N]	1.17	1.38	1.60	1.37	0.1	7.10	0.44(a)	0.28(B)
Porosity[N]	40.52	49.79	59.03	50.70	4.43	8.90	-0.36(c)	-0.37(C)
Sand[N]	38.18	43.02	52.24	42.84	2.88	6.69	1.51(b)	3.68(B)
Clay[N]	13.20	16.29	20.92	16.17	1.52	9.32	0.77(a)	2.00(B)

*Anderson-Darling normality test; (NN) - did not follow a normal distribution, (N) - normal distribution; Asymmetry - symmetrical distribution (a) positive asymmetry (b), negative asymmetry (c); Kurtosis - mesokurtic (A), platykurtic (B), leptokurtic (C); SD - standard deviation.

The Pearson's linear correlations revealed strong correlations between porosity and particle density and between porosity and bulk density (Table 2). In addition, a strong correlation occurred between the sand and clay contents. The other variables showed no significant correlations, which corresponded with the results of KIEHL (1979). KIEHL (1979) explained that a decrease in bulk density indicates the predominance of fine particles in the soil, which results in a greater water holding capacity and increased porosity. The strong and positive relationship between particle density and porosity is related to smaller diameter of soil particles, which are denser and result in greater numbers of micropores and greater total porosity.

TABLE 2. The Pearson's correlation coefficients for total porosity, bulk density, particle density, sand content and clay content.

Variables	Clay	Particle density	Bulk density	Porosity
Particle density	0.080 (ns)	-	-	-
Bulk density	-0.169 (ns)	0.048 (ns)	-	-
Porosity	0.177 (ns)	0.601 (strong)	-0.772 (strong)	-
Sand	-0.606 (strong)	-0.099 (ns)	0.158 (ns)	-0.192 (ns)

(ns) - not significant according to a t-test at a probability of 5%

All analyzed variables showed spatial dependence (Table 3). According to CAMBARDELLA et al. (1994), the nugget effect coefficient (E%) showed strong spatial dependence for all attributes (E% ≤ 25). According to PANOSSO et al. (2008), range (r) is an important parameter when studying semivariograms because it represents the maximum distance at which points of the same variable are spatially correlated. Thus, for the sand content variable, the data dependency (r) occurred at a radius of more than 14.25 m, which was greater than the soil collection grid (12 x 12). Model selection was based on the lowest error comparison index (ECI) value that was obtained from cross validation. The selected theoretical semivariogram models were exponential for the particle density variable, Gaussian for the bulk density and clay content variables, linear for the porosity variable and spherical for the clay content variable.

TABLE 3. The models and estimated parameters for the experimental semivariograms.

Attributes	Model	C_o nugget effect	$C_o + C$ plateau	A range	E%*
Particle density	Exponential	0.0026	0.023	21.78	0.888
Bulk density	Gaussian	0.0000	0.009	14.96	0.999
Porosity	Linear	20.2636	20.2636	39.20	0.000
Sand	Spherical	0.0100	7.1260	14.25	0.999
Clay	Gaussian	0.0010	2.1950	19.93	1.000

*E% - Nugget effect coefficient $(C_0 / C_0 + C)$ x 100

From the maps generated after data interpolation (Figure 1), the values for particle density (Figure 1A) varied from 2.48 to 2.89 kg dm^{-3}. In addition, the highest particle density values (2.81 to 2.89 kg dm^{-3}) covered most of the map and extended to the left and right edges of the area to near totality. The lowest values (2.56 to 2.48 kg dm^{-3}) were mainly concentrated in the center, upper and lower regions of the map.

The porosity varied from 41.8 to 57.3% in the total porosity map (Figure 1B). In addition, intermediate total porosity values (from 48.9 to 51.1%) were dominant, with higher values (51.1 to 54.2%) occurring in a small area of the upper region. The low soil porosity was related to the lack of soil disturbance because the soil had been covered with Brachiaria grass for over 5 years.

The bulk density values varied from 1.18 to 1.59 kg dm^{-3}, with the highest values (1.43 to 1.59 kg dm^{-3}) occurring over a large portion of the map and concentrated in the lateral regions (Figure 1C). The lowest values (1.18 to 1.25 kg dm^{-3}) occurred in the upper and lower regions of the map. In addition, most of the area had critical density values (more than 1.60 kg dm^{-3}). Above the critical density value, roots cannot penetrate clayey soils (KIEHL, 1979). Thus, appropriate management practices are required. JUNG et al. (2010) suggested a combination of management practices for mitigating or delaying soil compaction. Such practices include controlled farm machinery traffic and the use of crop rotations that include plants with deep roots that are strong, able to penetrate relatively compacted soils and provide good coverage and soil organic matter to

improve the physical soil properties and the chemical and biological soil conditions and help control invasive plants.

This area has been occupied by forage for more than 5 years without proper management, grading or plowing. According to ROSA FILHO et al. (2009), although the soil was subjected to little machine traffic, it was not plowed or graded, which potentially resulted in densification of the surface layer. Densification was confirmed based on the greater bulk density and lower total porosity.

In the map of the soil sand content, the values varied from 38.2 to 52.2%, with lower values (38.2 to 43.8%) in most regions and higher values (49.4 to 52.2%) in a small upper region of the area (Figure 1D).

The clay contents varied from 13.5 to 20.6%, with the lowest values (13.5 to 16.3%) observed in the central region (Figure 1E). The highest values (17.7 to 20.6%) occurred in a small region on the left side of the map.
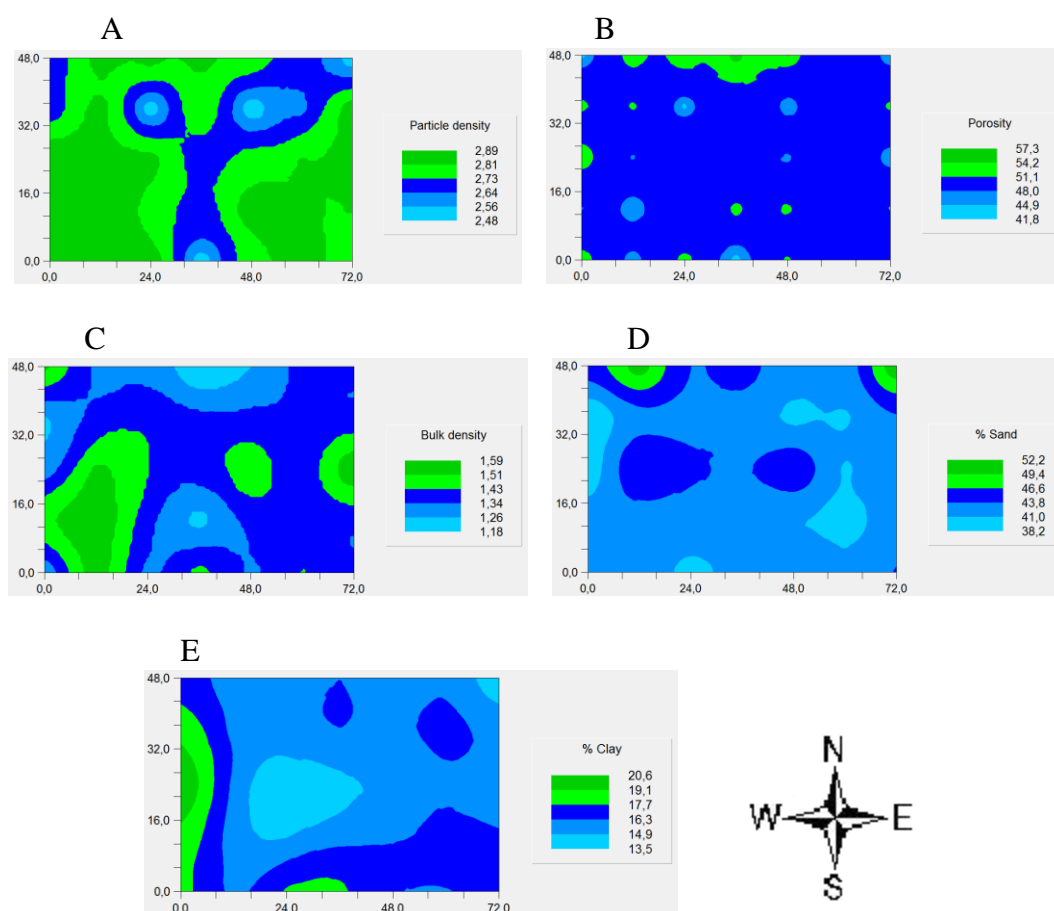

FIGURE 1. Spatial distribution of particle density, kg dm^{-3} (A); total porosity, % (B); bulk density, kg dm^{-3} (C); sand content, % (D); and clay content, % (E)

According to Table 2, cross correlations were only performed by using the geostatistics data for the attributes that showed significant Pearson's correlation coefficients.

The cross correlation graph of sand and clay content can be observed in Figure 2A. An inverse relationship was observed between the variables, with a regression coefficient of 0.366. From these data, 36.6% of the areas with predominant high sand contents (Figure 1D) had low clay contents (Figure 1E).

Similarly, the cross correlation between porosity and particle density is shown in Figure 2B. The regression index was 0.356, and the variables were directly related.

The relationship between porosity and bulk density resulted in the highest regression coefficient (0.596). This value corresponded with the results presented in Table 2, which presents a Pearson's linear correlation of -0.772 (the largest index in Table 2).

A

$Y = -1.149X + 61.73$
$R^2 = 0.367$

B

$Y = 0.019X + 1.79$
$R^2 = 0.356$

C

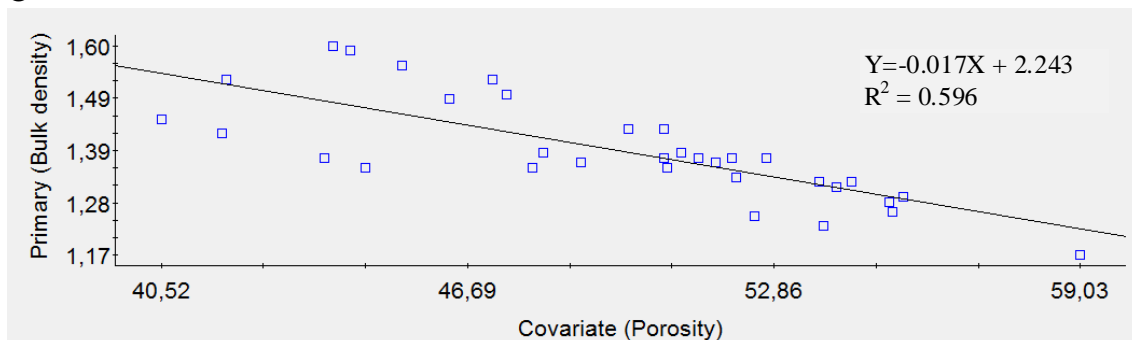$Y = -0.017X + 2.243$
$R^2 = 0.596$
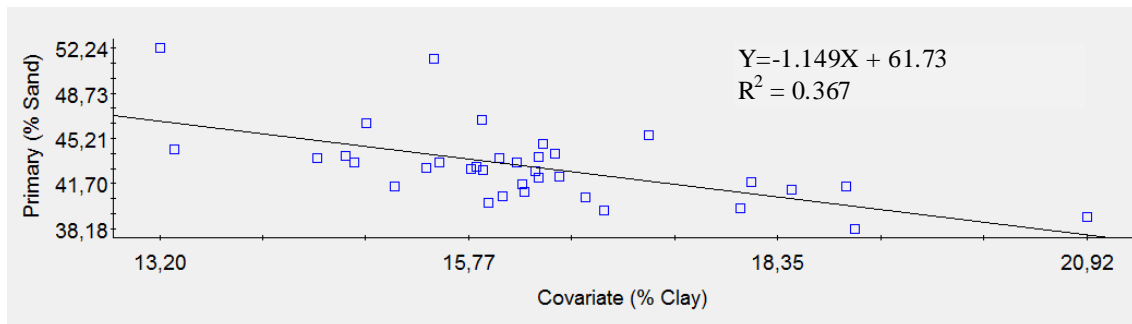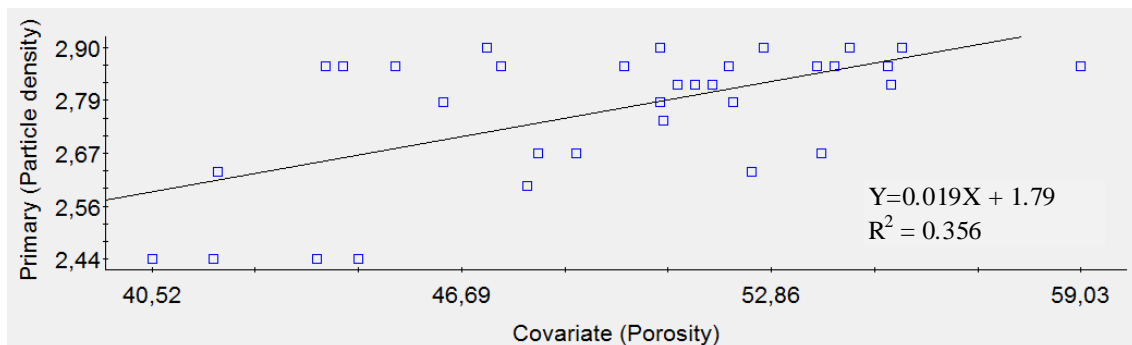
FIGURE 2. Cross correlation graphs between sand and clay content (A), particle density and porosity (B) and bulk density and porosity (C)

CONCLUSIONS

Under the experimental conditions, the following conclusions can be drawn:

- Spatial dependence occurs among the studied variables within the established sampling area.

- The areas with greater porosity are in the soil regions with greater particle density and lower bulk density.

- In addition, the geostatistical method may be used to identify the spatial dependence between porosity and bulk density.

ACKNOWLEDGEMENTS

REFERENCES

BONFIM-SILVA, E. M.; VALADÃO JÚNIOR, D. D.; REIS, R. H. P.; CAMPOS, J. J.; SCARAMUZZA, W. L. M. P. Establishment of Xaraés and Marandu grasses under levels of soil compaction. **Engenharia Agrícola**, Jaboticabal, v. 32, n.4, p. 727-735, jul./ago. 2012.

CAMBARDELLA, C. A.; MOORMAN, T. B.; NOVAK, J. M.; PARKIN, T. B.; KARLEN, D. L.; TURCO, R. F.; KONOPKA, A. E. Field-scale variability of soil properties in Central Iowa soils. **Soil Science Society of America Journal**, Madison, v. 58, p. 1501-1511, 1994.

CARVALHO, J. R. P.; ASSAD, E. D.; PINTO, H. S. Interpoladores geoestatísticos na análise da distribuição espacial da precipitação anual e de sua relação com altitude. **Pesquisa Agropecuária Brasileira**, Brasília, v. 47, p. 1235-1242, 2012.

EMBRAPA - EMPRESA BRASILEIRA DE PESQUISA AGROPECUÁRIA. **Manual de métodos de análise de solo**. 2. ed. Rio de Janeiro, 1997. 212p.

GOMES, F. P.; GARCIA, C. H. **Estatística aplicada a experimentos agronômicos e florestais**. Piracicaba: FEALQ, 2002. 305p.

GREGO, C. R.; RODRIGUES, C. A. G.; NOGUEIRA, S. F.; GIMENES, F. M. A.; OLIVEIRA, A.; ALMEIDA, C. G. F.; FURTADO, A. L. S.; DEMARCHI, J. J. A. A. Variabilidade espacial do solo e da biomassa epígea de pastagem, identificada por meio de geoestatística [Variability of soil and pasture epigeal biomass identified by geostatistics]. **Pesquisa Agropecuária Brasileira**, Brasília, v. 47, p. 1404-1412, 2012.

IAPAR - INSTITUTO AGRONÔMICO DO PARANÁ. **Características geográficas do município de Cafelândia**. Disponível em: <http://www.cafelandia.pr.gov.br/cafelandia>. Acesso em: 4 mar. 2009.

JUNG, K.; KITCHEN, N. R.; SUDDUTH, K. A.; LEE, K.; CHUNG, S. Soil compaction varies by crop management system over a clay pan soil landscape. **Soil and Tillage Research**, New York, v. 107, p. 1-10, 2010.

KIEHL, E. J. **Manual de edafologia: Relações solo-planta**. São Paulo: Agronômica Ceres, 1979. 264 p.

KOE, W. L.; OMAR, R.; MAJID, I. A. Factors associated with propensity for sustainable entrepreneurship. Procedia - **Social and Behavioral Sciences**, Washington, v. 130, p. 65-74, 2014.

MIGUEL, F. R. M.; VIEIRA, S. R.; GREGO, C. R. Variabilidade espacial da infiltração de água em solo sob pastagem em função da intensidade de pisoteio. **Pesquisa Agropecuária Brasileira**, Brasília, v. 44, p. 1513-1519, 2009.

PANOSSO, A. R.; PEREIRA, G. T.; MARQUES JÚNIOR, J.; LA SCALA JÚNIOR, N. Variabilidade espacial da emissão de CO_2 em Latossolos sob cultivo de cana-de-açúcar em diferentes sistemas de manejo. **Engenharia Agrícola**, Jaboticabal, v. 28, n.2, p. 227-236, abr./jun. 2008.

ROSA FILHO, G.; CARVALHO, M. P.; ANDREOTTI, M.; MONTANARI, R.; BINOTTI, F. F. S.; GIOIA, M. T. Variabilidade da produtividade da soja em função de atributos físicos de um Latossolo Vermelho distroférrico sob plantio direto. **Revista Brasileira de Ciência do Solo**, Viçosa, MG, v. 33, p. 283-293, 2009.

SCHAFFRATH, V. R.; TORMENA, C. A.; GONÇALVES, A. C. A.; FIDALSKI, J. Variabilidade e correlação espacial de propriedades físicas de solo sob plantio direto e preparo convencional. **Revista Brasileira de Ciência do Solo**, Viçosa, MG, v. 32, p. 1369-1377, 2008.

SILVA, A. F.; BARBOSA, A. P.; ZIMBACK, C. R. L.; LANDIM, P. M. B. Geostatistics and remote sensing methods in the classification of images of areas cultivated with citrus. **Engenharia Agrícola,** Jaboticabal, vol. 33, n. 6, p. 1245-1256, nov./dez. 2013.

SILVA, A. J. P. da; COELHO, E. F. Estimation of water percolation by different methods using TDR. **Revista Brasileira de Ciência do Solo**, Viçosa, MG, v. 38, p.73-81, 2014.

SPERA, S. T.; SANTOS, H. P. dos; FONTANELI, R. S.; TOMM, G. O. Atributos físicos de um Hapludox em função de sistemas de produção integração lavoura - pecuária (ILP), sob plantio direto. **Acta Scientiarum. Agronomy**, Maringá, v. 32, p. 37-44, 2010.

VIEIRA, S. R.; DECHEN, S. C. F. Spatial variability studies in São Paulo, Brazil along the last twenty-five years. **Bragantia**, Campinas, v. 69, p. 53-66, 2010.