

Variability of physical attributes in tropical weathered soil cultivated with irrigated beans (*Phaseolus vulgaris* L.)

Guilherme Adalberto Ferreira Castioni^{1*}, Zigomar Menezes de Souza¹, Aline Azevedo Nazário¹, Bernardo Melo Montes Nogueira Borges², José Luiz Rodrigues Torres³, Marcelo Rodrigues Soares Dayron⁴ and Milton César Costa Campos⁴

¹ Faculty of Agricultural Engineering, University of Campinas (FEAGRI/UNICAMP) - Campinas, São Paulo, Brazil

² Brazilian Bioethanol Science and Technology Laboratory (CTBE/CNPEM) - Campinas/SP, Brazil

³ Federal Institute of Mining Triangle (IFTM) – Uberaba, Minas Gerais, Brazil

⁴ Federal University of Amazonas, Humaita, Amazonas, Brazil

*Corresponding author: guilhermecastioni@hotmail.com

Abstract

Soil physical attributes are affected by several events. The ability to identify the variation of those attributes can be used to decide the best crop management. Although it is known that smaller grids are more representative, predicting the least number of points while maintaining accuracy is a tool that might reflect a gain in yield and time. The aims of this study were to evaluate the spatial physical variability and to define the minimum sampling density in a tropical Typic Haplustults soil using a scaled semivariogram in a central pivot area with pinto bean (*Phaseolus vulgaris* L.) after the eighth bean harvest in Cristalina, Goiás State. Soil samples were collected at a regular grid of 10-m intervals, totaling 180 points, and at depths of 0.00–0.10 m, 0.10–0.20 m, and 0.20–0.30 m to determine total sand content (TS), silt (SIL), clay (CL), water-dispersed clay (WDC), mean weight diameter of soil aggregates (MWD), soil penetration resistance (PR), soil macroporosity (Ma), soil microporosity (Mi), and soil bulk density (BD). The results demonstrated that management promoted superficial soil compaction with increasing BD and Mi and decreasing Ma and TP. The scaled semivariogram demonstrated similarity between attributes in the three studied soil layers, evidencing strong spatial dependency. The sample density showed a strong influence of WDC in the irrigated soil properties. Adoption of a scaled semivariogram is a strategy that can be used to determine a minimum number of points that represents the spatial variability of soil physical attributes and to assist the best management in irrigated soils.

Keywords: compaction; common bean; geostatistics; scaled semivariogram; soil structure.

Introduction

Brazil is a large bean producer (*Phaseolus vulgaris* L.), with an output of 2.8 million tons per year (CONAB, 2017). The beans majority are crops with low input of technology, which consequently decreases yield (Efetha et al., 2011). It can be cultivated as a winter crop. It produces better quality and yields three to five times higher than when cultivated in irrigated systems, on average producing 10 kg ha⁻¹ mm⁻¹ of water (Munoz-Perea et al., 2007). Thus, irrigation can serve as an alternative to farmers to produce food year-long. Irrigation of beans by aspersion in a central pivot is recommended for individual and large areas because of the price oscillation, while the stakeholder's financial return is linked to the yield.

However, adoption of an irrigation system enables successive cropping, in which usually two crops, cereals and grains, are harvested (i.e. corn and beans). Additionally, it is necessary to insert cover crops during the winter season, which would provide a constant addition of vegetative residues favoring the increase of organic composts, thereby

promoting improvements in soil physical quality (i.e. decrease in density, increase in porous volume, and favoring aeration and water infiltration) (Cintra and Meilniczuk, 1983).

Intensive use of soil in irrigated areas has caused alterations in soil physical attributes due to the management practices such as soil disturbance and machinery traffic (Reichert et al., 2003). Long-term soil degradation is reported with a greater intensity on the soil surface with the formation of compacted layers and superficial sealing. This effect might facilitate the erosion process, causing a decrease of essential soil functions, mainly those linked to structure stability, aggregated fractioning, density increase, microporosity (Mi) increase, and aeration porosity decrease, influencing root growth and, consequently, affecting yield (Neykova et al., 2011).

Irrigation systems such as a central pivot cover large areas. Soil modification occurs in different forms in the landscape, adding variability as the topography and soil type change.

One of the most efficient ways to detect changes in soil physical attributes is to analyze and describe spatial variability data by geostatistics techniques to elucidate the maximum inter-correlation of variable and its contribution to soil alteration in a crop area (Alho et al., 2014). This method can correlate soil attributes and crop yield according to the observed variations (Montanari et al., 2013). Analysis of spatial variability helps managing crop practices, orient future projects, and expands understanding of pedogenetic processes and soil quality (Sana et al., 2014).

According to MacBratney et al. (2003), various interpolation techniques are being utilized within geostatistics, presenting different degrees of reliability. Most of these techniques use a large sampling intensity, decreasing their viability, especially when observations have to be performed several times (Ferreira et al., 2002), which is usually a limiting factor in subsequent crop management. On the other hand, less-dense sampling is less expensive, but it can be imprecise and omit special patterns of the soil. However, the strategy to decrease cost and increase precision is to adopt enhanced mapping techniques that truly characterize spatial variability and provide more precise maps using a minimum number of sampling points (Silva et al., 2015).

Soil physical attributes are affected by several factors, the most impactful is water in the form of rainfall or irrigation. Identification of variation of those attributes might support precise decisions for the best crop management. It is known that the smaller grids are more representative. They predict the least number of points while maintaining accuracy. It is a tool that might reflect a gain in yield and time and be valuable in precision agriculture. In this context, the objective of this work was to evaluate the spatial variability of soil physical attributes in an irrigated pinto bean area to determine the minimum sampling density in tropical weathered soil.

Results and Discussion

Assessment of normality

Analysis of Table 1 demonstrates that the mean and median values are similar for all variables, indicating that the data did not present accentuated asymmetry in soil depths, which is confirmed by the values of asymmetry and near kurtosis of zero. These values may present an approximate normality, evidencing that it may represent a reference that measures central tendency, not having domain of discrepant values in their distribution (Cambardella et al., 1994). Therefore, physical attributes in this study approximate to a normal distribution and can be considered suitable for the use of geostatistics.

According to Souza et al. (2004) and Alho et al. (2014), the normality condition in data distribution is not mandatory in a geostatistic analysis, since the data collected from the field creates a normal distribution which is simply an approximation. However, it is desirable that data distribution does not present long tails, which might compromise the analysis based in medium values.

Classification of spatial dependency of soil attributes

The variability of an attribute can be classified by its CV magnitude. According to the criteria proposed by Pimentel Gomes and Garcia (2002), it classifies as low (CV <10%),

medium (10% < CV >20%), high (20% < CV >30%), and very high (CV >30%), since it is a dimensionless measure and enables comparison of two variables.

Among the studied variables, silt (SIL), mean weight diameter (MWD), and RP presented the highest variabilities in soil depths, classified as very high, which probably reproduced its spatial dependency. In a similar study with beans, Carvalho et al. (2006) reported high CV values; consequently, the geostatistical analysis pointed to moderate spatial dependency structure for RP in the soil layers of 0.05–0.10 and 0.10–0.15 m and strong for grain yield (GY). However, the same authors also reported that joint spatial analysis showed no correlation; thus, spatial variability of RP did not influence GY.

In the present study, CV values were low for clay (CL) and sand fractions, total porosity (TP), and bulk density (BD), showing lower heterogeneity of these attributes in the area and lower variability of the data collected. Souza et al. (2004) analyzed texture spatial variability of a Rhodic Oxisol under sugarcane cultivation and presented a high CV for coarse sand (CS). For all physical attributes evaluated, the mean CV was 31% at the depth of 0.00–0.10 m, 28% at 0.10–0.20 m, and 26% at 0.20–0.30 m. The authors concluded that management increases the variability of the surface compared to the subsurface.

Spatial variability of soil physical attributes

The semivariograms analyzed did not indicate direction preferences or present anisotropy. The spatial variability presented the same pattern for all directions (Table 2). Cross-validation facilitated the choice of semivariogram model and provided higher accuracy for the spatial continuity of soil attributes. According to Wackemagel (1995), when values are close to one, previsions are close to real values, characterizing the model as suitable to study the phenomenon. All studied attributes presented the data adjusted to the exponential mathematical model of the semivariograms (Table 2). However, the SIL and RP in the depth of 0.00–0.10 m; macroporosity (Ma) at 0.10–0.20 m; and CS, CL, and water-dispersed clay (WDC) values at 0.20–0.30 m, respectively, presented a coefficient of spatial determination (R^2) equal to or above 0.90, indicating that they presented the best semivariographic adjustment. In a similar study, Montanari et al. (2013) evaluated the correlation among soil attributes and bean yield under a Cerrado Oxisol and reported that the geostatistical analysis showed attributes with a pure nugget effect, with no spatial dependence. The other attributes presenting spatial dependency can be analyzed by the magnitude of the spatial determination coefficient (R^2). According to Siqueira et al. (2008), spherical and exponential mathematical models predominate in soil science studies. In their study, they emphasized that the lowest values were attributed to SIL, Ma, and BD in the layer of 0.00–0.10 m; TP in the layers of 0.10–0.20 m and 0.20–0.30 m; and RP in the layer of 0.10–0.20 m, which represented 27% of the sample mesh. The largest reaches obtained in this study were observed in the WDC attributes in the 0.10–0.20-m layer (Table 2). According to Montanari et al. (2013), when the same attributes are involved, the values of the scopes, obtained in their study, can be used in the geostatistical packages, which will feed the computational packages used in precision agriculture.

Table 1. Mean, median, coefficient of variation (CV), asymmetry and kurtosis values for the physical attributes of the evaluated soil.

Variables	TS	Clay	Silt	WDC	MWD	Mi	Ma	TP	BD	PR
0.0-0.1 m										
Mean	552.58	384.44	62.98	170.90	1.76	0.29	0.19	0.49	1.33	3.34
Median	559.50	383.75	59.5	163.75	1.67	0.29	0.19	0.48	1.33	3.32
CV	11.01	14.44	38.62	21.56	29.87	18.58	20.03	9.21	9.92	37.82
Asymmetry	-0.29	-0.01	1.76	0.48	0.36	-0.26	0.86	1.25	0.34	1.42
Kurtosis	0.08	0.05	5.69	-0.14	0.19	1.23	7.24	5.89	0.41	2.93
0.1-0.2 m										
Mean	556.47	388.04	58.01	182.91	1.63	0.28	0.19	0.47	1.36	5.17
Median	564.00	384.25	53.00	180.25	1.61	0.28	0.19	0.47	1.37	4.69
CV	10.07	14.43	40.19	19.24	31.71	17.12	19.28	10.19	9.38	31.63
Asymmetry	-0.01	-0.29	4.35	0.10	0.58	0.56	0.93	2.09	-0.91	1.98
Kurtosis	0.20	0.90	34.57	0.05	2.24	4.43	4.03	11.67	1.50	7.12
0.2-0.3 m										
Mean	543.72	400.65	55.32	191.56	1.70	0.27	0.20	0.47	1.37	5.63
Median	550.50	399.25	54.25	193.75	1.66	0.27	0.19	0.46	1.37	5.38
CV	11.03	14.75	38.17	20.04	31.64	16.26	19.68	10.29	10.56	35.07
Asymmetry	0.02	-0.60	2.63	-0.60	0.59	-0.47	1.87	0.42	0.46	2.27
Kurtosis	0.15	0.90	20.62	1.60	1.73	2.81	8.62	2.58	3.75	5.59

TS = Total sand; WDC = Water disperse clay (ADA); DMP = Mean weight diameter of soil aggregates; Mi = Microporosity; Ma = Macroporosity; TP = Total porosity; SD = Soil Density; PR = Penetration resistance.

Table 2. Semivariograms adjusted for soil physical attributes evaluated in an exponential model in 2011.

Variables	SC	Clay	Silt	WDC	WAD	Mi	Ma	TP	BD	PR
0.0-0.10 m										
¹ C ₀	797.000	49.000	68.000	750.000	0.0200	0.0002	0.8500	0.0001	0.0017	0.5030
² C ₀ /C ₀ +C ₁	3061.00	815.00	75.03	1501.00	0.89	0.0010	0.002	0.0012	0.0143	10.070
Reach	41.70	47.70	15.60	85.80	17.70	20.40	13.16	21.00	12.90	52.20
³ R ²	0.88	0.88	0.91	0.71	0.71	0.71	0.54	0.71	0.72	0.90
⁴ VC	0.87	0.82	0.55	0.80	0.56	0.80	0.68	0.70	0.31	0.74
⁵ GDE	26.04	6.01	9.06	49.97	9.27	12.65	15.55	11.02	12.45	49.95
0.10-0.20 m										
¹ C ₀	1364.00	17050.00	150.60	671.00	0.0100	0.0002	0.5000	0.0001	0.0007	0.0400
² C ₀ /C ₀ +C ₁	3318.0	3411.0	30.140	1343.0	0.8900	0.0010	0.0020	0.8800	0.0069	0.9190
Alcance	72.00	91.50	59.00	98.10	21.00	20.40	41.30	14.10	22.20	12.9
³ R ²	0.87	0.87	0.51	0.85	0.74	0.47	0.96	0.57	0.74	0.71
⁴ VC	1.02	1.06	0.88	0.85	0.82	0.59	0.71	0.36	0.41	0.63
⁵ GDE	41.11	49.99	49.97	49.96	1.12	13.07	49.91	8.80	10.27	4.35
0.20-0.30 m										
¹ C ₀	1337.0	1452.0	72.000	40.000	0.0700	0.0001	0.5000	0.0001	0.0012	0.0740
² C ₀ /C ₀ +C ₁	3770.0	3458.0	29.270	34.800	0.7200	0.0011	0.0020	0.0010	0.0091	0.9040
Alcance	76.80	72.00	20.10	34.80	46.50	20.70	37.80	14.70	18.00	20.70
³ R ²	0.93	0.94	0.73	0.91	0.88	0.61	0.86	0.48	0.74	0.60
⁴ VC	1.13	1.15	0.80	0.86	0.54	0.76	0.71	0.24	0.55	0.58
⁵ GDE	35.46	41.99	2.46	2.46	49.83	11.71	49.91	12.89	13.60	8.19

¹C₀ = Nugget effect; ²C₀/C₀+C₁ = Spatial dependency degree; ³R² = Determination coefficient; ⁴VC = Cross-validation; ⁵GDE = Degree of spatial dependency. TS = Total sand; WDC = Water dispersed clay; WAD = Weighted average diameter; Mi = Microporosity; Ma = Macroporosity; TP = Total porosity; SD = Soil density; PR = Penetration resistance.

Table 3. Sample density for the physical attributes of the soil in the layers 0.0-0.1, 0.1-0.2 and 0.2-0.3 m.

Variables	SC	Clay	Silt	WDC	MWD	Mi	Ma	TP	BD	PR
0.0-0.10 m										
Points	46	4	41	1	32	24	58	50	20	4
Spacing	8.18	10.73	28.69	16.02	22.19	13.8	14.88	6.84	7.37	28.09
0.10-0.20 m										
Points	2	1	3	1	23	24	6	50	20	60
Spacing	7.48	10.72	29.86	14.29	23.56	12.72	14.32	7.57	6.97	23.5
0.20-0.30 m										
Points	2	2	25	8	5	23	7	46	31	23
Spacing	8.19	10.96	28.35	14.89	23.5	12.08	14.62	7.64	7.84	26.05

Comparing the degree of CL dispersion in central pivot-irrigated soil under annual and perennial cultivation, Dantas et al. (2012) observed greater dispersion of CL under annual cultivation. This confirms that the use of central pivot irrigation in an area without soil cover benefits the impact of water droplets on its surface, surface aggregates, and dispersed CL. The C_0+C_0/C_0+C_1 ratio is used to define the spatial dependency of soil attributes, so the values of this relation showed that spatial dependency was classified as strong and moderate to the attributes in this study. This highlights significant variability and sampling efficiency; however, successive sampling may reflect in the further spatial structure of soil attributes (Corá et al., 2004).

Scaled semivariogram of soil physical attributes

The scaled semivariogram range was observed as 14.29 m in the three studied depths. These characteristics allowed us to affirm that soil attributes were heterogeneous and strongly influenced by management. The use of irrigation allowed continuous cropping yet promoted significant alterations of soil physical attributes. Regarding the data obtained by the spatial dependency range, it was possible to establish a sampling amplitude, showing different values for soil attributes. Based on the semivariogram range, we determined the minimum sampling density of each attribute in the three studied soil layers (Tables 2 and 3). Individual analysis of the attributes demonstrated that minimum sampling density showed values ranged from 1 to 58 points ha^{-1} . The medium spacing of 15.67 m in the 0.00–0.10-m soil layer, to the 0.10–0.20-m soil layer showed values of 1 and 30-point ha^{-1} , the average spacing of 15.09 m, and to layer 0.20–0.30 from 2 and 46 points ha^{-1} and average spacing of 15.41 m. We verified a similarity among soil attributes, when we analyzed the performance of the scaled semivariogram, showing more intense variability for WDC, CL, and PR in the 0.00–0.10-m layer, presenting an average number of points of 1, 4, and 4, respectively (Table 3). In the 0.10–0.20-m layer, CL, total sand (TS), SIL, and WDC presented sampling points of 1, 2, 3, and 1, respectively. In the 0.20–0.30-m layer, TS, CL, MWD, and Ma presented sampling points of 2, 2, 5, and 7, respectively. These characteristics allowed us to conclude that the granulometric fractions were well defined in the proposed sampling and that a strong influence of WDC in the soil layers was evidenced (Table 3). According to Dantas et al. (2012), there is a possibility of higher occurrence of WDC in irrigated areas compared to rain-fed systems. In the 0.00–0.10-m layer, the lowest sample density was observed for the PR attribute, indicating that soil presented surface compaction (Table 3). In the 0.20–0.30-m layer, MWD and Ma presented the smallest sample densities, due to TP obtained by the arrangement of the contact of solid particles. There was a predominance of solids in the soil sample due to TP. On the other hand, if soil particles are not arranged in aggregates, the voids predominate, and the TP is high.

Materials and Methods

Site description

The experiment was conducted in Cristalina, Goiás State (16°53'36" S; 47°32'17" W at 1,021 m asl). Soil samples were collected in an eight-year-old pinto bean crop area. The

climate in the region is classified as Aw according to the Köppen classification, with an average annual cumulative rainfall of 1,500 mm. The soil at the experimental site is Typic Haplustults (Soil Survey Staff, 2014), with the following physical and chemical characteristics in the 0.0–0.2-m layer: 441, 514, and 45 $g\ kg^{-1}$ CL, sand, and SIL content, respectively; pH (H₂O) 5.2; 27 $mmol_c\ dm^{-3}$ of Ca⁺ Mg; 31.0 $mmol_c\ dm^{-3}$ of H+Al; 33.1 $mmol_c\ dm^{-3}$ of S, 64.1 31.0 $mmol_c\ dm^{-3}$ of CTC; 52% of V; and 2.2 $g\ kg^{-1}$ of organic matter. The area relief is classified as an upland plateau, where 70% or more is plain or gently wavy. Detailed mapping was performed for 78 ha utilizing a GPS. We selected 1.8 ha from the total area to conduct the experiment.

Crop and irrigation management

The pinto beans were cultivated for eight seasons, one per year, in a seeding density of 9.4 plants per m, with 0.45 m between rows. The crop was seeded in succession to soybean under a no-till system. Irrigation was performed by a central pivot system, with sprayers with fixed swivel. Fertilization was performed by applying during seeding 30, 90, and 30 $kg\ ha^{-1}$ of N, P₂O₅, and K₂O, respectively. The topdressing was performed by applying 60 and 40 $kg\ ha^{-1}$ of N and K₂O, respectively.

The irrigation management was based on monitoring the soil water tension (SWT) with the water reposition of the water blade of 50% of the crop's evapotranspiration (ET_c), calculated based on the previous year. To monitor SWT, we installed tensiometers at 0.15 and 0.30-m depth. Soil moisture was estimated by water retention regression curve when reaching the critical tension of 35 kPa. The water blade varied from 8 to 10 mm every other day.

Soil sampling

Soil samples were collected with an Ullhand probe, using volumetric rings of 0.04-m height by 0.05-m diameter, at the soil layers of 0.0–0.10 m, 0.10–0.20 m, and 0.20–0.30 m at the grid crossing points that were georeferenced, with regular intervals of 10 m, in three positions with a slope of 1.8 ha.

Soil physical characteristics analysis

Granulometric analysis was performed by the pipette method, using NaOH 0.1 N as a chemical dispersant and agitation with a low-rotation apparatus. The WDC was determined as presented by Embrapa (2011).

We determined Mi in a water tension table, with samples submitted to a 0.006 MPa after saturation. TP and SBD were obtained by following the methodology of EMBRAPA (2011), in which, Ma was determined by the difference of TP and Mi. Aggregate stability was evaluated by the method described by Kemper and Chepil (1965), which constitutes weighting two replicates of 50 g of air-dried soil that were moistened by capillarity for 10 minutes. These samples were transferred to a set of sieves in vertical oscillation under water for 15 minutes. After the procedure, aggregates were separated in the following classes: C1 (9.52–4.76 mm), C2 (4.76–2.0 mm), C3 (2.0–1.0 mm), C4 (1.0–0.5 mm), C5 (0.5–0.25 mm), and C6 (< 0.25 mm). The content of each sieve

was air dried for 24 h at 105°C and weighted. From the values of aggregate dry weight, we calculated the MWD of soil aggregates, mean geometric diameter, and aggregated distribution by class of diameter.

The soil water content was determined by the gravimetric method in deformed samples (EMBRAPA, 2011). In order to determine PR, we utilized an impact penetrometer model IAA/Planalsucar, with a 30°-angle cone. The transformation of the equipment penetration in the soil (cm per impact) into resistance to penetration was obtained by equation 1 (Eq 1):

$$RP = \frac{(Mg+mg) + \left(\frac{M}{M+m} \times \frac{Mg+h}{x}\right)}{A} \quad (1)$$

Where; PR = Penetration resistance (kgf cm⁻²); M = piston mass (4 kg) (Mg = 4 kgf); m = equipment mass without piston (3.2 kg); h = piston drop height (40 cm); x = equipment penetration (cm per impact); A = cone area (1.29 cm²); and g = gravity acceleration (9.8 m s⁻²).

Statistical and geostatistical analysis

Soil physical attributes were analyzed by descriptive statistical analysis, in which values higher than average plus four standard deviations and the inferior number were discarded (Cahn et al., 1994). The number of discarded data was always less than 10% in each 180 data set.

Spatial dependency was analyzed by means of semivariogram adjusts, based on the presumption of the stationary intrinsic hypothesis, which is estimated by equation 2 (Eq 2) (Vieira, 2000):

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

Where; N(h) is the number of observation experimental pairs Z(x_i) and Z(x_i + h) separated by an h distance.

The semivariogram is represented by the graphic $\int \hat{\gamma}(h) \times h$. The adjustment of the mathematical model was calculated to the values of $\hat{\gamma}(h)$. We estimated the coefficients of the semivariogram theoretical model, nugget effect (C0), plateau (C0+C1), and range (a).

In order to analyze the degree of special dependency of the attributes in the study, we utilized the classification proposed by Cambarella et al. (1984), in which the semivariograms that have a nugget effect < 25% of the plateau are considered of strong special dependency, between 25% and 75% moderate, and > 75% weak.

Scalded semivariogram

The semivariograms were staggered and used with the objective to apply the same scale to all attributes. They were used as an information base to calculate the minimum number of soil samples and to determine the variability of soil physical attributes, using equation 3 (Eq 3) (Ceddia et al., 2009):

$$N = \frac{A}{(a^2)/10000} \quad (3)$$

Where; N = minimum number of samples necessary to determine a sampling grid; A = total area in hectares; and a = semivariogram range in m.

Cline approach

Based on the coefficient of variation, we determined the number of subsamples necessary to compose a sample and

to estimate the average value of variables using equation 4 (Eq 4), described by Cline (1944):

$$n = \left(\frac{t_{\alpha, cv}}{D}\right)^2 \quad (4)$$

Where; n = minimum number of samples necessary to determine the sampling grid; t_α = Student's t value (at 95% probability); CV = coefficient of variation; and D = percentage of variance from the mean value (5%).

Conclusion

Several years of irrigation promoted soil surface compaction, increased BD and Mi of the soil, and decreased Ma and TP. The scaled semivariogram demonstrated similarity among the attributes in all soil layers, which presented strong spatial dependency. The sample density showed the strong influence of WDC on irrigated soil attributes. A scaled semivariogram can be utilized as a strategy to determine the minimum scale of points in a sampling area. We became able to represent the spatial variability of soil physical attributes faithfully and thus assist the management of agricultural practices that directly affect physical parameters of irrigated tropical weathered soils.

Acknowledgements

The authors thank the School of Agricultural Engineering, University of Campinas (FEAGRI/UNICAMP) – Campinas, Brazil, for the available infrastructure and National Council for Scientific and Technological Development (CNPq) for funding the project and granting the first author's scholarship.

References

- Alho LC, Campos MCC, Silva DMP, Mantovanelli BC, Souza ZM (2014) Variabilidade espacial da estabilidade de agregados e estoque de carbono em Cambissolo e Argissolo. *Pesq Agro Trop*. 44: 246-254.
- Cahn MD, Hummel JW, Brouer BH (1994) Spatial analysis of fertility for site-specific crop management. *Soil Sci Soc Am J*. 58:1240-1248.
- Cambardella CA, Moorman TB, Novak JM, Parkin TB, Karlen DL, Turco RF, Konopka AE (1994) Field scale variability of soil properties in Central Iowa soils. *Soil Sci Soc Am J*. 58: 1501-1511.
- Carvalho GJ, Carvalho MP, Freddi OS, Martins MV (2006) Correlação da produtividade do feijão com a resistência à penetração do solo sob plantio direto. *Rev Bras de Eng Agr e Amb*. 10:765-771.
- Ceddia MB, Vieira SR, Villela ALO, Mota LS, Anjos LHC, Carvalho DF (2009) Topography and spatial variability of soil physical properties. *Sci Agr*. 66:338-352.
- Cintra F, Mielniczuk J (1983) Potencial de algumas espécies vegetais para a recuperação de solos com propriedades físicas degradadas. *R Bras Cienc Solo*. 7:197-201.
- Cline MG. Principles of soil sampling. *Soil Sci*. 58: 275-288.
- Conab - Companhia Nacional de Abastecimento (2017). Acompanhamento da safra brasileira de grãos. V. 5 - SAFRA 2016/17 N.1 - Primeiro levantamento Outubro de 2017. Monitoramento Agrícola: <http://http://www.conab.gov.br/graos outubro 2017.pdf> 23 Jan 2018.

- Corá JE, Araujo AV, Pereira GT, Beraldo JMG (2004) Variabilidade espacial de atributos do solo para adoção do sistema de agricultura de precisão na cultura de cana-de-açúcar. *Rev Bras de Cienc Solo*. 28:1013-1021.
- Dantas JDN, Oliveira TS, Mendonça ES, Assis CP (2012) Qualidade do solo sob diferentes usos e manejos no perímetro irrigado de Jaguaribe-Apodi, Brasil. *Rev Bras de Eng Agr e Amb*. 16: 1012-1022.
- Efetha A, Harms T, Bandara M (2011) Irrigation management practices for maximizing seed yield and water use efficiency of Othello dry bean (*Phaseolus vulgaris* L.) in southern Alberta, Canada. *Irrigation Sci*. 29:103-113.
- EMBRAPA - Empresa Brasileira de Pesquisa Agropecuária (2011) Manual de métodos de análise de solos. 3 ed. Ministério da Agricultura e do Abastecimento. Rio de Janeiro, 230.
- Ferreira RA, Apezteguía, HP, Sereno R and Jones, JW (2002). Reduction of soil water spatial sampling density using scaled semivariograms and simulated annealing. *Geoderma*. 110, 265-289.
- Kemper WD, Chepil WS (1965) Size distribution of aggregates. In: Black CA. *Methods of soil analysis*. Madison: Amer Society Agron. 499-510.
- McBratney, AB, Santos MLM, Minasny B (2003). On digital soil mapping. *Geoderma*. 117: 3-52
- Montanari R, Rodrigues GG, Carvalho MP, Dalchiavon FC, Machado FC, González AP (2013) Atributos químicos de um Latossolo espacialmente relacionados com a produtividade e componentes de produção do feijão em Selvíria (MS). *Rev de Cienc Agrovet*. 12: 271-281.
- Munoz-Perea CG, Allen RG, Westermann DT, Wright JL, Singh SP (2007) Water use efficiency among dry bean landraces and cultivars in drought-stressed and non-stressed environments. *Euphytica*. 3: 393-402.
- Neykova N, Obando J, Schneider R, Shisanya C, Thiele-Brunh S, Thomas FM (2011) Vertical root distribution in single-crop and intercropping agricultural systems in Central Kenya. *J Soil Sci Plant Nut*. 174: 742-749.
- Pimentel-Gomes FP, Garcia CH (2009) *Estatística aplicada a experimentos agrônômicos e florestais FEALQ*. Piracicaba. 309.
- Sana RS, Anghinoni I, Brandão ZN, Holzschuh MJ (2014) Variabilidade espacial de atributos físico-químicos do solo e seus efeitos na produtividade do algodoeiro. *Rev Bras de Eng Agr e Amb*. 18: 994-1002.
- Reichert JM, Reinert DJ, Braidá JA (2003) Qualidade dos solos e sustentabilidade de sistemas agrícolas. *Ci Amb*. 27:29-48.
- Silva SHG, Owens PR, Silva BM, Geraldo CO, Menezes DM, Pinto LC, Curi N (2015). Evaluation of conditioned latin hypercube sampling as a support for soil mapping and spatial variability of soil properties. *Soil Sci Soc Am J*. 79: 603-611.
- Siqueira GM, Vieira SR, Ceddia MB (2008) Variabilidade espacial de atributos físicos do solo determinados por métodos diversos. *Bragantia*. 67: 203-211.
- Soil survey staff. *Keys to soil taxonomy* (2014). 12th.ed. Washington, DC: United States Department of Agriculture/Natural Resources Conservation Service.
- Souza ZM, Marques Júnior J, Pereira GT (2004) Variabilidade espacial de atributos físicos do solo em diferentes formas do relevo sob cultivo de cana-de-açúcar. *Rev Bras de Cienc Solo*. 28: 937-944.
- Vieira SR (2000) Geoestatística em estudos de variabilidade espacial do solo. In: Novais RF, Alvarez VVH, Schaefer GR. *Tópicos em Solos*. 1:1-54.
- Wackemagel H (1995) *Multivariate geostatistics: An Introduction with applications* Springer. Berlin.