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Sampling Design of Soil Physical Properties in a Conilon Coffee Field

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ABSTRACT: Establishing the number of samples required to determine values of soil physical properties ultimately results in optimization of labor and allows better representation of such attributes. The objective of this study was to analyze the spatial variability of soil physical properties in a Conilon coffee field and propose a soil sampling method better attuned to conditions of the management system. The experiment was performed in a Conilon coffee field in Espírito Santo state, Brazil, under a 3.0 × 2.0 × 1.0 m (4,000 plants ha^{-1}) double spacing design. An irregular grid, with dimensions of 107 × 95.7 m and 65 sampling points, was set up. Soil samples were collected from the 0.00-0.20 m depth from each sampling point. Data were analyzed under descriptive statistical and geostatistical methods. Using statistical parameters, the adequate number of samples for analyzing the attributes under study was established, which ranged from 1 to 11 sampling points. With the exception of particle density, all soil physical properties showed a spatial dependence structure best fitted to the spherical model. Establishment of the number of samples and spatial variability for the physical properties of soils may be useful in developing sampling strategies that minimize costs for farmers within a tolerable and predictable level of error.

Keywords: *Coffea canephora*, geostatistics, soil sampling.

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INTRODUCTION

Currently, Conilon coffee (*Coffea canephora* Pierre ex A. Froehner) farmers have embraced a modernization process through use of agricultural machinery and tractors to accomplish various management tasks such as soil conditioning, fertilization, chemical spraying, harvest, and other farming practices. However, inadequate soil management and intense agricultural machine traffic may result in a change in soil physical properties, leading to many problems, such as soil degradation and compaction (Berisso et al., 2013).

Crop yield is influenced by soil properties; the spatial pattern of yield could be the result of a corresponding variation in certain physical soil properties (Mzuku et al., 2005). Thus, determining a more efficient soil sampling design can help achieve more effective site-specific management and, consequently, increase crop yield.

The soil under study was within a region denominated as coastal plains. Soils within this region were previously studied by Duarte et al. (2000) and Melo et al. (2002) in the state of Espírito Santo. These authors reported the presence of primarily Ultisols and Oxisols, with particular properties such as low contents of Fe and the presence of a cohesive subsurface horizon.

Determination of soil physical properties is important for monitoring the development of a coffee field since these are primordial factors for the characterization of soil structural quality and a determining factor for increasing and preserving high yield areas, as well as for sustaining the practice of coffee farming. Spatial variation may occur even within homogeneous areas and across short distances, influencing the yield of Conilon coffee (Oliveira et al., 2009). In this respect, Gontijo et al. (2007) emphasize that during the traditional sampling process, sub-samples may end up being collected next to each other, thus duplicating information on the values attributed to the soil. Therefore, knowledge regarding the continuity of the spatial distribution between sub-samples, represented by the range, will allow the construction of independent datasets, enabling the use of classical statistics without restrictions.

The soil sampling process is one of the most important procedures in research programs and for monitoring agricultural crop development since there is no use in subjecting soil samples to rigorous and sophisticated analysis if they do not appropriately characterize the area where soil management will be performed (Chung et al., 1995). A representative sampling system is one which best characterizes the area under study yet is designed with the least number of sampling points so as to avoid overloading the sampling system. That way, descriptive statistics may help indicate an adequate number of sampling points to bring the variation in results down to an acceptable level (Rozane et al., 2011).

Due to variation in values of soil properties across the field area, rigorous criteria must be established during the sampling process, which will ultimately allow representative information to be extracted from a determined area by using adequate sampling methods (Montanari et al., 2012). In the case of descriptive statistics, which does not consider spatial dependence between sub-samples of a determined soil property, an excessive quantity of sub-samples may be collected in order to attain a desired precision. Therefore, knowledge of soil spatial variability by means of geostatistical methods is essential for guiding the sampling process, thus avoiding non-representative sampling (Gontijo et al., 2007).

The hypothesis of this study was that it is possible to determine a sampling design to efficiently characterize soil physical properties, associating better sampling representativeness with less sampling effort. The objective of this study was to analyze the spatial variability of soil physical properties in a Conilon coffee field and to propose a method for soil sampling which will better fit the conditions of the management system.

MATERIALS AND METHODS

The experimental area was located in a Conilon coffee field in the municipality of São Mateus, state of Espírito Santo, Brazil, at coordinates UTM 7935440 m latitude South and 384440 m longitude West, with mean altitude of 81 m, zone 24K *datum* WGS 1984. The region has a tropical climate, Aw according to Köppen's classification system, with a dry winter and maximum rainfall during summer (Alvares et al., 2013). The annual mean temperature was 24.6 °C, with monthly mean values of 17.1 and 32.2 °C during the coldest and the hottest months of the year, respectively, and average cumulative rainfall of 1,296 mm (Incaper, 2016).

The soil was classified according to the U.S. Soil Taxonomy as a Typic Hapludox (Soil Survey Staff, 2010), with sandy clay loam texture and contents of clay, silt, and total sand of 231, 150, and 619 g kg^{-1}, respectively.

The experimental area was planted to Conilon coffee of the 'Bamburral' genotype. The crop was established in 2010, using a 3.0 × 2.0 × 1.0 m (4,000 plants ha^{-1}) double spacing between plants under a drip irrigation system, in an area previously planted to papaya. When coffee plantation was implemented, 1,500 kg ha^{-1} of dolomitic limestone was added to the soil, throughout the area. At the planting, for each meter of furrow, 5 kg of chicken manure were added, in addition to 100 g of simple superphosphate at the planting pit. After removal of a papaya crop in 2012, when the coffee field was 2 years old, the planted area received a fertigation system. Management of soil fertilization and liming was performed manually, following technical recommendations based on soil and leaf analyses according to Prezotti et al. (2007).

Weeds were controlled by manual hoeing and/or by herbicides applied with the aid of a 2,000 L capacity sprayer. Plant health was controlled according to the incidence of pests and diseases in the crop. To perform these agricultural operations, a tractor (front wheel assist) with an approximate weight of 1,620 kg, 7.00-18 front tires, 12.4-28 rear tires, 55 HP, and 45.6 power takeoff HP was used.

Undisturbed soil samples were collected in December 2013 using a stainless steel volumetric core, and disturbed samples were obtained with the aid of a probe sampler. Samples were collected from the area under the projection of the coffee tree canopy at a 0.00-0.20 m depth in an irregular grid of 107 × 95.7 m (10,240 m^2), with 65 sampling points (Figure 1). The coordinates of each sampling point were defined with the aid of a pair of GPS TechGeo® receptors, model GTR G2 geodesic.

To determine soil microporosity (Mi), water content at field capacity (θ_{CC}), and permanent wilting point (θ_{PMP}) according to Donagema et al. (2011), undisturbed samples were saturated for a 48 h period by gradual addition of water to a plastic tray until achieving a level of ⅔ of the cores' height and then weighed and subjected to tensions of 6 kPa in a Eijkelkamp® tension table and to 10 and 1,500 kPa in a Richards Soil Moisture® chamber with porous plate. Finally, samples were placed in a laboratory oven at 105 °C for 24 h to obtain values for the weight of dry soil.

Soil bulk density (BD), Mg m^{-3}, was calculated by the ratio between the soil's dry weight and the internal core volume. The total porosity (TP), in m^3 m^{-3}, was estimated by the ratio between BD and particle density (PD) through the equation TPV = [1 - (BD/PD)]. Soil macroporosity (Ma) was determined by the difference between TP and the soil microporosity (Mi). Disturbed samples were used to determine the PD (Mg m^{-3}) by the volumetric flask method and the particle size fractions by the densimeter method. Physical analysis of the soil was performed and the values of the attributes were determined according to Donagema et al. (2011). Values of soil water storage capacity (SWSC) at the 0.00-0.20 m depth, expressed in mm, were calculated by the expression SWSC = $[(\theta_{CC} - \theta_{PMP}) \times BD \times 200]$.

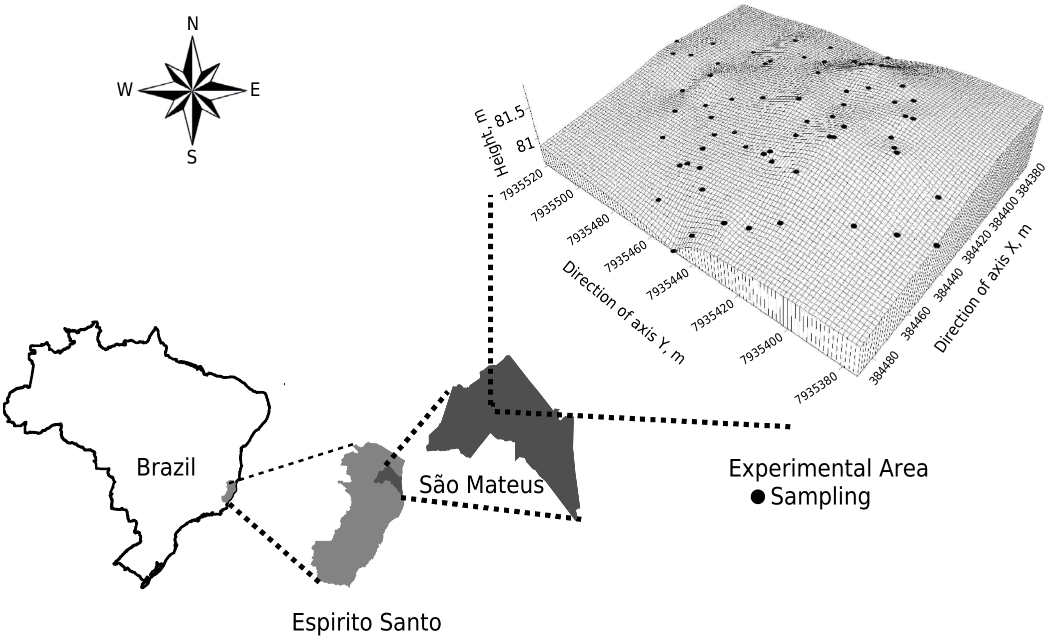

Figure 1. Location of the study area and sampling points used in the experiment.

Initially, the results of soil attributes were analyzed by descriptive statistics, obtaining the following outcomes: arithmetic mean, median, sample variance, standard deviation, maximum and minimum values, and coefficient of variation of asymmetry and kurtosis, as well as normality, by the Shapiro-Wilk test at 5 % probability, with the aid of the Action 2.3 statistical software (Estatcamp Team, 2014).

The number of samples (n) required to obtain representative mean values of the soil physical properties under study to achieve a desired level of confidence were calculated by equation 1 (Cline, 1944), as also suggested by different authors, such as Buczko et al. (2012), Tewolde et al. (2013), and Franzen and Mulla (2015):

$$n = \left(\frac{t_{\alpha/2} \cdot CV}{er} \right)^2 \quad \text{Eq. 1}$$

in which $t_{\alpha/2}$ is the value in the Student distribution table (1.9976) for the probability level α/2 (bilateral); CV, the coefficient of variation (%); and er, the admissible relative error to the mean (5-30 %).

The effectiveness of strategic soil sampling could be enhanced through incorporation of a spatial variability model (Mcbratney and Webster, 1983). Thus, in order to characterize the spatial variability of the soil physical properties, a geostatistical method was used by means of fitted semivariograms (Vieira et al., 1983), based on the presumption of stationarity of the intrinsic hypothesis, which was estimated by equation 2:

$$\gamma(h) = \frac{\sum_{i=1}^{n(h)} [z(x_i + h) - z(x_i)]^2}{2n(h)} \quad \text{Eq. 2}$$

where *γ(h)* is the semivariance, *n(h)* is the number of experimental pairs of observations $z(x_i)$ and $z(x_i + h)$ at locations x_i and $x_i + h$ separated by the lag distance h.

The semivariograms were staggered to standardize the values of semivariances from the variables under study. Semivariograms were staggered by dividing the semivariance values by the sample variance (Vieira et al., 1997).

Geostatistical analysis was performed with the aid of the software GS+ Version 7® (Gamma Design Software, 2004). To fit semivariograms, theoretic models such as the spherical, exponential, and Gaussian models were tested, and their parameters were defined: nugget effect (C_o), sill (C_o + C), and range (a). When undecided about more than one model for the same semivariogram, the highest value for the regression coefficient (CVRC) was considered, obtained by the crossed validation method (Amado et al., 2007). The spatial dependency index (SDI) was determined, defined as the proportion in percentage of the nugget effect (C_o) relative to the sill (C_o + C), given by equation 3:

$$SDI = \frac{C_0}{C_0 + C}\,100 \qquad \text{Eq. 3}$$

The spatial dependency index was classified according to Cambardella et al. (1994) as follows: (a) strong SDI ≤25 %; (b) moderate SDI between 25 and 75 %, and (c) weak SDI ≥75 %.

Subsequently, models of fitted semivariograms were used to develop interpolated maps of the variables under study through interpolation of their values, using the ordinary kriging method. The software ArcGIS 10.2.2 (ESRI, 2014) was used to elaborate spatial variability maps.

RESULTS AND DISCUSION

The mean and median values of particle density (PD), macroporosity (Ma), soil water storage capacity, and the particle size fractions of total sand and clay are very close, indicating symmetric distribution (Table 1), a fact confirmed by the asymmetry values near zero.

However, data normality by the Shapiro-Wilk test at 5 % probability was observed for the properties of soil density, May, total sand, and clay. Isaaks and Srivastara (1989) confirm that when applying geostatistical analysis, the occurrence or lack of the proportional effect, in which the mean and the variance of data are not constant within the area under study, is more important than the normality of data.

The coefficient of variation (CV) was considered low (≤12 %) for BD, PD, TP, and total sand, and medium (12 % < CV < 62 %) for the rest of the soil properties, according to the classification criteria proposed by Warrick and Nielsen (1980). Similar classifications were

Table 1. Descriptive statistics of bulk density (BD), particle density (PD), macroporosity (Ma), microporosity (Mi), total porosity (TP), soil water storage capacity (SWSC), total sand (TS), silt content (Silt), and clay content (Clay) obtained from 65 sampling points in a Conilon coffee field

Descriptive statistic	BD	PD	Ma	Mi	TP	SWSC	TS	Silt	Clay
	Mg m^{-3}		m^3 m^{-3}			mm	g kg^{-1}		
Mean	1.43	2.54	23.35	22.35	45.79	8.92	620.26	151.12	228.62
Median	1.43	2.53	23.66	21.65	46.28	8.73	624	148	220
SV	0.01	1 10^{-3}	41.54	18.05	20.16	9.11	2,924.4	775.67	1,749.62
SD	0.11	0.03	6.45	4.25	4.49	3.02	54.08	27.85	41.83
CV	7.62	1.34	27.60	19.0	9.81	33.84	8.72	18.43	18.30
Minimum	1.12	2.44	4.62	16.43	28.08	3.49	510	104	140
Maximum	1.84	2.63	36.98	40.62	54.48	16.79	716	256	320
Ass.	0.49	-0.05	-0.31	1.46	-0.84	0.65	-0.32	0.92	0.22
Kurt.	2.05	0.93	-0.29	3.47	2.17	0.34	-0.84	1.56	- 0.53
p-value	0.07*	1 10^{-4}	0.42*	4 10^{-5}	0.02	0.03	0.05*	0.01	0.08*

SV: sample variance; SD: standard deviation; CV: coefficient of variation; Ass.: asymmetry coefficient; Kurt.: kurtosis coefficient. *: normal distribution by the Shapiro-Wilk test at 5 % probability.

found by Kamimura et al. (2013) for all soil physical properties, except for microporosity (Mi), in a Typic Hapludox soil under coffee. Grego and Vieira (2005) found a medium CV for soil water storage capacity (SWSC). The SWSC generally shows high variation since it depends on a series of factors, including relative distribution of the size, the form, and the arrangement of soil particles (Moraes and Libardi, 1993), factors that are related to soil and water management.

Representative sampling is imperative to provide adequate monitoring of soil conditions, especially those related to compaction. The soil compaction process restricts the normal growth of roots, nutrient uptake, and water infiltration, which may affect the sustainability of the Conilon coffee field.

The number of sampling points required to obtain representative mean values from physical soil properties for the desired confidence level may be calculated by equation 1. Figure 2 shows the number of soil samples required to represent the area under study, at the 5 % level, for variations from 5 to 30 % of the mean value, measured by the relative error. The number of samples required to obtain a variation of 10 % of the mean value, with a significance level of 5 %, was 1 for PD, BD, TP, and total sand; 3 for clay and silt; 4 for Mi; 8 for Ma, and 11 for SWSC. Definition of the number of sampling points to make a compound sample is conditioned on the level of precision desired (Rozane et al., 2011) by associating better representation of the properties evaluated with less sampling effort, thus optimizing the sampling process.

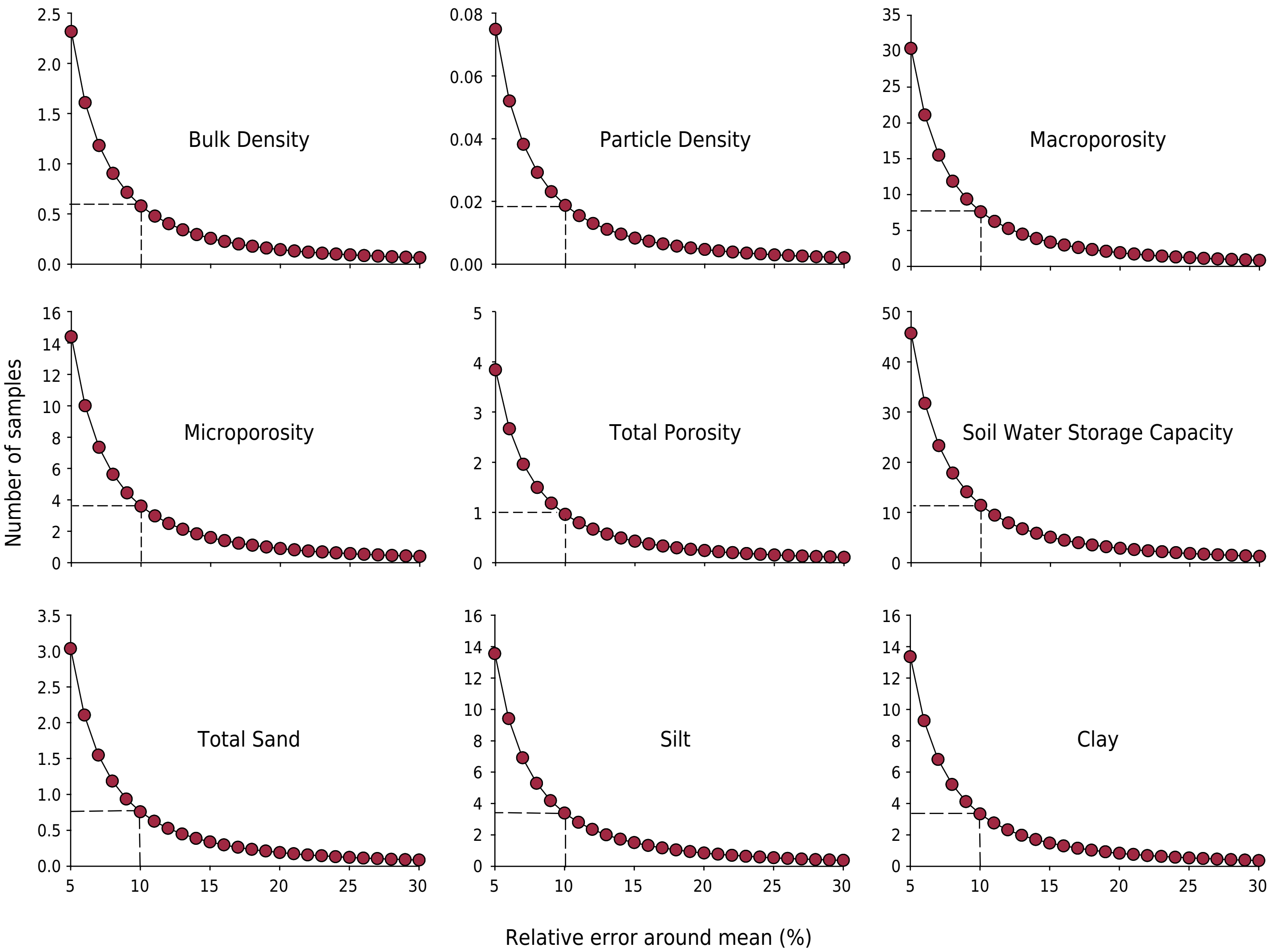

Figure 2. Number of sampling points for estimation of soil density, particle density, soil macroporosity and microporosity, total porosity, soil water storage capacity, total sand, silt, and clay, according to the relative error from the mean, at 5 % significance.

In the present study, having certified an admissible error within the tolerance range of 10 % of the mean value, we suggest proceeding with sampling of three disturbed soil sub-samples and 11 undisturbed soil samples. Disturbed soil samples are used to determine the contents of total sand, clay, and silt and PD, and undisturbed samples are used to determine BD, TP, Ma, Mi, and SWSC; in neither case is sampling performed separately for each soil physical property. This means that the final precision obtained after the sampling process will depend on the variables considered (Souza et al., 1997; Santos et al., 2014).

The spatial dependence structure was absent only for particle density (Figure 3). Thus, the pure nugget effect was observed for this property, due to the impossibility of fitting a semivariogram model to the distance scale used between the sampling points (Tavares et al., 2012). Anthropic interference, verified by successive croppings on this soil, adds sources of heterogeneity, promoting short distance variation, which may not be detected by the sampling grid. Montanari et al. (2013), while studying spatial variability in an Oxisol cultivated with dry edible beans, obtained similar results for PD in samples collected at depths of 0.0-0.10, 0.10-0.20, and 0.20-0.30 m.

All other variables showed spatial dependence structure and fit the spherical model. Similar fits were found by Resende et al. (2014) for clay, silt, and total sand in a Typic Hapludults, by Sana et al. (2014) for clay in a Typic Hapludox, and by Guimarães et al. (2016) for Ma, TPV, and BD in an Oxisol.

According to the classification proposed by Cambardella et al. (1994), only soil Mi and clay exhibited strong SDI (≤25 %), whereas the other variables under study showed moderate SDI (25 % < SDI < 75 %). For these authors, physical properties of the soil that show strong spatial dependency are most influenced by the soil forming factors (intrinsic properties), whereas moderate spatial dependence will probably be the result of agricultural practices such as soil amendment, fertilization, liming, and machinery traffic, among others (extrinsic properties).

Similar classification were found by Aquino et al. (2014) for clay and total sand fractions and BD; by Ribeiro et al. (2016) for BD and TP; by Leão et al. (2010) for clay and silt fractions; and by Silva and Lima (2013a) for clay and BD. Lima et al. (2006; 2010) confirmed that the lower the SDI (the proportion between the nugget effect in relation to the sill), the higher the spatial dependence of the soil physical properties under study will be. Thus, it is possible to verify higher continuity of the phenomenon, lower variance of the estimate, and higher confidence in the value estimated.

In the present study, values of the coefficient of determination (R^2) ranged from 0.886 to 0.998. That means that more than 0.886 of the variability in the estimated semivariance values may be explained by the models fitted. It was shown that CVRC ranged from 53.3 to 103.3 % for TP and total sand, respectively. The higher CVRC shows that the estimate of the particle size fraction of total sand using the kriging method exhibits a lower error and is therefore more reliable.

The range of spatial dependence is an important parameter in the study of semivariograms. Chaves and Farias (2009) define it as the maximum distance where the sampling points of the soil property are correlated spatially among themselves. This means that sampling points located at distances higher than the range have independent random distribution; therefore classical statistical methods can be applied for analysis.

Concerning the range, lower values for the clay and total sand fractions (21.3 and 24.6 m, respectively), intermediate values for TP, silt, and BD (38.8, 41.0, and 58.1 m, respectively), and higher values for SWSC, Ma, and mi (65.0, 74.1, and 93.0 m, respectively) (Figure 3) were verified in the present study. The lower range of values for the clay and total sand fractions evidenced poor structural continuity of the soil in the Conilon coffee field.

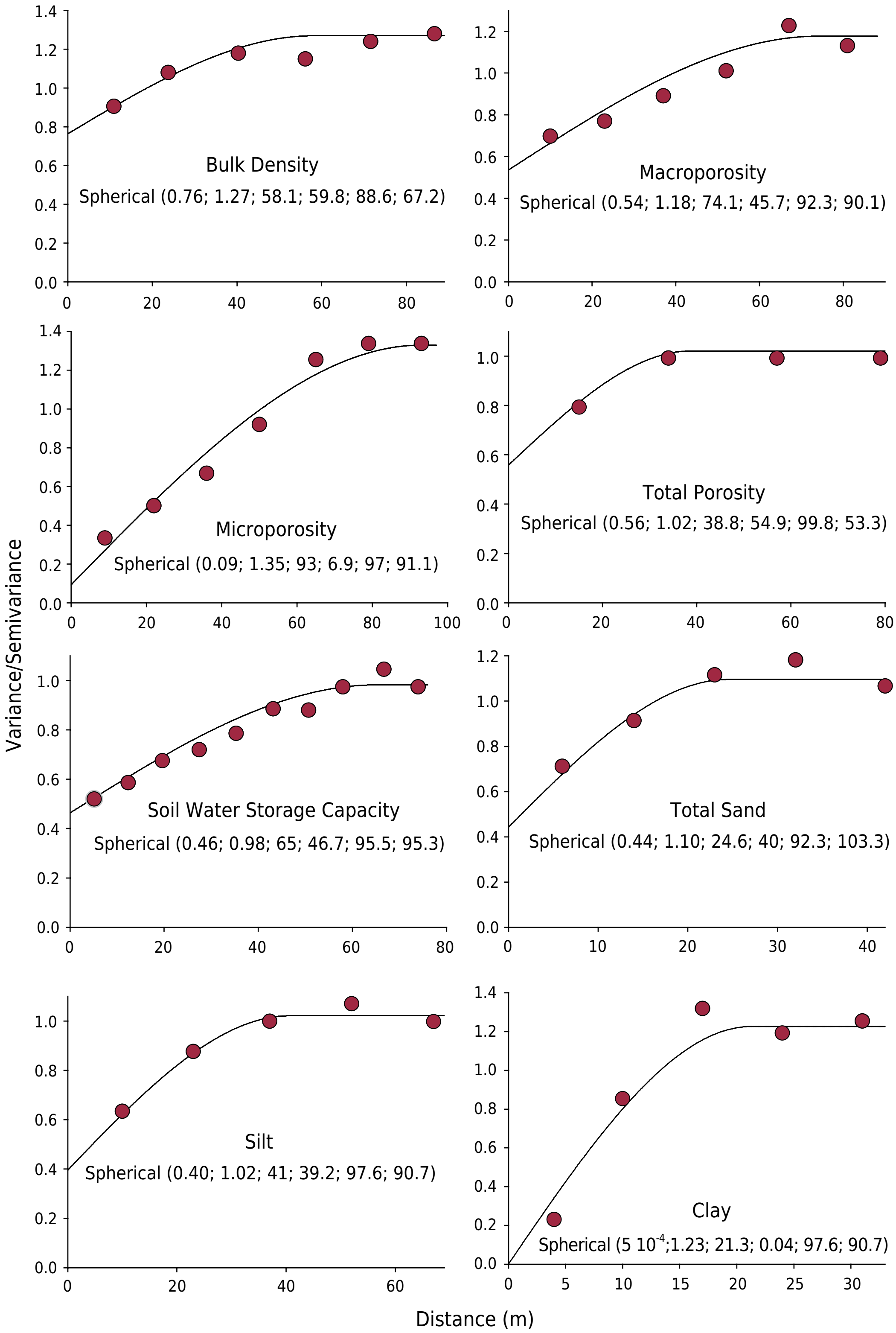

Figure 3. Experimental semivariogram models fitted to soil density, soil macroporosity and microporosity, total porosity, soil water storage capacity, and total sand, silt, and clay in a Conilon coffee field. Values in brackets are nugget effect (C_0), sill (C_0+C), range (a), spatial dependence index (SDI), coefficient of determination (R^2), and cross-validation regression coefficient (CVRC), respectively.

The lower range of values provides information concerning the heterogeneity of the spatial distribution regarding the attributes of the soil under study (Oliveira et al., 2015). In contrast, the properties showing a higher range of spatial dependence tend to be more spatially homogeneous, as can be observed in the interpolated maps of SWSC, macroporosity, and microporosity (Figure 4).

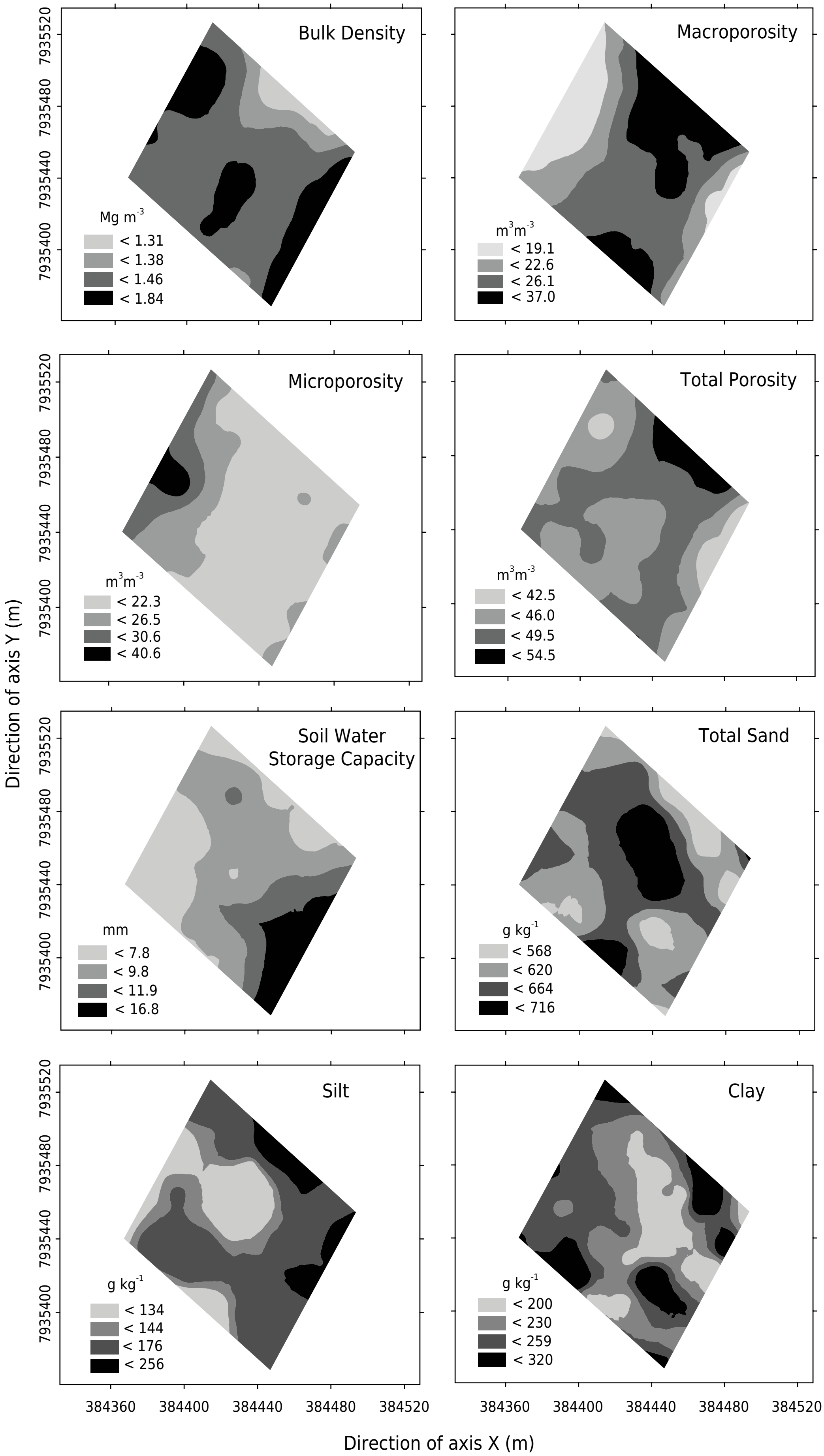

Figure 4. Interpolated soil maps for soil density, soil macroporosity and microporosity, total porosity, soil water storage capacity, and total sand, silt, and clay in a Conilon coffee field.

Once semivariograms of soil properties under study are fitted and after identifying their spatial dependence structure by means of the kriging technique, it is possible to perform interpolation of values at any point in the field without unbiased estimates and with minimum variance (Oliver and Webster, 2014), thus making kriging an optimal estimator. The parameters of models fitted to semivariograms utilizing the kriging process allow production of spatial variability maps of the physical attributes from soils planted to Conilon coffee (Figure 4).

In the spatial variability map of soil density, higher values (1.46-1.84 Mg m^{-3}) represented 25.2 % of the area under study and were located at the extremities (Figure 4). Silva and Lima (2013b) emphasize that regions of the field with higher values of BD tend to reduce availability of nutrients to plants, with consequent reduction in yield. Regarding the SWSC map, higher values of SWSC, represented by the range of values from 9.8 to 16.8 mm, are located in the southern region of the field.

The range of values for soil macroporosity are from 22.6 to 37.0 m^3 m^{-3}, and values for soil microporosity are lower than 22.3 m^3 m^{-3}, corresponding to 65.2 and 65.5 % of the experimental area (Figure 4), respectively, and are located in the central-south and northeast regions of the experimental area. In the spatial variability map of TP, values from 42.5 and 49.5 m^3 m^{-3} correspond to 88.3 % of the area under study and are well distributed throughout the field. It should be noted that gas flow in the soil, that is, oxygenation of the root system of the coffee plant, is intimately related to the volume of soil macro-pores (Silva et al., 2005).

The values of total sand contents ranging from 568 to 664 g kg^{-1} correspond to 74.2 % of the experimental area and are well distributed throughout the field. An inverse relation between the interpolated maps from clay and sand is verified, which is to say, in regions with higher contents of clay, lower contents of total sand are observed, and *vice-versa*.

The semivariogram range may assist in the sampling process since it provides the correct distribution of the number of samples for estimation of soil properties, according to the scale under study (Santos et al., 2013). Thus, in order to ensure spatial independence, disturbed soil samples must be collected from a distance higher than the range value. However, for undisturbed soil samples that show high range values, the process of sampling 11 points in a zigzag pattern is recommended.

CONCLUSIONS

In a Conilon Coffee plantation, cultivated in a Typic Hapludox, with sandy clay loam texture, collecting three disturbed soil samples (total sand, silt, and clay) and 11 undisturbed soil samples (soil bulk density and particle density, macroporosity, microporosity, total pore volume, and soil water storage capacity) is recommended in order to determine mean values for physical soil properties, associating low sampling expenses and better representation.

Determination of the number of samples and spatial variability of soil physical properties may be used to develop sampling strategies that minimize costs to farmers within a tolerable and identifiable level of error.

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