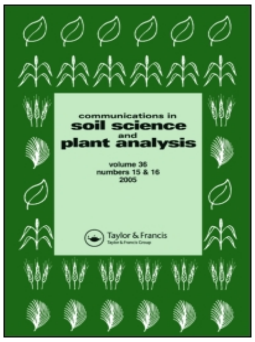

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Spatial Variability of Soil Organic Matter and Cation Exchange Capacity in an Oxisol under Different Land Uses

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ABSTRACT

Soil properties may exhibit large spatial variability. Frequently this variability is auto-correlated at a certain scale. In addition to soil-forming factors, soil management, land cover, and agricultural system may affect the spatial variability of agricultural soils. Soil organic matter (OM) is an important soil property contributing toward soil fertility and a key attribute in assessing soil quality. Increasing soil OM increases cation exchange capacity (CEC) and enhances soil fertility. We analyzed the impact of land use on the spatial variability of OM and CEC in a tropical soil, an Oxisol, within São Paulo state, Brazil. Land uses were prairie, maize, and mango. Soil samples were taken at 0–10 and 10–20 cm depths at 84 points within 1-ha plots, i.e., 100 m × 100 m. Statistical variability was higher for soil OM than for CEC. The mango plot contained the highest soil OM, whereas prairie the lowest. Also, soil OM and CEC were significantly related at all land use treatments and depths studied. All soil OM data sets and most of the CEC data sets (with two exceptions) exhibited spatial dependence. When spatial variability was present, the semi-variograms showed a nugget effect plus a spherical or an exponential structure. Patterns of soil OM and CEC spatial variability (i.e., model type, ranges of spatial dependence, and nugget effects) were different between land uses and soil depths. In general, CEC exhibited a lower spatial auto-correlation and a weaker spatial structure than soil OM. Moreover, soil OM displayed a higher autocorrelation and was more strongly structured at the 0–10 cm depth than at the 10–20 cm depth. Interpolation by kriging or inverse distance weighting (IDW) allowed to illustrate how the spatial variability of soil OM and CEC differed due to land cover and sampling depth. Modeling and mapping the spatial distribution of soil OM and CEC provided a framework for spatially implicit comparisons of these soil properties, which may be useful for practical applications.

KEYWORDS
Geostatistics; kriging; land use; soil monitoring; spatial autocorrelation; spatial structure; tropical soil

Introduction

Latosolic, oxic, and ferrallic horizons, which are found primarily in inter-tropical regions of the world, are not always equivalent, although all three taxonomic categories correspond to highly weathered soils. These soils are classified as Latosols by the Brazilian Soil Classification System (EMBRAPA 2006), Oxisols by Soil Taxonomy system (Soil Survey Staff 2010), and Ferralsols in the World Reference Base for Soil Resources (2006). Even if these soils are not the same, all three are

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characterized by the presence of few weatherable minerals and high concentrations of iron (Fe) and aluminum (Al) oxide minerals, kaolin, and quartz. Most of these tropical or subtropical soils also exhibit moderate to low soil organic matter (OM) content and low cation exchange capacity (CEC). Improved soil management systems, land uses, and agricultural practices can increase soil OM, which also produces a rise in CEC, and thereby enhance the fertility status of these soils, leading to increased productivity.

The variability of soil properties within plots and fields has been commonly described by conventional statistical analysis. Classical statistics assumes independent random variation of the soil properties. Geostatistics, however, assumes that some proportion of the variation is not independent, but auto-correlated (Burgess and Webster 1980; Dafonte et al. 2010). Earlier studies have revealed that soil properties frequently display spatial dependences (Cambardella et al. 1994; Paz, Taboada, and Gómez 1996; Vieira et al. 1983). Therefore, geostatistics has been used to assess the spatial dependence of soil properties (Burgess and Webster 1980; Goovaerts 1998; Morales, Vázquez, and Paz-Ferreiro 2011). The theory of regionalized variables considers differences between pairs of values of a property to be a function of their separation distance and expresses these differences as their variances. The calculated semivariograms can then be used to produce maps of the investigated property by "kriging", an interpolation method that yields unbiased estimates with minimal estimation variance (Burgess and Webster 1980; Goovaerts 1998; Vieira et al. 1983).

Spatial heterogeneity is considered inherent to many soil attributes (Kravchenko et al. 2006; Sun, Zhou, and Zhao 2003; Worsham, Markewitz, and Nibbelink 2010). As soil is a continuum, its properties are expected to be spatially auto-correlated at a certain scale (Burgess and Webster 1980; Goovaerts 1998; Schöning et al. 2006; Trangmar, Yost, and Uehara 1985). Therefore, the spatial variation may be described quantitatively by geostatistical methods. For example, a number of studies carried out at scales of about 1-ha have concluded that soil properties frequently exhibited spatial dependence (Camargo et al. 2013; Fraterrigo et al. 2005; Paz, Taboada, and Gómez 1996; Schöning et al. 2006). Spatial variability of soil attributes in natural landscapes results mainly from soil formation factors. In cultivated soils additional heterogeneity can occur as a result of land use, agricultural systems, and management practices. Moreover, intrinsic variability has been associated with natural variation in soils, whereas extrinsic variability means variations imposed by crop production practices (Cambardella et al. 1994; Paz, Taboada, and Gómez 1996).

Characterization of spatial variability of soil attributes is essential to achieve a better understanding of the complex relations between soil properties and both intrinsic and extrinsic sources of variation. Moreover, incorporation of spatial variability and its associated uncertainty is increasingly required for several applications, such as effective design of soil sampling strategies, evaluating land management practices, and assessing soil ecosystem services, including carbon sequestration, biodiversity, and preservation of water quality (Kravchenko et al. 2006; Schöning et al. 2006; Sun, Zhou, and Zhao 2003). For example, fertilizer and amendment application to soils is frequently based on mean values over an entire field area that may result in overestimation or underestimation for specific sites. A detailed knowledge of the spatial variability of soil properties using geostatistical techniques may optimize site-specific application and management of fertilizers and amendments, thus improving crop production, while allowing control of environmental contamination (Camargo et al. 2013; Cambardella et al. 1994; Trangmar, Yost, and Uehara 1985).

Conventional statistical methods have been employed to analyze the effect of agricultural management and land use on soil physical, chemical, and biological properties around the world (Paz-Ferreiro et al. 2010, 2011). Also, there is an increasing number of studies relying on the geostatistical approach for assessing land use effects on the spatial correlation of soil properties (Fraterrigo et al. 2005; Morales, Vázquez, and Paz-Ferreiro 2011; Schöning et al. 2006). In spite of this, the quantitative information on the spatial variability of Oxisols at the hectare scale still remains scarce.

In consideration of the above rationale, the objectives of this study were: (1) to describe and quantify statistical variability of soil OM and CEC in an Oxisol with three contrasting land uses; (2)

to characterize spatial variability and to assess strength of spatial correlation of some soil properties in the three land uses; and (3) to map soil OM and CEC at the 1-ha scale and to assess usefulness of the obtained contour maps for more effective soil management.

Materials and methods

Study area

The data for this study were collected on three neighboring 1-ha fields located within a small catchment in the municipality of Ilha Solteira, in northwest of the state of São Paulo, Brazil (latitude 22° 25′ S, longitude 51° 21′ W, mean altitude 310 m.a.s.l.). The climate of the region is hot humid tropical (Aw in the Köppen classification), with wet summers (October to March) and dry winters (April to September). Mean annual temperature and rainfall are 24.1 °C and 1400 mm, respectively. The primary vegetation of the region is "cerrado" (Brazilian savannah) and seasonal rainforest (Camargo et al. 2013; Paz-Ferreiro and Alves 2012).

The soil in the study area has been described as a coarse to medium textured, dystrophic, red Latosol according to the Brazilian Soil Classification System (EMBRAPA (Brazilian Agricultural Research Corporation), 2006) developed on sedimentary materials. The respective equivalents are Ferralsol in the World Reference Base for Soil Resources (2006) and Oxisol in the Soil Taxonomy System (Soil Survey Staff 2010).

The land covers in these three farmer-operated fields were: (1) prairie (*Brachiaria decumbens*, Stapf) used for extensive grazing, established 6 years before sampling; (2) conventionally tilled (disk ploughing plus harrowing) maize (*Zea mays*, L.) cultivated for 16 years; and (3) mango (*Mangifera indica*, L.) orchard planted 10 years before sampling. The area has a gently rolling topography and the fields were relatively flat. Average terrain slopes at the studied sites were <3°.

Field sampling and laboratory analysis

Representative plots measuring 100 m × 100 m were marked in the fields under three land covers (i.e., prairie, maize, and mango orchard). A total of 84 soil samples (0–10 cm and 10–20 cm depth) were collected from each plot in a combination of grid and transects schemes (Figure 1). Within each plot, 64 samples were taken in the nodes of a square grid at 12.5 m distance and additional 20 were taken off-grid, along five random transects at distances of 2, 4, 8, and 16 m from a reference node point. Sample collection was performed with a 5-cm diameter auger.

Prior to soil analysis, the samples were air dried, cleaned of visible plant residues, and sieved (2 mm mesh). All samples were analyzed for pH, sand, silt and clay, OM, exchangeable bases calcium, magnesium, and potassium (Ca, Mg, K), and exchangeable acidity hydrogen and aluminum (H^+ + Al^{3+}), following general methods described in van Raij et al. (2001). Specifically, soil OM was determined by wet combustion, following a modified Walkley–Black method (Dias et al. 2013; van Raij et al. 2001), whereas CEC was computed as the sum of exchangeable bases plus exchangeable acidity (van Raij et al. 2001).

Statistical and geostatistical analysis

Analysis of variance was performed to test the effects of land use and sampling depth on soil OM and CEC. Pearson product-moment correlation was used to test for linear correlation between the soil attributes studied. Exploratory statistical analysis included examination of mean and median values, coefficients of variation, and coefficients of skewness and kurtosis. Although all the analyses used do not require knowledge of the exact frequency distribution (Goovaerts 1998; Vieira, de Carvalho, and Paz González 2010), proximity to the normal distribution was judged on the basis of

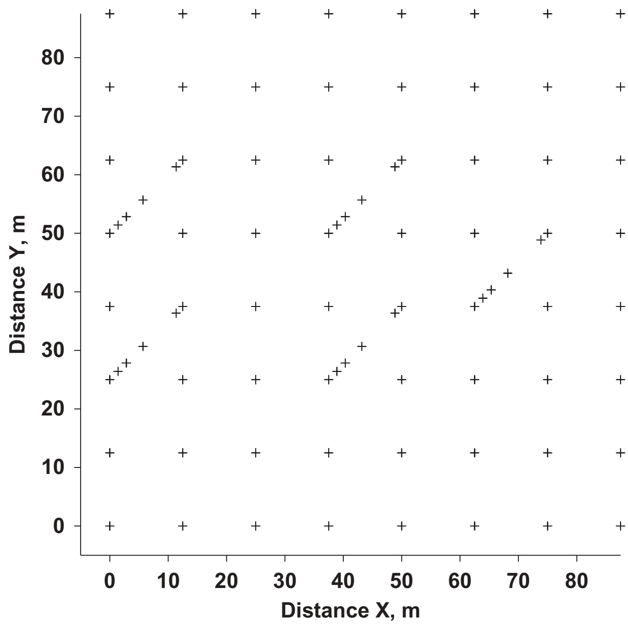


Figure 1. Scheme showing the sampling points in the experimental plots.

how close the values of skewness and kurtosis were to 0. All statistical analyses were carried out using SPSS, version 15.0 (Chicago IL).

The analysis of spatial variability through geostatistics is based on the assumption that measurements separated by small distances are more likely to be similar to each other than those farther apart (i.e., spatial autocorrelation exists). This assumption can be verified through examination of semivariograms for the attributes under investigation (Burgess and Webster 1980; Goovaerts 1998; Vieira, de Carvalho, and Paz González 2010; Vieira et al. 1983). The semivariogram is a statistical tool used to measure the between-sample autocorrelation. Therefore, the first step of the geostatistical analysis was to calculate sample semivariograms.

To obtain a semivariogram for each variable, a graph was constructed which showed the amount of variance between points as a function of distance. In a semivariogram, the semivariance as a function of the sample distance, γ(h), is calculated as follows:

$$\gamma(\mathrm{h}) = \frac{1}{2\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{s}} [\mathrm{z}(\mathrm{xi}) - \mathrm{z}(\mathrm{xi}+\mathrm{h})]^2$$

where γ = semi variance, n = the number of data points, z = the value of a data point at location x_i, and h = the lag [m] between two data points under consideration.

There are several mathematical models to describe sample semivariograms. All these models incorporate three parameters, namely range of spatial dependence, a, full sill, (C_0 +C_1), and nugget, C_0. The full sill consists of a structural variance (C_1) and a nugget variance (C_0). The ratio of nugget variance to total sill variance, i.e., $C_0/(C_0 + C_1)$ may vary between 0 and 1; note that for the particular case where C_1 = 0, no spatial dependence occurs. Lack of spatial dependence is referred to as pure nugget effect. In this work the spatial correlation was characterized by range (a) and the strength of the spatial structure was characterized by nugget/sill ratio.

The best-fitting semivariogram model was chosen based on subjective visual inspection, together with the help of parameters gathered from comparison of measured data and data estimated with cross-validation performed by ordinary kriging. Those parameters were: (1) the highest coefficients of determination between sampled and modeled semivariances (R^2); (2) the lowest values of mean error (ME); and (3) the value of the non-dimensional mean quadratic error (NMSE) closest to 1 (Morales, Vázquez, and Paz-Ferreiro 2011, 2010; Vieira et al. 2002).

When models of spatial dependence between neighboring data were found, the kriging approximation was used for interpolation at unsampled locations and for assessing the spatial uncertainty of the estimates. The kriging method uses a linear combination of the observations to make unbiased predictions of unsampled values with minimum error variance (Goovaerts 1998; Vieira 2000). However, for variables displaying a pure nugget effect interpolation was performed by the IDW method (Caridad-Cancela et al. 2005).

Semivariogram analysis and kriging were performed using codes described in Vieira (2000). Contour maps were drawn using Surfer 7.0 (Golden Software 1999). In summary, spatial variability was primarily evaluated through semivariogram calculation, model fitting, mapping, and comparison for each variable (Burgess and Webster 1980; Vieira et al. 2002).

Results and discussion

Statistical variability

Mean pH and mean sand, silt, and clay content at the studied plots are listed in Table 1. The soil in all the studied fields was acidic; moreover, mean pH increased with sampling depth under prairie, but decreased with depth under maize and mango. Mean sand content ranged from 626.6 to 889.2 g kg^{-1}, whereas clay content ranged from 58.5 to 274.9 g kg^{-1}. On average, clay content was much lower under the prairie than under maize or mango orchard. Accordingly, soil texture varied between sand and loamy sand under prairie, but was between sandy loam and sandy-clay-loam under maize and mango orchard. However, soils under all the three land cover types exhibited higher clay contents at the 10–20 cm depth than at the 0–10 cm depth, reflecting the presence of illuviation-eluviation processes in the soil profile.

Results of the descriptive statistical analysis for soil OM and CEC at the two soil depths are summarized in Table 2. On average, at the 0–20 cm depth soil OM was 13.3 g kg^{-1} under prairie, 14.5 g kg^{-1} under maize, and 15.9 g kg^{-1} under mango, and differences between the three soil covers studied were significant ($P < 0.001$). Also, mean CEC was significantly higher at 0–10 cm depth than at 10–20 cm depth ($P < 0.001$). On the other hand, interaction between land use and depth again was statistically significant ($P < 0.01$). Similarly, mean CEC values at the 0–20 cm depth were 36.1 mmol(+) kg^{-1} under prairie, 50.8 mmol(+) kg^{-1} under maize, and 54.8 mmol(+) kg^{-1} under mango, and differences between CEC of these soil covers were significant ($P < 0.001$). Moreover, mean CEC was significantly higher at 0–10 cm depth compared with 10–20 cm depth, and there was an interaction between land use and soil depth ($P < 0.05$). Differences in soil OM and CEC between land uses were also significant ($P < 0.05$) for each of the two soil depths (0–10 and 10–20 cm).

Mean soil OM and CEC values recorded under prairie were significantly lower than under the two other land covers. In general, higher levels of soil OM are expected under prairie than under conventionally tilled maize (Paz-Ferreiro et al. 2010) for plots with similar soil texture. Thus, the

Table 1. Mean soil pH, sand, silt, clay content, and texture under three different land covers.

Land cover	Depth (cm)	pH	Sand (g kg^{-1})	Silt (g kg^{-1})	Clay (g kg^{-1})	Texture
Prairie	0–10	5.10	889.2	52.3	58.5	Sandy
	10–20	5.17	856.0	65.3	78.7	Loamy sand
Maize	0–10	5.50	700.1	102.7	197.2	Sandy loam
	10–20	5.28	666.4	106.5	227.1	Sandy clay loam
Mango	0–10	4.56	670.7	98.9	230.4	Sandy clay loam
	10–20	4.44	622.6	102.5	274.9	Sandy clay loam

Table 2. Summary statistics for soil organic matter (OM) and cation exchange capacity (CEC) under three different land covers.

Variable	Cover	Depth (cm)	Mean	Std	CV	Minimum	Maximum	Skewness	Kurtosis
SOM	Prairie	0–10	16.5	4.5	27.2	8.0	30.0	0.716	0.230
($g\ kg^{-1}$)		10–20	10.1	4.0	39.8	3.0	24.0	0.899	0.889
	Maize	0–10	16.3	3.8	23.2	9.0	28.0	0.570	0.632
		10–20	12.7	3.5	27.3	7.0	25.0	1.277	2.457
	Mango	0–10	17.9	5.3	29.4	10.0	44.0	2.017	7.178
		10–20	14.0	4.0	28.8	8.0	29.0	1.527	2.704
CEC	Prairie	0–10	38.1	7.1	18.8	25.8	61.0	0.834	0.736
($mmol(+)\ kg^{-1}$)		10–20	34.1	6.7	19.7	22.2	55.3	0.952	0.804
	Maize	0–10	55.2	11.8	21.4	32.7	105.1	1.357	3.162
		10–20	46.5	8.6	18.4	31.6	83.2	1.769	5.340
	Mango	0–10	56.3	12.0	21.3	43.5	132.8	3.738	20.03
		10–20	53.3	9.1	17.2	38.4	86.9	1.763	3.845

Std, standard deviation.

reasons for our results should be addressed even if it is also true that there may be some exceptions to this rule as earlier studies have reported higher values of soil OM in the soil surface of tilled treatments than in those not tilled or with permanent vegetation (Kravchenko et al. 2006; Perfect and Caron 2002). In our study, lower soil OM and CEC measured under pasture could be driven by factors such as texture and slope. Analysis of possible topographical effects is beyond the scope of this study. Clay content (Table 1) and soil OM (Table 2) increased following the sequence: prairie < maize < mango. This outcome supports the hypothesis that the relatively low CEC under prairie is related to the coarser sandy and sandy loam texture. On the other hand, higher soil OM in the mango plot may be attributed to the joint effect of absence of tillage and maintenance of a grassed understory, which produced additional organic residues to increase OM.

For all the studied land uses and sampling depths, soil OM and CEC showed a significant linear relationship ($P < 0.01$), with coefficients of correlation, R, ranging from 0.54 to 0.88 (data not shown). The overall relationship between mean soil OM and mean CEC, however, was obscured by differences in soil texture between land uses and between sampling depths. However, when CEC was plotted against clay content it was apparent that, irrespective of texture, the upper soil layer (0–10 cm) with a higher soil OM has also a higher CEC compared with the lower soil layer (10–20 cm).

The spread and the coefficients of variation of the soil OM and CEC data are also listed in Table 2. The spread of soil OM values decreased as a function of soil depth in the three land uses studied and was lowest for maize and highest for mango. Coefficients of variation for soil OM oscillated from 23.2% to 39.8%. Again, CV values of soil OM were lowest under the maize cover. The highest spread of CEC was 72.4 mmol (+) kg^{-1} at the 0–10 cm depth, under maize, and the lowest was 32.3 mmol (+) kg^{-1} at the 10–20 cm depth, under prairie. All the CEC data sets exhibited lower CV values than those of the respective soil OM data sets. Moreover, CVs for all CEC data sets were relatively close, as they varied from 18.4% to 21.4%. Different thresholds have been used in order to rank coefficient of variations. Following Warrick and Nielsen (1980), low variation has been defined as CV values <12%, medium variation spans between 12% and 25%, high variation between 25% and 50%, and a CV above 50% is indicative of very high variation. Accordingly, statistical variation for soil OM was high in most of the studied data sets, with the only exception of 0–10 cm depth under maize, whose CV ranked as medium. However, CEC consistently displayed medium statistical variability.

Overall, the statistical variability of soil OM was lower under maize than under prairie or mango orchard. The higher CVs observed in plots that remained untilled for years (prairie, mango orchard) compared with the ploughed maize plot support the hypothesis that, in agricultural systems, soil mixing by tillage reduces soil OM variability (Kravchenko et al. 2006). Higher heterogeneity in soil OM has been also reported in undisturbed forest soils when compared with agricultural soils

(Schöning et al. 2006; Worsham, Markewitz, and Nibbelink 2010). Statistical variability of CEC, however, was of the same order of magnitude for the three studied land covers and the two depths.

Distributions of soil OM and CEC were positively skewed, indicating that there were a few extreme values in all the data sets analyzed. Moreover, skewness coefficients of CEC were higher than those of soil OM, for all the depths and land covers studied. Also kurtosis coefficients were always positive. The most skewed and kurtotic distributions were observed under mango orchard. In spite of some large values for skewness and kurtosis coefficients, a Kolmogorov–Smirnov test showed frequency distributions of the study data set could be approximated by a normal distribution.

Asymmetry and kurtosis coefficients close to 0 have been used frequently as indicative of normal frequency distributions (Vieira et al. 2002). A few data sets in our study were clearly skewed and kurtotic (Table 2). However, the Kolmogorov–Smirnov test revealed that all data sets analyzed approached normal distributions. Indeed, normality could be improved by natural log transformation (Burgess and Webster 1980; Kravchenko et al. 2006; Worsham, Markewitz, and Nibbelink 2010). Although normal distributions are best suited for kriging interpolation, the non-normality of the data is not considered to be limiting for the use of geostatistics (Camargo et al. 2013; Vieira 2000), provided the distribution is not highly skewed. Therefore in our study no log transformation of the measured data was performed.

Spatial variability

Table 3 lists information about the semivariogram models that were fitted to describe the observed patterns of spatial variability of soil OM and CEC, as well as the associated geostatistical parameters. The spatial dependence of soil OM was best described by exponential models under prairie and by spherical models under maize and mango orchard. In two out of the six CEC data sets the semivariance did not change significantly with increasing lag distance, which indicates lack of spatial dependence, i.e., pure nugget effect. In the other four CEC data sets again exponential and spherical models were adjusted to the sample semivariograms.

For soil OM, the range, a, of the semivariogram varied from 12.2 to 55.0 m, whereas the sill to nugget ratios, $C_0/(C_0+C_1)$, varied from 0.15 to 0.69 (Table 3). The top layer (0–10 cm) had a broader range of spatial dependence than the second layer sampled (10–20 cm) in the prairie and maize plots, whereas in the mango orchard plot the range was of the same order of magnitude at the two sampled depths; therefore, in the prairie and maize plots the spatial autocorrelation, i.e., the

Table 3. Model type, parameters (range, full sill, and nugget) of the best-fitted semivariogram, and selected indicators obtained by cross-validation (determination coefficient, mean error, non-dimensional mean quadratic error) for soil organic matter (OM) and cation exchange capacity (CEC) as a function of land cover and sampling depth.

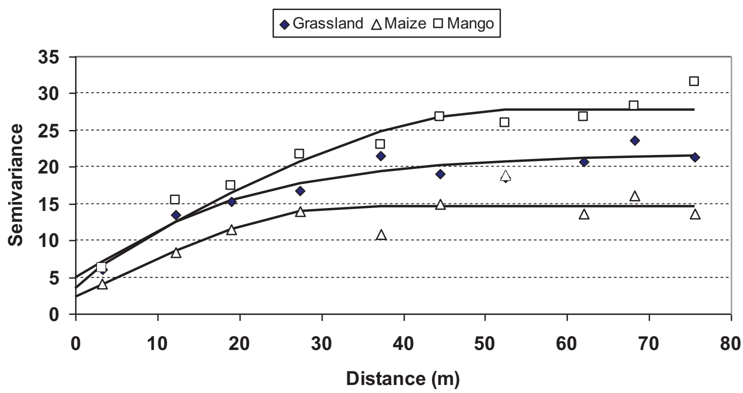
	Cover	Depth (cm)	Model	Range (a)	Full sill (C_0+C_1)	Nugget (C_0)	Nugget/sill (C_0)/(C_0+C_1)	R^2	ME	NMSE
SOM ($g\ kg^{-1}$)	Prairie	0–10	Exponential	53.4	21.72	3.44	0.16	0.919	−0.014	1.120
		10–20	Exponential	32.9	17.05	3.78	0.22	0.993	0.007	0.945
	Maize	0–10	Spherical	34.9	14.70	2.26	0.15	0.767	0.021	1.238
		10–20	Spherical	12.2	12.10	8.33	0.69	0.287	−0.014	1.120
	Mango	0–10	Spherical	54.4	27.81	5.00	0.18	0.858	−0.007	1.409
		10–20	Spherical	55.0	16.34	8.65	0.53	0.587	−0.010	1.144
CEC ($mmol(+)kg^{-1}$)	Prairie	0–10	Exponential	55.0	60.92	7.94	0.13	0.720	0.021	1.054
		10–20	Spherical	39.1	48.08	17.62	0.37	0.982	−0.001	0.973
	Maize	0–10	Spherical	61.1	131.48	54.14	0.41	0.787	0.019	1.082
		10–20	Pure nugget effect				1.00			
	Mango	0–10	Pure nugget effect				1.00			
		10–20	Exponential	60.0	88.38	39.10	0.44	0.723	−0.011	1.254

a = range of spatial dependence, in meters; C_0+C_1 = full sill; C_0 = nugget; R^2 = determination coefficient; ME = mean error; NMSE = non-dimensional mean quadratic error.

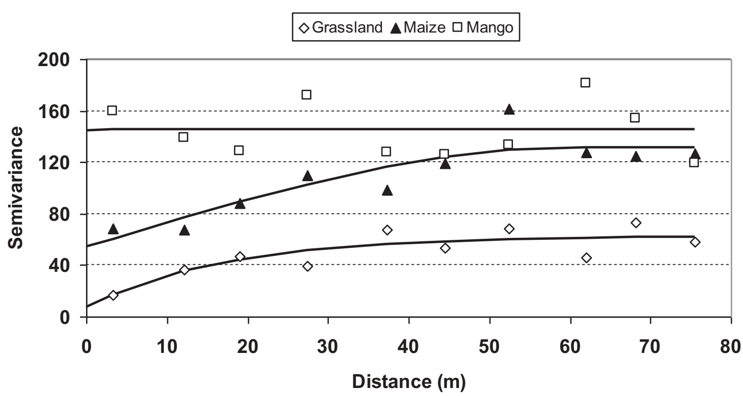
continuity in the spatial correlation of soil OM was higher at 0–10 cm depth than at the 10–20 cm depth. Moreover, maize plots exhibited a narrower range than either prairie or mango orchard plots at the two soil depths sampled, suggesting land use effects on the spatial autocorrelation of this variable. In contrast to the range, the nugget to sill ratio of soil OM increased with depth for the three studied land uses, and, therefore, increasing sampling depth weakened the spatial structure of this soil attribute.

The ranges of spatial dependence, a, of the four CEC data sets varied from 39.1 to 61.1 m and were broader than their corresponding soil OM ranges. The sill to nugget ratio varied from 0.13 to 1.0 (pure nugget effect), demonstrating values <0.4 only under prairie. Therefore, in general the parameter $C_0/(C_0+C_1)$ had a tendency to be higher for CEC compared to soil OM (Table 3, Figure 2), although two exceptions were observed for this broad rule.

At distances smaller than the range of spatial dependence, a, the measurements of a variable are correlated with each other. In case of soil OM, maize plots had a narrower range than prairie and mango orchard plots. The range parameter has been used for determining the most efficient distance between neighboring samples to improve accuracy in soil fertility studies (Paz, Taboada, and Gómez 1996) and in other applications such as preparing soil OM inventories (Worsham, Markewitz, and Nibbelink 2010). As a rule of thumb, it is proposed that sampling locations could be spaced at twice the average range, to account for spatial dependence (Vieira et al. 1983, 2002). Following this recommendation, and taking into account that the lowest modeled values of the range parameter



Soil organic matter (SOM) content



Cation exchange capacity (CEC)

Figure 2. Sampling semivariograms with respective fitted models for soil organic matter soil organic (OM) and cation exchange capacity (CEC) at 0–10 cm depth for three land covers.

were about 12 m for maize, 32 m for prairie, and 55 m for mango, inter-sampling distances of 24, 64, and 110 m, respectively, could be recommended as a first approach, for soils under these three land uses. However, in addition to the range, a, the strength of the spatial structure modeled also should be taken into account for increasing sampling accuracy.

Following Cambardella et al. (1994), the strength of the spatial dependence may be considered as strong, when values of the nugget to sill ratio, $C_0/(C_0+C_1)$, are lower than 0.25, moderate for values from 0.25 to 0.75, and strong for values greater than 0.75. According to these criteria, soil OM demonstrated a strong spatial structure in four out of the six analyzed data sets, namely in all those sampled at 0–10 cm depth, irrespective of land cover, as well as at 10–20 cm depth under prairie; however, the other two data sets, those measured under maize and mango orchard at 10–20 cm depth, displayed a moderate structure. In contrast, the spatial structures presented by the CEC data sets were much weaker, as they were ranked as strong for one data set (prairie, 0–10 cm depth), moderate for three other data sets, and pure nugget effect for the two remaining data sets. Therefore, in general, the spatial autocorrelation of CEC was poorer, and the spatial structure was weaker compared to soil OM.

The outcome of the semivariogram analysis showed that both the length of the spatial correlation, given by the range parameter a, and the strength of the spatial structure, given by the nugget to sill ratio $C_0/(C_0+C_1)$, showed noticeable differences between variables, land uses, and sampling depth. Differences in the patterns of spatial variability between land uses and depths are not surprising, considering between-plot variations in illuviation-eluviation processes and the associated divergences observed in the textural fractions (Table 1). Therefore, contrasting texture may be one of the main intrinsic sources of spatial variability. Extrinsic sources that contribute to the spatial variability may be land cover and other variables related to agricultural activities, such as tillage system (absence of tillage in the prairie and mango orchard versus conventional tillage in the maize); fertilization and grazing may also contribute to the spatial variability (Cambardella et al. 1994). The surface 0–10 cm layer is thought to be most affected by extrinsic sources of variability (Kravchenko et al. 2006; Worsham, Markewitz, and Nibbelink 2010). However, vertical differences in the patterns of spatial variability between 0–10 and 10–20 cm layer may also be due to the nature of the eluviation-illuviation processes. In addition, other studies have shown that topography also may drive the spatial variability of soil OM (Camargo et al. 2013; Kravchenko et al. 2006). There is also evidence suggesting that the history of land use in a given plot may affect patterns of spatial variability of the soil properties (Camargo et al. 2013; Paz, Taboada, and Gómez 1996).

Table 3 also lists parameters obtained by cross-validation that have been employed to assess the goodness of fit of the semivariogram models. Coefficients of determination were high ($R^2 > 0.587$) for most of the variables, with the exception of soil OM at 10–20 cm depth under maize, where the fit of the spherical model was rather poor ($R^2 > 0.287$). Mean errors (MEs), i.e., mean differences, between measured and kriged data obtained by cross-validation were close to 0. Also values of the NMSE obtained by cross-validation, which is considered as the most robust criterion, were reasonably close to 1, again except for 10–20 cm soil depth.

Geostatistical analysis is based on the regionalized variable theory, and relies on random statistical modeling. Therefore, application of geostatistics demands that at least intrinsic hypothesis must be fulfilled. In this study, the intrinsic hypothesis, which requires that the semivariograms must have a sill, was satisfied and validated using the coefficients of determination, R^2, mean errors, and the NMSE obtained by cross-validation (Vieira et al. 2002).

Spatial correlation within the studied plots can also be compared with values given by several studies conducted at similar sampling scales. For example, Kravchenko et al. (2006) found ranges of spatial dependence, a, varying from 20 to 30 m for organic carbon measured at the 0–5 cm in 1-ha plots in Michigan (USA); these plots were managed with two differently tilled and a no-tilled treatments, and minimum sampling lag was 1 m. Also, analyzing duplicated plots on a 1-ha scale Worsham, Markewitz, and Nibbelink (2010) found for organic carbon range values of 81 ± 17 m under hardwood, 77 ± 22 m under pine, and 66 ± 48 m under pasture; the study sites were located in

Georgia (USA), sampling depth was 0–7.5 cm, and minimum sampling spacing 10 m. Because this study was carried out using duplicated plots per land cover, it contributed to assess differences in spatial variability patterns between stands with a given vegetative cover.

The nugget effect (C_0) is a measure of the spatial discontinuity for distances lesser than the minimum distance between samples. In other words, smaller nugget indicates if the sampling interval is proper to reflect plot variance. Therefore, the sampling grid used was found to be useful to describe a higher proportion of the soil OM spatial variability at 0–10 cm depth than at 10–20 cm depth. On the other hand, lack of spatial structure, i.e., pure nugget effect, was demonstrated in two CEC data sets. Pure nugget effects may be due to the presence of variability at scales smaller or larger than the experimental 1-ha plots, but also due to the presence of extremely high or extremely low values that are potential outliers (e.g., Paz, Taboada, and Gómez 1996; Vieira et al. 1983; Worsham, Markewitz, and Nibbelink 2010). Any of these two circumstances may have driven randomness, weakening the ability of the geostatistical analysis to detect spatial patterns, which is mainly true for some of the studied CEC data sets.

The nugget to sill ratio, $C_0/(C_0+C_1)$, not only allows assessment of strength of the spatial structure but also defines the proportion of short range variability that is not explained by the semivariogram model. Small nugget to sill ratios indicate not only stronger spatial structure but also higher accuracy in mapping soil properties by kriging (e.g., Burgess and Webster 1980; Vieira 2000). Higher nugget to sill ratios probably reflect homogenizing effects due to management practices. Schöning et al. (2006) in a temperate beech forest of about 1 ha reported a sill to nugget ratio of 0.20 for soil organic carbon; sampling depth was 0–12 cm and minimum distance between samples was 0.2 m. However, the average nugget to sill ratios found for organic carbon by Worsham, Markewitz, and Nibbelink (2010), in duplicated plots, at 1-ha scale, were 0.66 under hardwood, 0.67 under pine, and 0.51 under pasture; again sampling depth was 0–7.5 cm and minimum sampling distance 10 m. These results suggested that sampling distance of the experimental design may greatly influence nugget variance and subsequently nugget to sill ratio.

Variogram models can be used not only for kriging purposes but also in several practical applications, including improvement of future grid sampling designs or for assessing temporal changes in the spatial variability of soil properties, as for example organic carbon content (Kravchenko et al. 2006; Worsham, Markewitz, and Nibbelink 2010), which is beyond the scope of this work.

Contour maps of soil OM and CEC in surface soil layer (0–10 cm) were constructed using the kriging interpolation technique, except for CEC under mango orchard where the IDW method was used due to the lack of spatial dependence (Figures 3, 4 and 5). These contour maps exhibit well-defined patches for both the soil properties studied, with varying values of range, and different spatial patterns for the three land covers. These maps are valuable to identify where particular levels of soil OM and CEC are located within a plot.

Figure 3 displays contour maps at 0–10 cm depth under prairie. Both soil OM and CEC exhibit a typical patchy spatial distribution, modeled by exponential semivariograms. The range and therefore the continuity in spatial distributions of both variables were similar; however, the soil OM contour map matched a notably stronger spatial structure than the CEC contour map as nugget to sill ratio was much lower in the former case than the latter. Mapped levels of soil OM varied from 9 to 30 g kg^{-1}, and those of CEC from 26 to 62 mmol(+) kg^{-1}. Patches with highest values for both soil OM and CEC were located at the diagonal connecting upper corner on the left to lower corner on the right of the map (Figure 3); in general a reasonable match of locations with maximum and minimum soil OM and CEC could be visually observed.

The spatial distribution of soil OM and CEC under maize at 0–10 cm soil depth (Figure 4) also displayed a well-structured pattern of spatial variability. This pattern however was relatively smoother, i.e., not so patchy, compared with that under prairie, which is consistent with a spherical semivariogram (Goovaerts 1998; Paz, Taboada, and Gómez 1996). The range of spatial dependence in this case was much greater for CEC than for soil OM, resulting in greater continuity of the former soil property compared to the latter. Mapped values of soil OM varied from 10 to 28 g kg^{-1}, whereas those of CEC were from 26 to 62 mmol(+) kg^{-1}. Maximum values of both soil OM and CEC in Figure 5 were located at the left side of the map.

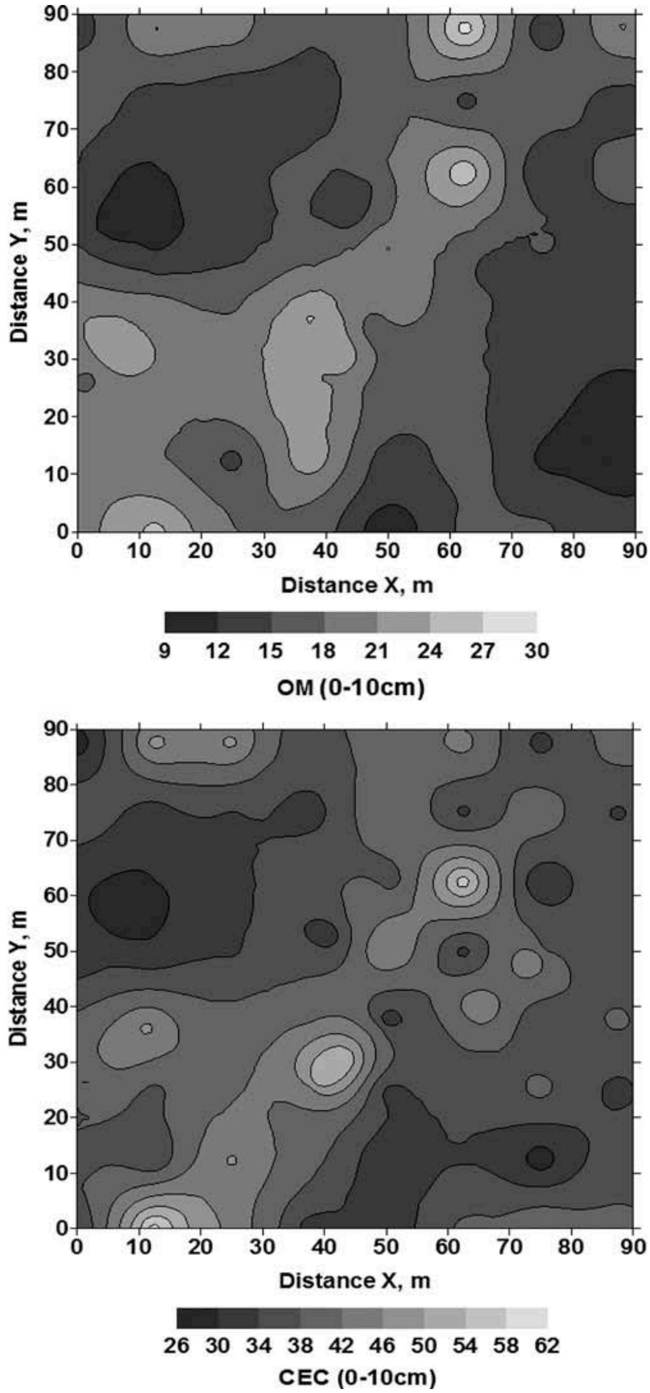


Figure 3. Contour maps obtained by kriging for soil organic matter (OM) and cation exchange capacity (CEC) at 0–10 cm depth under prairie.

Soil OM under mango orchard at 0–10 cm depth exhibited a pattern of spatial structure that was also fitted by a spherical model, but the spatial variability of CEC was described by a pure nugget effect (Figure 5), indicating a lack of continuity of this variable at the studied scale. Interpolation maps under mango orchard showed more uniform spatial distributions compared to maps either under prairie or

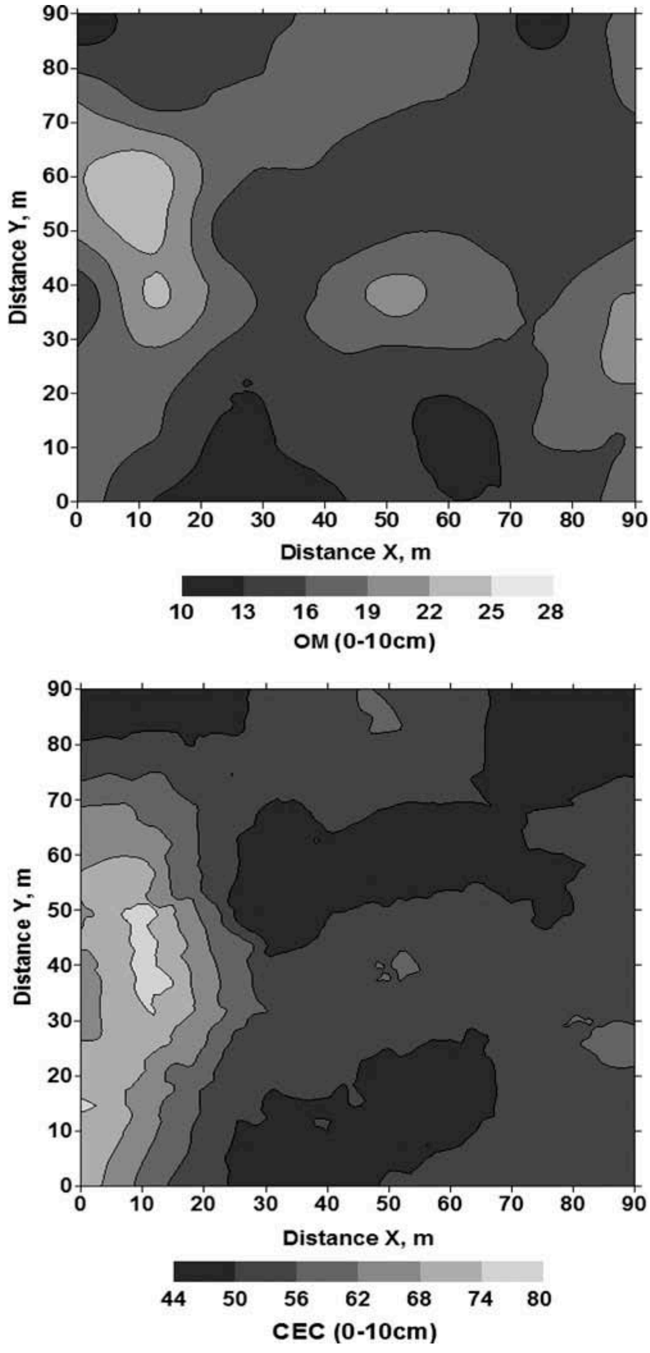


Figure 4. Contour maps obtained by kriging for soil organic matter (OM) and cation exchange capacity (CEC) at 0–10 cm depth under maize.

under maize. Thus, the amplitude of the kriged soil OM map varied from 12 to 36 g kg^{-1}, whereas that of the CEC obtained by the IDW method was between 50 and 80 mmol(+) kg^{-1}.

On average, the amplitudes of mapped soil OM values oscillated about 21 g kg^{-1} and those of CEC about 34 mmol(+) kg^{-1}, respectively, and these amplitudes exhibited little difference between

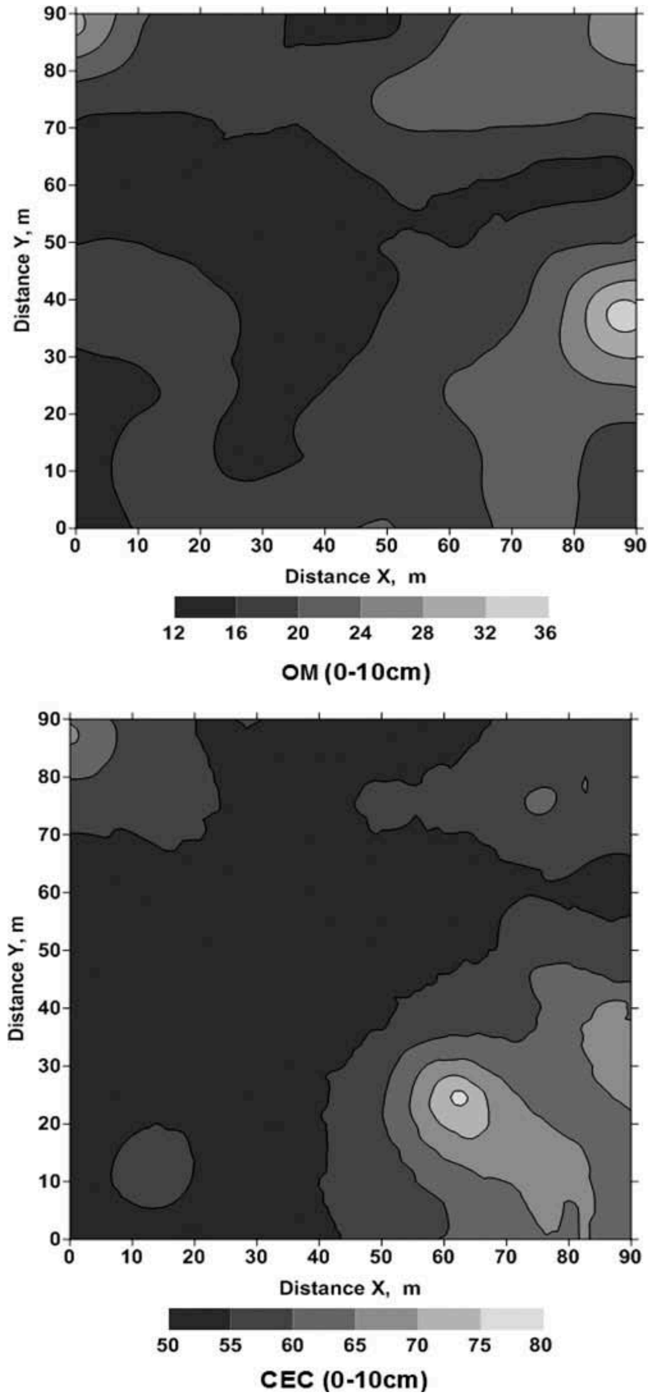


Figure 5. Contour maps obtained by kriging for soil organic matter (OM) and by inverse distance interpolation for exchange capacity (CEC) at 0–10 cm depth under mango orchard.

land uses. However, as stated earlier, the prairie cover displayed the lowest soil OM and CEC values, while highest values of these soil attributes were recorded under mango orchard.

Conclusions

Spatial variability of soil OM and CEC in the studied Oxisol under three different land uses can be summarized as follows:

(1) The soil under mango orchard contained highest soil OM concentrations, while the prairie plot exhibited lower soil OM than maize plot, which could be partly explained by its coarse texture. For the studied land uses and sampling depths, soil OM and CEC were linearly correlated.
(2) Coefficients of variation for soil OM were higher than those for CEC. In addition, the soil OM of the maize plot exhibited lowest coefficient of variation, which could be attributed to soil horizon mixing by annual ploughing operation. Therefore, in statistical terms, the maize plot was more homogeneous than the prairie and the mango plots.
(3) In general, soil OM displayed a higher spatial correlation and was strongly structured than CEC spatial variability. On the other hand, spatial autocorrelation showed a trend to decrease and the spatial structure weakened as a function of soil sampling depth, and this was more apparent for soil OM than for CEC.
(4) Assessing and mapping the spatial distribution of soil OM and CEC provided a framework for spatially implicit comparison of these soil properties in the three land covers studied. Differences found in spatial structure can be applied in addressing practical issues such as improving soil sampling design and detecting temporal changes in soil properties.

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