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USE OF SCALED SEMIVARIOGRAMS IN THE PLANNING SAMPLE OF SOIL CHEMICAL PROPERTIES IN SOUTHERN AMAZONAS, BRAZIL

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ABSTRACT

The lack of information concerning the variability of soil properties has been a major concern of researchers in the Amazon region. Thus, the aim of this study was to evaluate the spatial variability of soil chemical properties and determine minimal sampling density to characterize the variability of these properties in five environments located in the south of the State of Amazonas, Brazil. The five environments were archaeological dark earth (ADE), forest, pasture land, agroforestry operation, and sugarcane crop. Regular 70 × 70 m mesh grids were set up in these areas, with 64 sample points spaced at 10 m distance. Soil samples were collected at the 0.0-0.1 m depth. The chemical properties of pH in water, OM, P, K, Ca, Mg, H+Al, SB, CEC, and V were determined at these points. Data were analyzed by descriptive and geostatistical analyses. A large part of the data analyzed showed spatial dependence. Chemical properties were best fitted to the spherical model in almost all the environments evaluated, except for the sugarcane field with a better fit to the exponential model. ADE and sugarcane areas had greater heterogeneity of soil chemical properties, showing a greater range and higher sampling density; however, forest and agroforestry areas had less variability of chemical properties.

Keywords: geostatistics, Amazonian soils, archaeological dark earth, sampling density.

RESUMO: *USO DE SEMIVARIOGRAMAS ESCALONADOS NO PLANEJAMENTO AMOSTRAL DE ATRIBUTOS QUÍMICOS DO SOLO EM AMBIENTES NA REGIÃO SUL DO AMAZONAS*

A escassez de informações sobre o comportamento espacial dos atributos dos solos na região amazônica tem sido preocupação de muitos pesquisadores. Assim, este trabalho teve como objetivos avaliar a variabilidade espacial de atributos químicos do solo e determinar a densidade amostral mínima para caracterizar a variabilidade desses atributos em cinco ambientes amazônicos. Este estudo foi realizado ao sul do Estado do Amazonas, em área com terra preta arqueológica (TPA), floresta, pastagem, agrofloresta e cana-de-açúcar. Nessas áreas, foram estabelecidas malhas de 70 × 70 m, com espaçamento regular de 10 m, totalizando 64 pontos em cada ambiente. Os solos foram coletados na profundidade de 0,0-0,10 m. Foram determinados os atributos químicos (pH em água, MO, P, K, Ca, Mg, H+Al, SB, CTC e V). Os dados foram analisados utilizando-se técnicas de estatística descritiva e geoestatística. Grande parte dos atributos estudados apresentou estrutura de dependência espacial. O modelo esférico foi o que melhor se ajustou aos atributos químicos nos diferentes ambientes, onde somente a cana-de-açúcar evidenciou melhor ajuste ao modelo exponencial. As áreas de TPA e cana-de-açúcar mostraram maior heterogeneidade dos atributos químicos do solo, apresentando menor alcance e maior densidade amostral, e a área com floresta e agrofloresta apresentaram menor variabilidade dos atributos químicos.

Palavras-chave: geoestatística, solos da Amazônia, terra preta arqueológica, densidade amostral.

INTRODUCTION

Southern Amazonas is characterized by various landscapes, with natural and anthropogenic features. Within this context, areas of Archaeological Dark Earth (ADE) stand out, which include soils of high fertility. These soils are found throughout the entire Amazon region (Petersen et al., 2001; Lehmann et al., 2003; Glaser et al., 2004; Glaser, 2007; Woods et al., 2009). They are usually associated with bodies of water or higher altitude lands, with a notable characteristic of dark coloring and pottery fragments and/or lithic scatters mixed in the surface horizon (Kämpf and Kern, 2005).

In contrast, adjacent low fertility soils covered by forest play an important role in improving soil nutritional quality and physical properties. Consequently, studying these properties is essential for rational management, sustainable productivity, and prediction of the characteristics of forest ecosystems, since forest and soil are connected (Wojciechowski et al., 2009).

Other agroecosystems such as agroforestry, crops with pasture, and sugarcane fields are also in the region under study. However, there are no studies focusing on the variability of soil properties in these environments. In this regard, a main difficulty in studying spatial variability has been finding the appropriate sampling spacing, which, in some circumstances, may affect determination of the behavior of soil properties. Souza et al. (2006a) used the soil-topography relationship to define sampling density in estimating the variability of chemical properties in Oxisols, resulting in a decreased number of samples.

Sampling density is an important factor for soil property determination. Siqueira et al. (2010) stated that about 80-85 % of errors in the application of agricultural inputs, such as fertilizers and soil amendments, may be attributed to poorly planned sampling. Thus, studying aspects of soil sampling to assist in defining the use of sampling techniques and in recommending them for different environments has been a constant concern of researchers (Webster and Oliver, 1990; Van Groenigen et al., 1999; Lark, 2000; Montanari et al., 2005, 2012; Siqueira et al., 2010).

For that reason, some techniques are employed so as to establish a standard for soil sampling that best expresses the soil properties. Many studies have been based on the results of geostatistical analysis (Souza et al., 2006b), using techniques such as the scaled semivariogram with *Sanos* software to assist sample design in other regions (Montanari et al., 2012). Nevertheless, these techniques have not yet been applied in southern Amazonas, though they are fundamentally important for mapping the spatial variability of soils and their properties.

Studies that generate results to assist soil fertility management in the state of Amazonas, Brazil are of great importance. Thus, we aimed to use scaled semivariograms to determine sample design of soil chemical properties in five different environments in southern Amazonas.

MATERIAL AND METHODS

The study was carried out on farms located in the south of the State of Amazonas, Brazil. These farms

are near Santo Antônio do Matupi in municipality of Manicoré, AM, and in the municipality of Humaitá, AM. Soil mapping was carried out for five different environments: a natural environment or forest, soil with anthropic alterations or archaeological dark earth (ADE), pasture areas under brachiaria (*Brachiaria brizanta*) grass, an agroforestry environment, and a sugarcane crop.

The forest area at 7º 54' 44.5" S, 61º 31' 44.7" W and average altitude of 140 m is characterized as a Dense Tropical Rain Forest fragment with 20 to 50 m high trees. Adjacent to this, there is an area composed of Archaeological Dark Earth (ADE) at 07º 55' 02.1" S, 61º 31' 45.2" W, and average altitude of 102 m, under maize cultivation for approximately 120 days at the time of this study. The pasture area at 07º 54 '42 "S, 61º 31' 50" W and an average altitude of 135 m, has been under brachiaria (*Brachiaria brizanta*) grass for approximately 10 years in extensive pasture with around 1.0 animal ha^{-1}. These areas are located in Manicoré. The agroforestry land is at 7º 28' 29" S, 63º 02' 07" W, and average altitude of 63 m, which has been under coffee, cocoa, palm tree, and andiroba, among other crops for around 20 years. The sugarcane field at 7º 54' 38" S and 63º 14' 27" W and average altitude of 70 m has been under burned sugarcane cropping for approximately 10 years. These latter two areas are located in the municipality of Humaitá (Figure 1). A detailed description of the characterization the physical properties was given by Aquino et al. (2015).

The Manicoré environments are on weathered soil originating from Rondonia granite from the Late Precambrian Eon (Brasil, 1978). The environments in Humaitá have old alluvial sediments as source material, which are chronologically from the Holocene Epoch (Brasil, 1978). According to the Köppen classification, the climate is rainy tropical with a short dry season (*Am*), mean temperatures ranging from 25 to 27 °C, and mean annual rainfall from 2,250 to 2,750 mm, with rains concentrated from October to June (Brasil, 1978). Soil types were classified as Red Ultisol in Manicoré and Haplic Cambisol in Humaitá (Embrapa, 2013).

A 70 × 70-m grid covering 0.49 ha was set up in these areas. Soil samples were collected at crossover points within the grid, with regular intervals of 10 m, making for 64 sample points per grid (Figure 1). These points were georeferenced by Garmin Etrex GPS equipment (South American´69). Subsequently, soil samples were obtained from the 0.0-0.1-m layer for analysis of chemical properties.

Exchangeable Ca, Mg and K contents, available P, and potential acidity (H + Al) were determined by of the method of Raij et al. (2001). Based on chemical analysis, sum of bases (SB), cation-exchange capacity (CEC), and base saturation (V) were calculated.

The soil pH was measured with a potentiometer using the 1:2.5 ratio (soil:water) (Embrapa, 1997). Organic carbon content (OC) was monitored by the Walkley-Black method, which was modified by Yeomans and Bremner (1988), and organic matter (OM) was estimated based on OC determination.

Data were analyzed by ANOVA and mean values were compared by the Tukey test at 5 % probability using the Minitab statistical software (Minitab, 2000).

Data exploratory analysis was performed by calculating mean, median, coefficient of variation (CV), skewness, and the Kolmogorov-Smirnov test. The CV was calculated based on the Warrick and Nielsen (1980) criterion that classifies the CV as low (CV < 12 %), medium (from 12-24 %) and high (CV > 24 %).

Semivariograms were designed to determine spatial dependence through geostatistics (Matheron, 1963; Vieira et al., 1983; Isaaks and Srivastava, 1989). Under the theory of intrinsic hypothesis, the experimental semivariogram was estimated by equation 1:

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

where γ(h) = semivariance value at distance h; N (h) = number of pairs of experimental Z observations; Z (x$_i$) = value of the Z property at location x$_i$; and Z (x$_i$ + h) = value of the Z property separated by a distance h from location x$_i$.

The scaled semivariogram was built based on parameters of experimental semivariograms of soil properties, which were scaled through division of semivariances by statistical variance (Guimarães, 1993; Vieira et al., 1997). In this study, semivariograms were scaled to reduce them to the same scale, facilitating comparison among results of different variables. Moreover, we aimed to represent several semivariograms simultaneously to better understand patterns of similarity and causes of spatial variability (Ceddia et al., 2009).

Spherical (Equation 2) and exponential (Equation 3) models were fitted to the scaled experimental semivariograms, which were identified as Sph. (C$_0$, C$_1$+ C$_0$, [(C$_0$/(C$_0$ + C$_1$) × 100], a, R^2):

$$\begin{cases} \hat{\gamma}(h) = C_0 + C_1 \left[\frac{3}{2}\left(\frac{h}{a}\right) - \frac{1}{2}\left(\frac{h}{a}\right)^3 \right], se\, 0 < h < a \qquad (2) \\ \hat{\gamma}(h) = C_0 + C_1, se\, h \geq a \end{cases}$$

$$\gamma(h) = C_0 + C_1 \left[1 - \exp(-\frac{3h}{a}) \right], \; h \geq 0 \qquad (3)$$

where C$_0$ = nugget effect; C$_0$ + C$_1$ = sill; h = distance between experimental observations; and a = spatial dependence range.
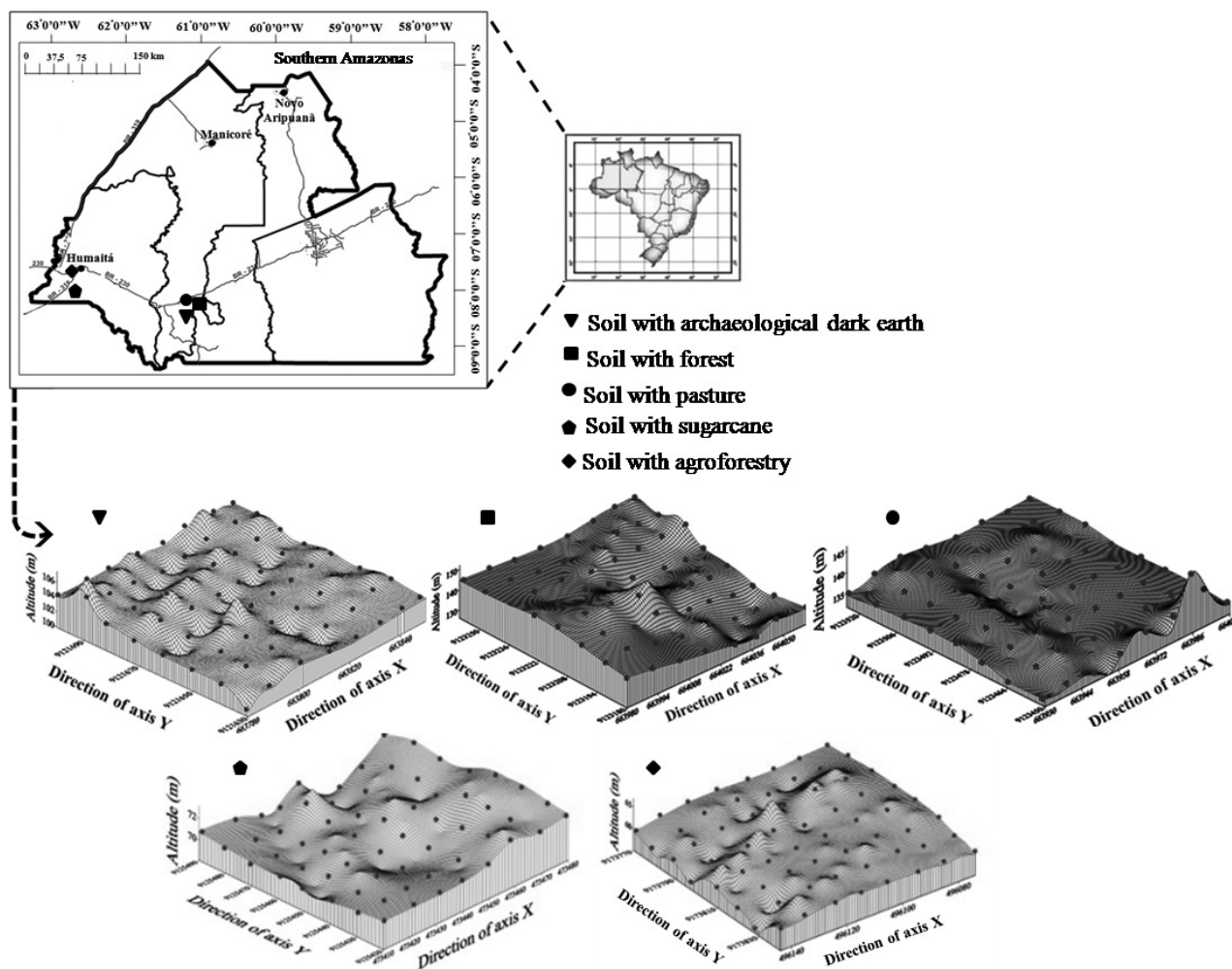
Figure 1. Area location and Digital Elevation Model (DEM) of the environments in southern Amazonas.

Subsequently, scaled semivariograms served as an information source to calculate the minimum number of soil samples to determine the variability of all properties within the areas under study (Equation 4):

$$N= \frac{A}{(a^2)/\ 10000} \qquad (4)$$

where N = minimum number of samples necessary to determine a sample grid; A = total area (ha); and a = semivariogram range (m).

In analysis of the degree of spatial dependence (DSD) of the variables under study, we used the classification proposed by Cambardella et al. (1994) in which dependence values of $[(C_0/(C_0 + C_1) \times 100]$ lower than 25 % are considered strong, values from 25 to 75 % are moderate, and values greater than 75 % have poor dependence.

RESULTS AND DISCUSSION

Mean values of the chemical properties were significantly different among the environments under study (Table 1). The ADE values in the 0.0-0.1-m layer were greater than the values for the forest, pasture, agroforestry and sugarcane lands, which highlighted the improved quality and greater fertility of the soils with ADE.

For ADE, higher values for OM, SB, and V were noted, as well as for the properties of pH, P, Ca, Mg, and CEC. In contrast, other environments have a higher potential acidity (Table 1). This can explain the high fertility of ADE in relation to adjacent lands because, according to Lehmann et al. (2003) and Glaser (2007), ADE soils generally have high fertility, with high levels of P, Ca, Mg, Zn, and Mn, and high content of stable organic matter. On the other hand, Cunha et al. (2009) argued that the high fertility of ADE is strongly related to the molecular

Table 1. Means test of chemical properties for the environments evaluated from the municipalities of Humaitá and Manicoré in southern Amazonas

Property	Forest	ADE[1]	Pasture	Agroforestry	Sugarcane
		Red Ultisol		Haplic Cambisol	
pH(H$_2$O)	3.97 C	6.27 A	4.30 B	3.78 C	4.43 B
H+Al (mmol$_c$ kg^{-1})	74.92 C	28.29 D	61.13 BC	189.52 A	89.64 B
OM (g dm^{-3})	18.66 C	68.19 A	27.47 B	20.58 C	30.48 B
P (mg dm^{-3})	6.09 B	309.4 A	4.61 B	8.19 B	6.36 B
K$^+$ (mmol$_c$ kg^{-1})	1.66 A	1.72 A	1.71 A	1.11 B	0.49 C
Ca^{2+} (mmol$_c$ kg^{-1})	4.77 C	166.02 A	10.27 BC	2.39 C	14.58 B
Mg^{2+} (mmol$_c$ kg^{-1})	2.52 D	29.45 A	4.64 C	1.36 D	8.06 B
SB (mmol$_c$ kg^{-1})	8.94 C	197.19 A	16.62 BC	4.86 C	23.13 B
CEC(mmol$_c$ kg^{-1})	83.86 D	225.49 A	77.74 D	194.37 B	112.77 C
V (%)	11.11 C	87.20 A	21.99 B	2.52 D	21.06 B

[1] ADE: Archaeological Dark Earth. H+Al: potential acidity; OM: organic matter; SB: sum of bases; CEC: cation-exchange capacity; and V: base saturation. Mean values followed by the same uppercase letter at the same depth do not differ from each other significantly by the Tukey test at 5 %.

characteristics of the alkali-soluble fraction within organic carbon (OC) content. These same authors found that *A* horizons in anthropogenic Amazon soils have higher total C content compared to adjacent non-anthropogenic soils.

Most of the properties of the systems under study have similar mean and median values (Table 2), indicating near-normal distribution, which is considered acceptable in geostatistical studies (Gonçalves and Folegatti, 2002). However, some properties have values distant from zero, indicating asymmetric distribution, which is confirmed by high asymmetry values, showing that they are affected by extreme values.

Results of the Kolmogorov-Smirnov test indicated normality for some properties in the lands under study (Table 2). However, most of the variables showed no data normality in the different environments, greater occurring in ADE, agroforestry and sugarcane. Nonetheless, according to Cressie (1991) and Isaaks and Srivastava (1989), data normality is not required for geostatistics; it is enough that the distribution not have very elongated tails, which could compromise kriging estimates, which are based on mean values.

The CVs indicated low variability (CV < 12 %) for pH in all management practices, V in ADE, CEC in pasture, and H+Al and CEC in agroforestry (Table 2). There were medium CVs (12 % < CV > 24 %) for H + Al, OM, Ca, CEC, Mg, SB in ADE; H + Al, and OM in pasture areas; OM, K, SB, P, and Ca in agroforestry; and H+Al, CEC, OM, and K in sugarcane. The other variables had high values (CV > 24 %). It was observed that sugarcane, agroforestry, and ADE had more variables with high CVs, indicating high variability of soil properties (Table 2).

Montanari et al. (2012), Souza et al. (2004), and Wortmann et al. (2009) also found low, moderate, and high CVs for some chemical properties, which may underscore the influence of fertilizer management in cropping systems.

Nevertheless, CV allows comparison of variability among samples of variables with different units, but it does not allow analysis of spatial variability of soil properties or their spatial standard (Camargo et al., 2008). For that purpose, soils chemical properties were subjected to geostatistical analysis to which had spatial correlation, being expressed by fitted semivariogram models (Figure 2). The spherical model was predominant for ADE, forest, agroforestry, and pasture areas. For the sugarcane crop, the exponential model best fit the data (Figure 2e).

According to Carvalho et al. (2002), the spherical model prevails in studies in soil science. In contrast, McBratney and Webster (1983), Bertolani and Vieira (2001), and Siqueira et al. (2010) emphasize spherical and exponential models as those most used in soil and environmental sciences. The fitting of models to properties accounts for the behavior of the properties. According to Isaaks and Srivastava (1989), exponential models are better fitted to erratic phenomena on small scales, whereas spherical models describe properties with high spatial continuity, i.e., less erratic at short distances.

Some variables showed no spatial dependence structure, characterized by the pure nugget effect model (PNE). When the variable under study is spatially independent, the nugget effect is equal to the sill. The PNE could occur due to measurement and sampling errors or undetected micro-variations when taking into account sample spacing larger

Table 2. Descriptive statistics for soil chemical properties in the municipalities of Humaitá and Manicoré in southern Amazonas

Parameter	pH(H$_2$O)	H+Al	OM	P	K$^+$	Ca^{2+}	Mg^{2+}	SB	CEC	V
				Forest – Red Ultisol						
Mean	3.97	74.92	18.66	6.09	1.66	4.77	2.52	8.94	83.86	11.11
Median	3.90	88.00	20.50	5.50	1.50	3.00	2.00	7.05	93.95	8.40
CV (%)	4.79	29.42	35.29	36.13	67.25	101.96	50.58	69.08	26.16	68.34
Ass.	0.74	-0.21	-0.28	0.49	2.97	4.50	1.80	3.27	-0.37	2.99
Nt	0.11*	0.15*	0.13*	0.08ns	0.14*	0.28*	0.15*	0.27*	0.19*	0.26*
				Archaeological Dark Earth – Red Ultisol						
Mean	6.27	28.29	68.19	309.4	1.72	166.02	29.45	197.19	225.49	87.20
Median	6.20	29.50	68.00	298.5	1.40	164.50	30.00	195.20	227.65	86.80
CV (%)	4.71	23.46	19.86	27.93	82.30	16.10	22.04	14.80	12.30	4.11
Ass.	0.58	-0.08	-0.26	0.53	4.66	-0.51	0.27	-0.46	-0.61	-0.20
Nt	0.09ns	0.06ns	0.06ns	0.07ns	0.26*	0.06ns	0.05ns	0.09ns	0.08ns	0.08ns
				Pasture – Red Ultisol						
Mean	4.30	61.13	27.47	4.61	1.71	10.27	4.64	16.62	77.74	21.99
Median	4.25	64.00	27.00	4.00	1.30	8.00	4.00	13.45	77.80	17.35
CV (%)	6.09	22.23	13.59	25.23	67.30	64.06	38.85	51.38	10.40	55.81
Ass.	1.38	-0.48	0.43	1.82	1.58	1.69	0.78	1.39	-0.34	1.32
Nt	0.11*	0.06ns	0.07ns	0.07ns	0.15*	0.16*	0.08ns	0.17*	0.07ns	0.18*
				Agroforestry – Haplic Cambisol						
Mean	3.78	189.52	20.58	8.19	1.11	2.39	1.36	4.86	194.37	2.52
Median	3.80	185.00	20.50	8.00	1.10	2.00	1.00	4.15	191.40	2.20
CV (%)	1.53	9.26	15.48	18.96	21.78	23.11	35.58	23.73	8.98	26.24
Ass.	-0.48	-0.51	0.79	0.57	0.59	1.03	0.60	0.67	-0.51	0.75
Nt	0.06ns	0.05ns	0.09ns	0.04ns	0.07ns	0.09ns	0.10ns	0.28*	0.24*	0.18*
				Sugarcane – Haplic Cambisol						
Mean	4.43	89.64	30.48	6.36	0.49	14.58	8.06	23.13	112.77	21.06
Median	4.50	80.00	30.50	7.00	0.50	15.00	8.00	23.30	107.50	21.6
CV (%)	3.39	23.52	20.52	24.64	22.98	28.63	35.21	29.90	16.27	32.44
Ass.	-0.85	2.96	-0.05	-0.06	0.02	0.07	0.75	0.33	3.30	-0.12
Nt	0.05ns	0.15*	0.07ns	0.04ns	0.04ns	0.03ns	0.07ns	0.06ns	0.19*	0.05*

CV: coefficient of variation; Ass.: asymmetry coefficient; Nt: normality test, at 5 % significance by the Kolmogorov-Smirnov test; H+Al: potential acidity; OM: organic matter; SB: sum of bases; CEC: cation exchange capacity; and V: base saturation. * and ns: significant and non-significant, respectively.

than that necessary to detect spatial dependence (Cambardella et al., 1994; Zanão Júnior et al., 2010).

Degree of spatial dependence (DSD), for scaled semivariograms expressed by the ratio between the nugget effect (C_0) and the sill ($C_0 + C_1$) (Cambardella et al., 1994), was classified as moderate for all environments under study (Figure 2). As suggested by Cambardella et al. (1994), variables with moderate spatial dependence may be due to soil homogeneity.

The range of the scaled semivariograms show that ADE and sugarcane areas have lower spatial dependence and greater variability, with ranges of 35 m, even in different soil classes. In this sense, range values are important measures for planning and experimental evaluations, as range can assist in sampling procedure definition (McBraitney and Webster, 1983; Souza et al., 2009).

In this respect, the range of the scaled semivariogram was used to estimate the minimum number of samples to characterize soil spatial variability of soil chemical properties (Table 3). The ADE and sugarcane environments are more heterogeneous in chemical properties and so they
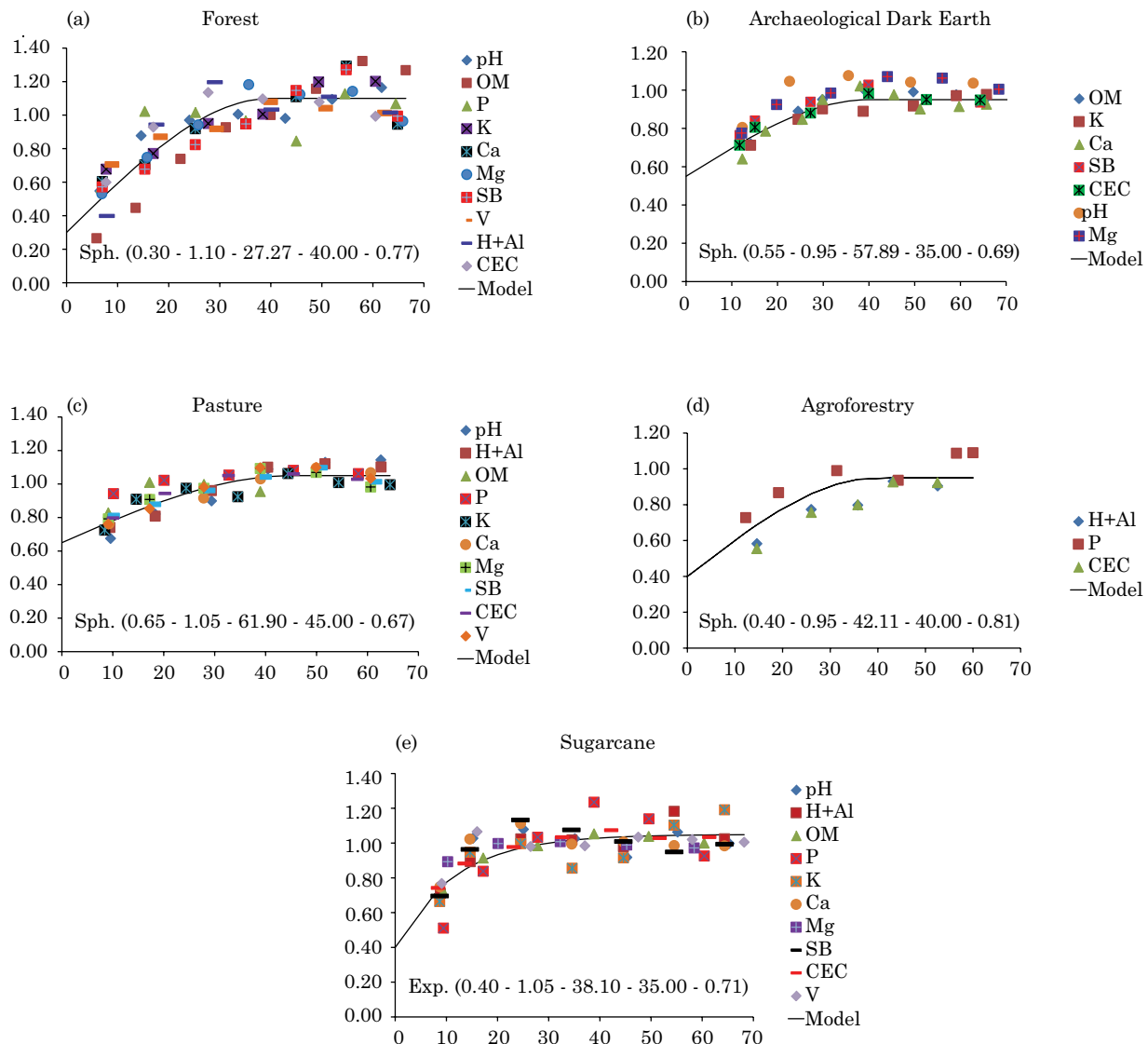
Figure 2. Scaled semivariograms for chemical properties of environments in municipalities of Humaitá and Manicoré in southern Amazonas. Exp.: exponential; Sph.: spherical; [model (nugget effect - sill - DSD - R² - range - residue)]. DSD: degree of spatial dependence; R²: coefficient of determination.

require a higher number of samples to analyze variability with a sampling density of eight points ha⁻¹ and spacing of 35 m. This aspect may be connected to intensive use of the soil surface layers, which are more heterogeneous. In contrast, the agroforestry area had lower variability for soil chemical properties; consequently, the sampling density required is lower than in the other environments (Table 3).

It may be seen that pasture land and forest had the same behavior, with a sampling density of six points ha⁻¹. Since these areas have the same soil class, this result may be due to the short time that establishment of the extensive

pasture system had to cause changes in soil characteristics (Barreto et al., 2006), as well as the proper use and management of pasture areas by the producer.

In this study, it was possible to estimate spacing and sampling density values in different environments in southern Amazonas. The ADE and sugarcane fields required greater sampling density (eight points ha⁻¹). These values may serve as basis for further studies on soil mapping since these environments represent the region and there are few studies of this nature for these environments.

Table 3. Minimum sampling density and spacing based on the range estimated by scaled semivariograms for soil chemical properties in different environments studied in southern Amazonas

Sample design	Forest	ADE	Pasture	Agroforestry	Sugarcane
	Red Ultisol			Haplic Cambisol	
Sampling density (points ha^{-1})	6	8	6	5	8
Spacing (m)	40	35	40	45	35

ADE: archaeological dark earth.

CONCLUSIONS

Archaeological Dark Earth (ADE) had better chemical quality with the lowest potential acidity.

The spherical model best fitted the chemical properties in the different environments, except for sugarcane, which was better served by the exponential model.

ADE and sugarcane had the greatest heterogeneity of chemical properties and, consequently, a lower range and the higher sampling density. The agroforestry area had the lowest variability of chemical properties.

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