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SPATIAL VARIABILITY OF SOIL FERTILITY UNDER AGROFORESTRY SYSTEM AND NATIVE FOREST IN EASTERN AMAZONIA, BRAZIL

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Abstract

The usage of spatial tools might be helpful in the optimization of decision-making regarding soil management, with technologies that assist in the interpretation of information related to soil fertility. Therefore, the present study evaluated the spatial variability of chemical attributes of the soil under an agroforestry system compared to a native forest in the municipality of Tomé-açu, Eastern Amazon, Brazil. Soil samples were performed at 36 points arranged in a 55 x 55 m grid. The soils were prepared and submitted to analysis in order to determine pH in H_2O, exchangeable calcium, magnesium, potassium and aluminium, available phosphorus, potential acidity, organic matter, bases saturation and aluminium saturation. For each soil attribute, the spherical, gaussian and exponential models were adjusted. After the semivariograms fitting, data interpolation for assessment of spatial variability of the variables was performed through ordinary kriging. The spherical and gaussian models were the most efficient models in estimation of soil attributes spatial variability, in most cases. Most of variables presented a regular spatial variability in their respective kriging maps, with some exceptions. In general, the kriging maps can be used, and we can take them as logistical maps for management and intervention practices in order to improve the soil fertility in the study areas. The results principal components indicate the need for integrated management of soil chemical attributes, with localized application of acidity correctors, fertilizers and other types of incomes, using the spatial variability of these fertility variables.

Keywords: Geostatistics. Income optimization. Kriging maps. Precision agriculture and silviculture. Soil chemical attributes.

1. Introduction

Agroforestry systems are a viable alternative for agricultural and forestry production to small and large farmers, since these systems present a diversification of production, in addition to contributing to the improvement of the characteristics of cultivated soils (Dhanya et al. 2013; Arévalo-Gardini et al. 2015; Laudares et al. 2017). Agroforestry crops have been widely used in Eastern Amazon, especially in the

Municipality of Tomé-açu, state of Pará, where agricultural producers have performed many planting experiments combining agricultural, forest and/or animal species (Bolfe and Batistella 2011).

In this region, as well as in most of the Brazilian tropical region, agricultural and agroforestry systems are inserted in areas of soils with low natural fertility and high acidity. This means that many producers have to resort to ostensible use of fertilizers and liming. Thus, the knowledge regarding fertility conditions in which the cultivated soil is inserted is considerably important for planting planning. However, homogeneous assessment of soil quality can lead to sampling errors, because the attributes of this soil can be highly influenced by the space variability (Rahman et al. 2013; Schwab et al. 2015; Rosemary et al. 2017).

This is one of the main prerogatives of precision agriculture and precision silviculture, which consist of the rationalization of resources in order to optimize production, based on the concept of localized application of fertilizers and other kinds of inputs. Such practices can turn the correction of problems more precise and efficient, leading to an increased crop productivity. This makes it important to map the attributes that are intended to be managed in the planting area, among which the soil fertility attributes highlight (Fu et al. 2010; Suzuki et al. 2012; Vasu et al. 2017).

The usage of tools based on spatial assumptions can be extremely helpful in the optimization of decision making with regard to soil management. This stands out the importance of developing technologies that help the interpretation of information regarding soil fertility based on the spatial dependence of such attributes (Zhang et al. 2010; Metwally et al. 2019).

The geostatistics plays an important role as an efficient technique for soil fertility assessment, since the soil management and conservation in agroforestry systems and other kinds of soil coverages depends on the efficiency in the soil evaluation (Moshia et al. 2014). However, only a few studies have been developed with focus to spatial variability of soil atributes under agroforestry system aiming to auxiliate the management of soil protection and fertilization (Silva et al. 2016; Silva et al. 2018; Panday et al. 2019). Therefore, the present study assessed the spatial variability of soil chemical attributes in an area of agroforestry system (AFS) compared to an adjacent forest (FOR), as a reference area, in the Municipality of Tomé-açu, Eastern Amazon, Brazil.

2. Material and Methods

Study Area

The study area belongs to Matsunaga Farm, located in the Microregion of Tomé-Açu, belonging to the Mesoregion of the Northeast of the State of Pará, Eastern Amazon, Brazil (2º 40’ 54’’S and 48º 16’ 11’’ W). The climate is humid mesothermal tropical, classified as Ami according to Koppen. The average annual temperature is 25 ºC. The average annual precipitation is 2250 mm, with a relative humidity of 80%.

The predominant forms of natural vegetation in the area are the Dense Forest of the Low Plateaus and Dense Forest of the Plateaus, in addition to the preponderance of Secondary Forests, according to the classification proposed by IBGE (2012). The predominant soils in Tomé-açu are the Oxisols, with texture ranging from medium to clayey. The predominant reliafe is flat to smooth wavy (IDESP 2011). The soil from the study area is classified as Yellow Oxisol distrophic. The two study sites (forest and agroforestry system) are adjacent (Figure 1).

For characterization purposes, 10 plots of 300 m² (30 x 10 m) were established, distributed in a completely randomized way in the Agroforestry (AFS) and Native Forest (FOR) systems, and the sampling of ten composite samples deformed at depth 0-0.2 m per system were made with the aid of a drill auger. Determinations of the granulometric fractions (sand, silt and clay) of the soil were carried out, with results ranging from soft to sandy sand to a depth of 0-0.2 m (Table 1).

Management History and Areas Characterization

The areas and their management history and characteristics are described below:

Agroforestry system (AFS): Plantation of 15.73 ha, composed by Cocoa (*Theobroma cacao* L.), with 14 years of implantation and 4 x 4 m spacing; Amazonian mahogany (*Swietenia macrophylla* King), 25 years old and 8 x 8 m apart; and Coconut palm (*Cocus nucifera* L.) with 18 years of implantation and 10 x 10 m spacing. Previously, the area consisted of a black pepper plantation spaced in 1 x 1 m, which received an application of dolomitic limestone of approximately 2 t ha^{-1} and an application of NPK fertilizer mixture in the composition 10-28-20 of 2 t ha^{-1}. All these fertilization practices were carried out in a pit. In the implementation of AFS, 1 t ha^{-1} of dolomitic lime (Total Neutralization Power: 90%) and 1 t ha^{-1} of phosphate fertilizer containing calcium, magnesium, and micronutrients (Yoorin) were applied. Both applications were performed only in the pit of the Cocoa plants. In addition, 1 t ha^{-1} of dolomitic lime, 0.6 t ha^{-1} of bone meal and 90 g of KCl per plant were applied in coverage, which is carried out annually. Before planting, the soil was prepared with a superficial cross harrow, using a disc harrow. In the area, a mowing is performed with a brush cutter attached to a tractor, every six months. The remaining vegetal material from the mowing is left on the agroforestry soil surface.

Native Forest (FOR): secondary vegetation of 14.98 ha, predominantly from dense and mixed ombrophilous forest, with 30 years of natural regeneration.

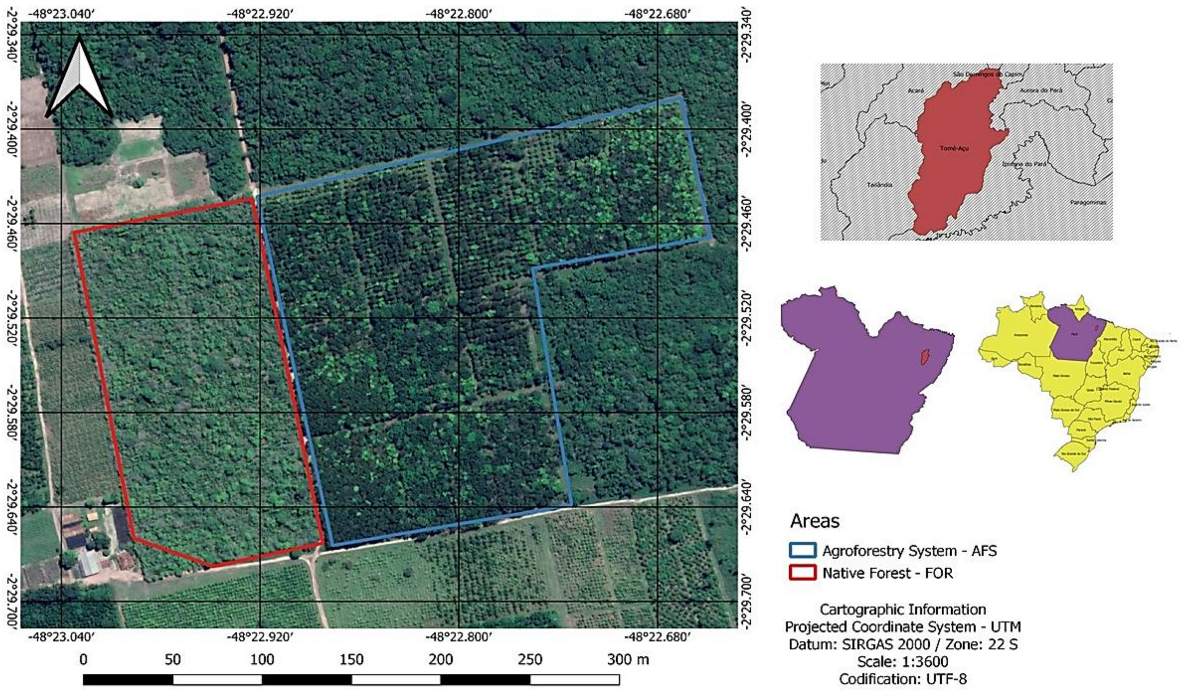

Figure 1. Location map with delimitation of agroforestry system (AFS) and native forest (FOR).

Table 1. Granulometry and textural type of an Oxisol at depth 0-0.2 m under Agroforestry System and Native Forest, in Tomé-açu, Pará.

Granulometric Fraction	System	
	Agroforestry System (AFS)	Native Forest (FOR)
	g dm^{-3}	
Coarse Sand	506.8	656.5
Fine Sand	273.0	195.5
Silt	948.0	483.0
Clay	125.3	998.0
Textural Type	Loamy Sand	Sand

Plots Spacialization and Soil Sampling

The soil sampling was carried out at 72 collection points (36 points in each area) in February 2015, systematically distributed in a regular 55 x 55 m grid, totaling, approximately, 30 ha sampled (Figure 2).

At each point, 5 simple samples were collected with distances of 5 m from the origin point, which were mixed and homogenized to obtain a soil composed sample. For soil sampling, a drill auger (for deformed samples) was used at a depth of 0.2 m. At each collection point, the coordinates were marked in the UTM (Universal Transverse Mercator) format, considering Fuso 22M and Datum WGS 84. The GPS device used belongs to the Garmin Interface eTrex model.

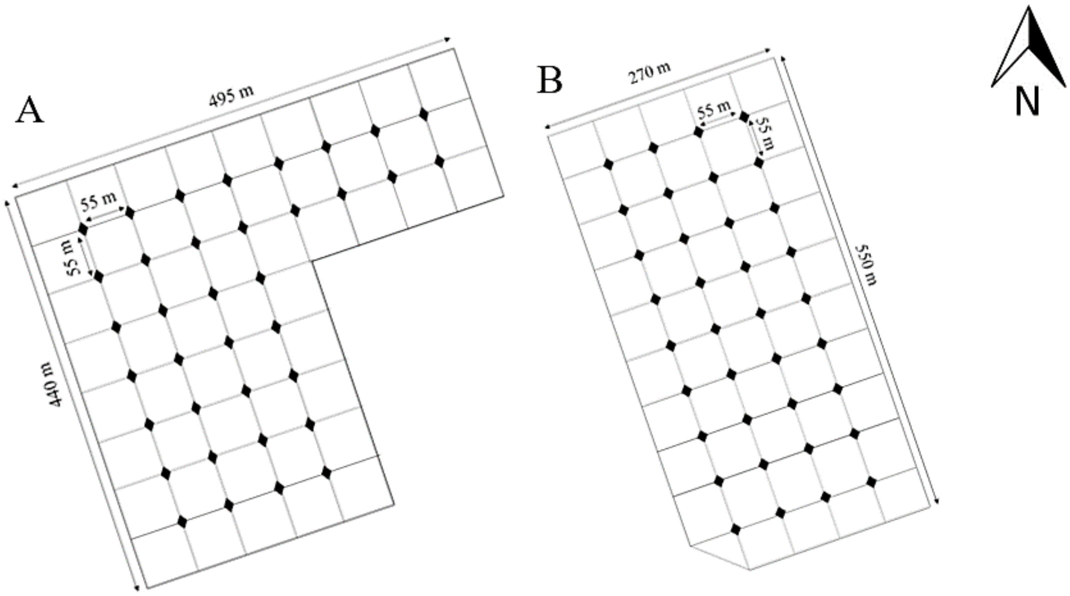

Figure 2. Samples spatialization for grid formation in A - Agroforestry System and B - Native Forest.

Assessment of Soil Chemical Attributes

For chemical analysis, the samples were separated and put to dry in the air and later sieved with a 2 mm mesh sieve, obtaining Air-dried Fine Sand (ADFS), in order to determine the following attributes: pH in H_2O; exchangeable calcium (Ca), magnesium (Mg), potassium (K) and aluminum (Al); available phosphorus (P), potential acidity (H+Al); soil organic carbon for posterior calculation and determination of soil organic matter (S.O.M.). Bases saturation (V%) and aluminum saturation (m%) were also calculated based on the exchangeable cations and potential acidity. The soil analyses, calculations and determinations followed the methodology described by Embrapa (2009).

Geostatistical Analysis

An exploratory analysis of the variables was carried out using the following parameters: mean (m), variance (ℓ2), standard deviation (ℓ), coefficient of variation (CV%), skew-ness, kurtosis and normality test by Kormogorov-Smirnov significant at the 5% level. The variables that did not show normality by the test ($p \leq 0.05$) were submitted to transfor-mation to normalization through fitting of Box-Cox model, using the Minitab 15 software.

Based on the positioning of each soil sample, adjustment was carried out for three semivariogram models for each soil variable: Spherical model (Eq. 1), Gaussian model (Eq. 2) and Exponential model (Eq. 3), aiming to estimate the spatial variability of the chemical attributes of the soil.

$$y(h)=C_0+C_1*\left[\frac{3}{2}*\frac{h}{a}-\frac{1}{2}*\left(\frac{h}{a}\right)^3\right] \quad (1)$$

$$y(h)=C_0+C_1*\left[1\text{-exp}\left(-3*\left[\frac{h}{a}\right]^2\right)\right] \quad (2)$$

$$y(h)=C_0+C_1*\left[1\text{-exp}\left(-3*\left[\frac{h}{a}\right]\right)\right] \quad (3)$$

In which, y(h): Estimated variable; C_0: nugget effect; C_1: contribution C_0+C_1: sill, h: distance between the points, α: range, and exp: exponential.

In order to verify which model obtained the best fitting, the following criteria were considered: lesser nugget effect and higher sill; higher spatial dependence degree (SDD) measured by the sill/nugget effect ratio, through the formula: SDD, expressed in percentage (%). The SDD was considered weak with 75% or more, moderate between 25% and 75%, and strong with less than 25% (Cambardella et al. 1994); the range could not be greater than the half of grid dimension (distance between the two most distant sampling points); smallest error, measured from the sum of residual squares (SQR); and higher determination coefficient (R^2). To adjust the semivariogram models and choose the best model for each variable, the GS+ software.

After calculating the semivariogram, the variables analyzed were interpolated to estimate the non-sampled area. To perform the estimation, ordinary kriging was used, assuming a linear association between the samples, since a systematic sampling was adopted in both study areas. From this estimate, an interpolation map was created for each of the variables, using ArcGIS 10.1 software. Among selected semivariogram models, only those with suitable values of R^2 (not extremely low) and SQR (not extremely high), with moderate or strong spatial dependence and with range lower than grid half dimension, were submitted to data interpolation data by kriging.

Ordination Assessment

The variables were also submitted to principal components analysis (PCA), through the formation of new components (axes) and usage of the two first components for creation of a graph with the variables' vectorial disposition and sampling points dispersion from both study areas (AFS and FOR). PCA was performed with the aim of assessing the responsiveness of the variables in relation to the sampling points.

3. Results

Variables Exploratory Assessment

Most of averages were higher than their respective variances, which normally characterizes a more homogeneous distribution of the data (Table 2). The greatest variability (CV > 100%) was found for P in AFS. The vast majority of the studied attributes had a coefficient of variation considered moderate (60%> CV ≥ 12%). Exception is given to pH in H_2O which, in both areas, presented a low coefficient of variation (CV <12%).

Regarding normality, pH in H_2O, Mg, H+Al, S.O.M. and m% variables showed normality in AFS. On the other hand, Ca, Al, P, K and V% were presented a distribution without normality. In FOR, Ca, Mg, K and V% had a non-normal distribution, turning necessary their transformation by Box-Cox model before the semivariogram assessment.

Semivariograms Fitting

Table 3 shows the results for cross validation of semivariogram estimates. In general, the values, specially Mean Standard Error, were considered suitable and satisfactory. All variables showed adjustment of semivariogram models with sill well established and a nugget relatively low, despite presenting considerable variation in the quality of the adjustments of such models. The spherical model and the Gaussian model were the ones that generated the best adjustments to the data based on the statistical criteria established (Table 4).

The spherical model showed the best fitting for 5 of the 9 soil fertility variables under agroforestry and 3 of the 9 soil variables under natural vegetation. Basically, pH in H_2O, Ca, Al, H+Al and P were the variables best expressed by this model in AFS. In FOR, the variables Ca, K and V% showed better adjustments with the spherical model. The Gaussian model, in turn, showed a better fit in three soil properties in AFS (K, S.O.M. and V%) and FOR in 5 variables (pH in H_2O, Mg, Al, K and m%). With regard to range (α), most of soil attributes presented suitable values, with exception to Al and S.O.M., which showed range higher than the half of grid size. Related to spatial dependence index (SDI), the models selected had satisfactory spatial dependence, in general. Most of soil chemical attributes showed strong spatial dependence in AFS and FOR, with exception to some variables, which showed moderate spatial dependence.

The R^2 in the AFS area ranged from 17.5 to 98.8% while the R^2 of the semivarogram models for FOR showed a variation from 23.3% to 76.2%. In AFS, the variables whose equations presented the highest R^2 were: Ca (98.8%), pH in H_2O (97.5%) and P (92.4%), all with spherical model. In FOR, the attributes with the best coefficients of determination were: H+Al, expressed by the exponential model, with 76.2%; available P, better estimated by the exponential model, with 75.8%; and Ca, expressed by the spherical model, with logarithmic transformation, of 74.9%. S.O.M. semivariogram showed extremely low R^2 values and high SQR in both areas. Additionally, this variable presented excessive high values of range in FOR. m% also presented high values of SQR in both areas as well as Al in FOR.

When comparing the quality criteria for the adjustment of each variable between the two areas under study, it is possible to note that, in general, the models adjusted for the AFS variables highlight in comparison to the same data for FOR. In general, AFS presented less nugget effect, greater range, higher level, greater spatial dependence, greater R^2 and less residual error.

Table 2. Descriptive statistics of soil chemical attributes in an Agroforestry System (AFS) and a Native Forest (FOR).

Attributes	m	ℓ	ℓ²	CV%	S	K	N
	Agroforestry System (AFS)						
pH in H_2O	5.3886	0.1860	0.0346	3.45	-0.25	-0.68	p>0.15
Ca	0.6599	0.2805	0.0787	42.51	0.93	2.03	p<0.05
Mg	1.0501	0.4128	0.1704	39.31	0.24	0.12	p>0.15
K	0.0054	0.0024	0.00001	44.64	0.41	0.04	p<0.05
Al	0.4406	0.2026	0.0411	46.00	1.38	2.30	p<0.05
H+Al	4.3711	0.5556	0.3087	12.71	0.63	0.47	p>0.15
P	2.0110	2.0760	4.3110	100.00	1.53	1.12	p<0.05
S.O.M.	19.322	4.4970	20.2277	23.28	1.07	0.84	p>0.05
V% (%)	30.4700	13.260	175.8400	43.51	4.11	21.70	p<0.05
m% (%)	20.190	9.9600	99.2500	49.34	0.36	-0.60	p>0.05
	Native Forest (FOR)						
pH in H_2O	5.2854	0.2652	0.0703	5.02	0.01	-0.68	p>0.05
Ca	0.7494	0.4501	0.2026	60.05	1.71	2.57	p<0.05
Mg	0.4169	0.1528	0.0234	36.65	1.41	3.29	p<0.05
K	0.0059	0.0024	0.00001	41.35	1.63	2.44	p<0.05
Al	0.5884	0.2017	0.0407	34.28	-0.36	-0.45	p>0.15
H+Al	5.6280	1.0040	1.0070	17.83	0.04	-0.84	p>0.15
P	0.3609	0.1081	0.0117	29.94	0.30	-0.75	p>0.15
S.O.M.	23.897	3.5980	12.9460	15.06	0.34	-0.68	p>0.15
V% (%)	17.240	6.9900	48.8900	40.57	0.85	-0.17	p<0.05
m% (%)	35.750	14.7300	216.9200	41.20	-0.19	-0.41	p>0.15

In which, m: mean; ℓ²: variance; ℓ: standard deviation; CV%: coefficient of variation; S: skewness; K: kurtosis; N: normality; Ca, Mg, K, Al and H+Al given in $cmol_c\ dm^{-3}$; P given in $mg\ dm^{-3}$ and; S.O.M. given in $g\ kg^{-1}$.

Table 3. Cross Validation data for the semivariogram models.

Variables	Model	Standardized Mean	Standardized Mean Square Root	Mean Standard Error
		Agroforestry System (AFS)		
pH em H_2O	Spherical	-0.034990	0.786700	0.28280
Ca	Spherical	-0.055900	1.136460	0.259470
Mg	Exponential	0.007600	0.961400	0.392010
Al	Spherical	0.007700	0.444700	0.497800
H+Al	Spherical	0.016480	0.997480	0.637370
P	Spherical	0.081690	4.473100	0.494930
K	Gaussian	0.000005	0.010130	0.203807
S.O.M.	Gaussian	-0.016360	0.895860	3.852450
V%	Gaussian	-1.561400	59.295670	0.114960
m%	Exponential	0.026000	0.927800	11.073500
		Natural Forest (FOR)		
pH em H_2O	Gaussian	0.004970	0.918280	0.284400
Ca	Spherical	-0.043900	1.400198	0.279300
Mg	Gaussian	0.001790	0.885160	0.187570
Al	Gaussian	0.005210	1.010440	0.202540
H+Al	Exponential	-0.015170	0.757790	1.250600
P	Exponential	-0.026600	0.788440	0.120920
K	Spherical	-0.000001	0.000020	13.900000
S.O.M.	Gaussian	-0.006790	1.261140	2.881660
V%	Spherical	-0.143840	28.081900	0.221420
m%	Gaussian	0.004980	0.799020	19.083260

Table 4. Fitting quality parameters of the selected models for each soil chemical attributes in an Agroforestry System (AFS) and a Native Forest (FOR).

Attributes	Selected Model	C_0	C_0+C_1	SDI (%)	α (m)	SDD	R^2 (%)	SQR
				Agroforestry System (AFS)				
pH in H_2O	Spherical	0.023	0.047	47.87	49.86	M	97.5	0.029
Ca	Spherical	0.012	0.047	24.75	43.87	S	98.8	0.009
Mg	Exponential	0.000	0.134	0.08	37.30	S	43.3	0.011
Al	Spherical	0.023	0.193	11.95	45.01	S	74.3	0.127
H+Al	Spherical	0.059	0.322	18.10	74.93	S	84.3	0.696
P	Spherical	0.043	0.168	24.71	19.94	S	92.4	0.181
K	Gaussian	0.000	0.039	0.26	56.10	S	78.6	0.000
S.O.M.	Gaussian	8.540	17.090	49.97	113.90	M	17.5	165.000
V %	Gaussian	0.002	0.010	18.18	44.38	S	42.0	0.004
m %	Exponential	15.000	91.000	16.48	27.58	S	79.0	17035.0
				Native Forest (FOR)				
pH in H_2O	Gaussian	0.056	0.125	44.44	225.00	M	44.2	0.005
Ca	Spherical	0.022	0.045	44.89	0.10	M	74.9	0.009
Mg	Gaussian	0.022	0.046	48.90	428.00	S	37.5	0.002
Al	Gaussian	0.034	0.069	49.92	493.00	M	63.3	0.000
H+Al	Exponential	0.383	1.712	22.37	181.70	S	76.2	0.362
P	Exponential	0.001	0.013	10.58	83.50	S	75.8	0.000
K	Spherical	710.000	14590.0	4.87	0.30	S	44.1	0.000
S.O.M.	Gaussian	5.100	41.200	12.38	293.10	S	65.4	285.000
V %	Spherical	0.014	0.028	49.82	0.10	M	57.0	0.002
m %	Gaussian	104.200	208.500	49.88	0.10	M	44.4	106021.0

C_0: nugget, $C_0 + C_1$: sill, SDI: spatial dependence index, α: range, SDD: spatial dependence degree (W: weak, M: moderate, S: strong), R^2: coefficient of determination, SQR: residuals sum of square.

Kriging

Mostly, the kriging maps showed a suitable and satisfactory representation of the spatial variability, with exception for some maps. These tendencies may represent an error of variability estimation. The patterns of spatial distribution of attributes in AFS, it was noticed greater uneven spatial variability (Figure

3 and 4). Unfortunately, the best models selected for S.O.M. and m%, for AFS and S.O.M. and m% for FOR showed exceptionally low values of R^2 and/or extremely high levels of SQR, as well as elevated values of range. Therefore, the semivariogram models selected for these variables were not able to be submitted to data interpolation by kriging.

The predominant values of pH in H_2O from AFS is ranging from 5.24 to 5.36 and from 5.36 to 5.48 (Fig. 3-A). Only a small part of the AFS area had pH values within 5.60 and 5.72, which fall within the pH range of 5.5 to 6.5. In FOR, most of the area has pH values between 4.95 and 5.14 (Fig. 4-A).

Both Ca and Mg had a spatial distribution with considerable variations in AFS (Figure 3-B; Figure 3-B). The results of the potential acidity (H+Al), in turn, corroborate those results found for Al with regard to the spatial distribution in both study areas. FOR had its area predominantly occupied by H+Al values ranging from 5.68 to 6.3 $cmol_c\ dm^{-3}$ (Figure 4-E), whereas in AFS, this attribute showed predominance between 3.79 and 4.6 $cmol_c\ dm^{-3}$ (Figure 3-E). For V%, FOR showed a predominance of values between 11.2 and 15.6% (Figure 4-I), while AFS presented values occupying most of the area between 28.9 and 32.3% (Figure 4-I), with small patches of particular major and minor intervals.

Ordination Assessment

For the two first components, eigenvalues were higher than 1 and therefore were satisfactory (Table 5). Regarding percentage of variance, components 1 and 2 presented 67,87 % of accumulated variance, which is can be considered suitable to explain the relationship between the soil fertility attributes from both areas with their respective sampling points.

The P, Mg, V% and pH were more responsive to sampling points belonging to AFS, while m%, Al, H+Al, S.O.M., K and Ca were more related to points from FOR (Figure 5). Mg, V% and pH presented more relationship among them and a negative relationship with m% and Al and, finally, H+Al, K, Ca and S.O.M. were highly related among each other and had a negative relationship with P.

Table 5. Eigenvalues and variance values for principal components formed soil chemical attributes in an Agroforestry System (AFS) and a Native Forest (FOR).

Components	Eigenvalue	Percentage of Variance (%)	Accumulated Variance (%)
1	4,9679	49,679	49,679
2	1,8185	18,185	67,864
3	0,9217	9,217	77,080
4	0,8587	8,587	85,667
5	0,7957	7,957	93,623
6	0,2984	2,984	96,608
7	0,2155	2,155	98,762
8	0,0908	0,908	99,670
9	0,0252	0,252	99,922
10	0,0078	0,078	100,000

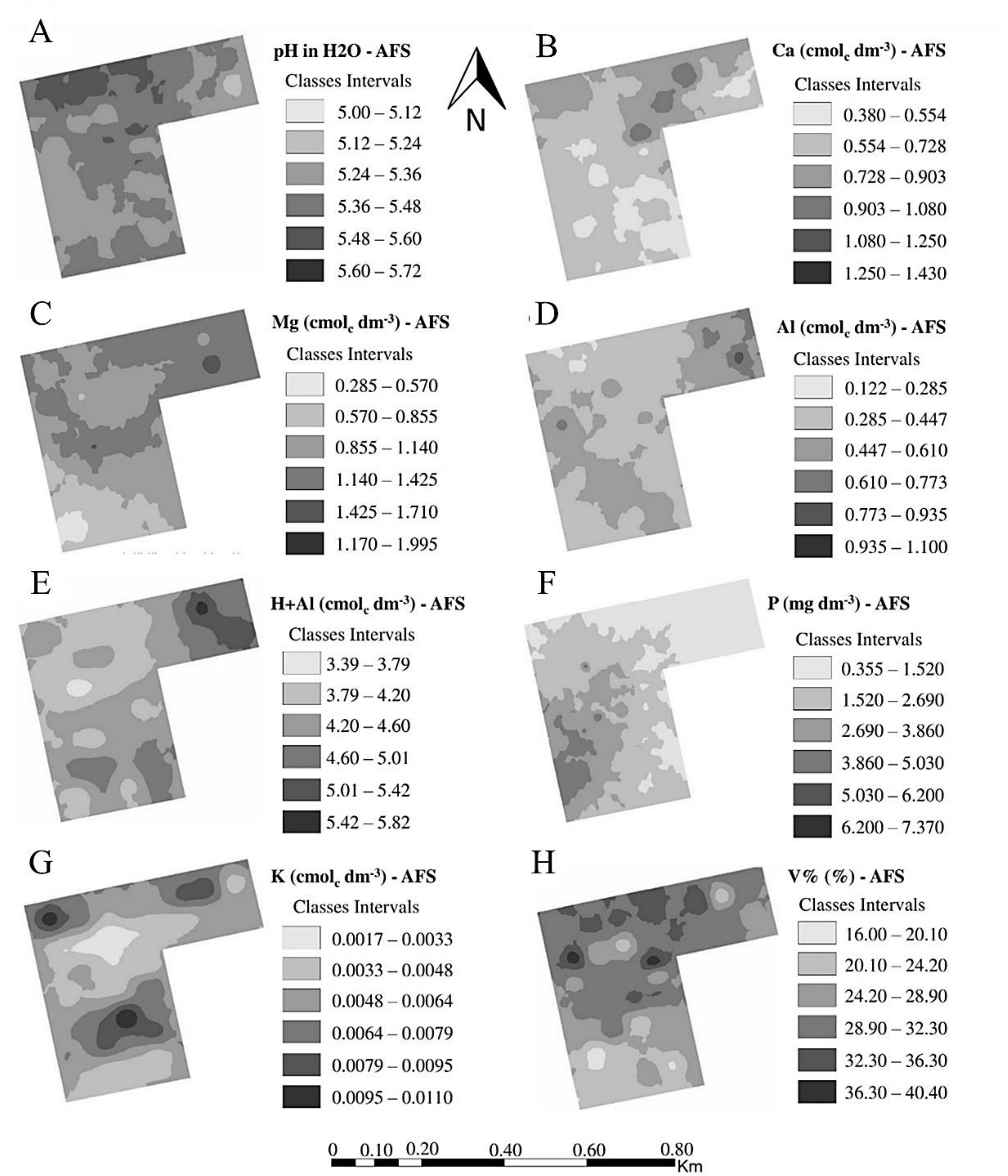

Figure 3. Kriging maps of soil chemical attributes in an Agroforestry System, notably: A – pH in H2O; B – Ca; C – Mg; D – Al; E - H+Al; F – P; G – K; H – V%.

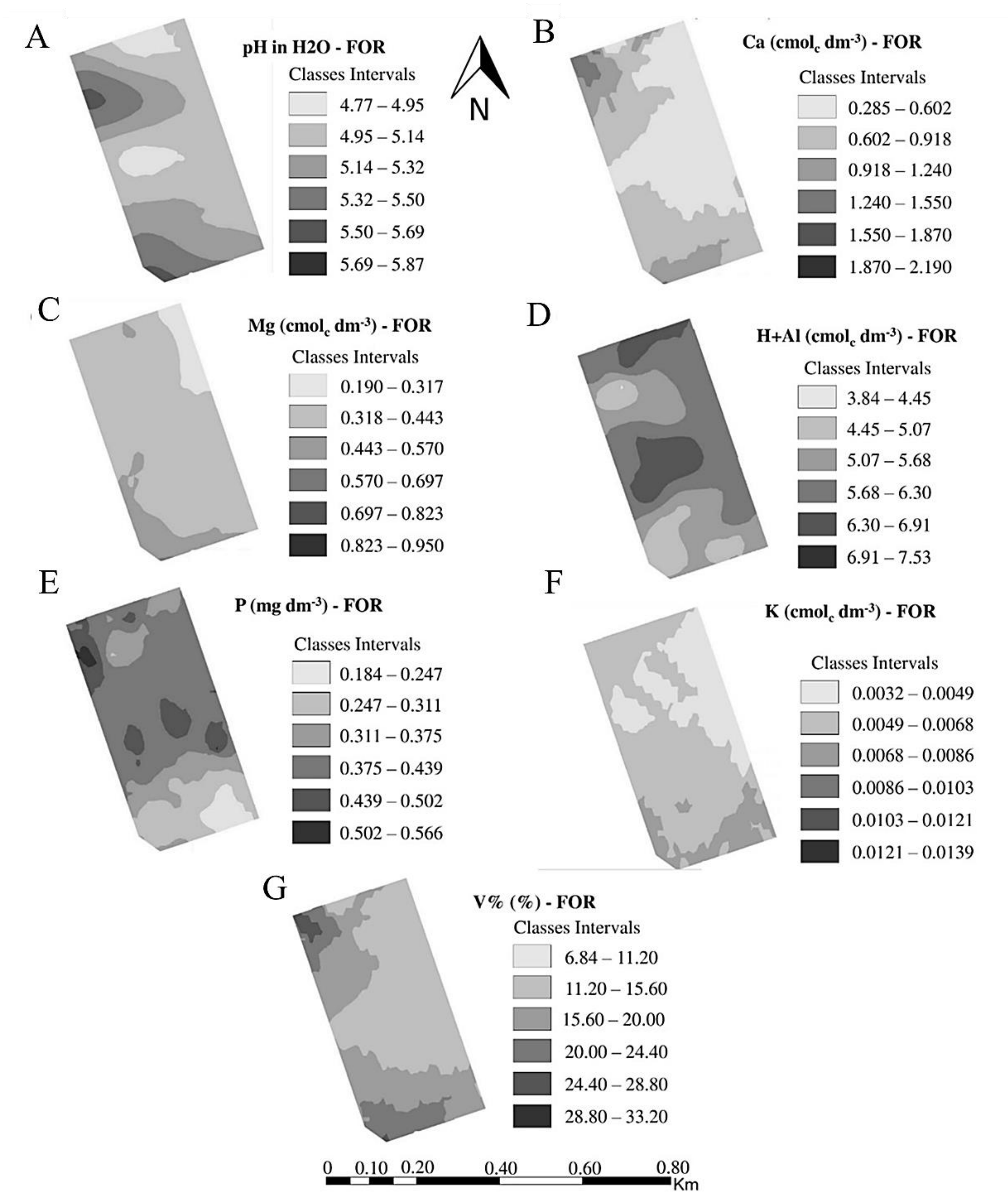

Figure 4. Kriging maps of soil chemical attributes in a Native Forest, notably: A – pH in H2O; B – Ca; C – Mg; D - H+Al; E – P; F – K; G – V%.

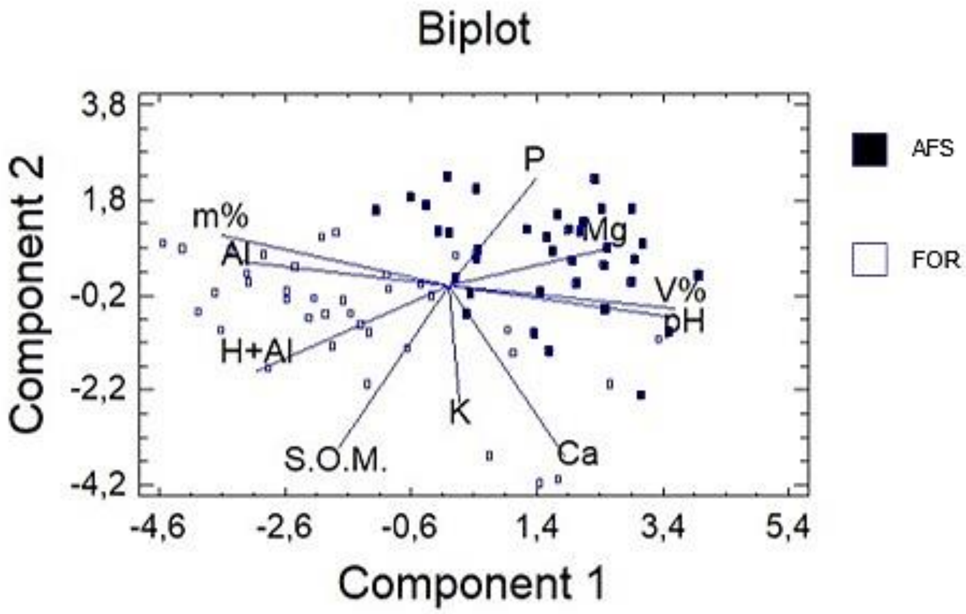

Figure 5. Principal componentes analysis, with vectorial disposition of soil chemical attributes from AFS and FOR.

4. Discussion

Variables Exploratory Assessment

The lowest mean values show the pattern of behavior of such soil attributes, which characterizes a preponderance of the spatial dependence regarding the influence of other environmental factors (Yamamoto and Landim 2013). This variation of data for most variables is considered important for the adjustment of spatial variation models.

Santos et al. (2017) developed a research evaluating the spatial variability of soil fertility in a cocoa cultivation area in Ilhéus-BA, results similar to the present study, with a large majority of the attributes moderate variation coefficient (2.40 <CV% <32, 10). These authors concluded that such behavior of attributes is required part for the adjustment of semirvariograms and for data interpolation by kriging corroborating the results found for the present study.

Semivariogram Fitting

The spherical model showed more precise adjustments for most of the soil fertility variables in both areas. According to Grego and Vieira (2005), the spherical model is the most used model in soil science studies because it is more effective in estimating the spatial variability of soil properties, especially fertility. The authors concluded that this model is the most recommended for most of soil variables to estimate their spatial variability.

This more effectiveness of spherical model is probably because such model is better fitted for variables that present a larger spatial continuity (Isaaks and Srivastava 1989), what is characteristic of most soil variables. This behavior was also observed in other studies, as that one developed by Glendell et al. (2014). These authors obtained that the spherical model and secondly the exponential model were the most chosen to estimate the spatial variability of the studied edaphic variables. In the work developed by Metwally et al. (2019), they found that the spherical model was the one that best fit the data of almost all of the analyzed soil variables. These researches confirm the efficiency of spherical model in prediction of spatial variability of soil attributes.

The Gaussian model also described well the spatial behavior of many chemical attributes of the soil in the present study. According to Botega et al. (2013), the Gaussian model is also efficient in predicting extremely continuous phenomena, what justifies the efficiency of this semivariogram model in estimating soil attributes. A similar result occurred with a study by Artur et al. (2014), when evaluating the spatial behavior of some chemical attributes of a soil under different topographic conditions, also found that the Gaussian model, next to the spherical model, was the one that best fit its attributes. The authors observed that pH and H+Al at both depths were better estimated by the Gaussian model. These results confirm the effectiveness of Gaussian model for the explanation of soil spatial variability.

As expected, the vast majority of variables showed spatial dependence ranging from moderate to strong. This is a fundamental condition for the prediction of the variable. In the agroforestry area, almost all variables showed an elevated sill with a relatively low nugget effect, and these variables are considered highly regionalized, due to their respectively selected models. The presence of some moderate spatial dependence, with relatively high values of nugget, can be associated to external factor such as the management practices adopted, as also observed by Vasu et al. (2017), when evaluating the spatial variability of soil attributes for nutrients management.

For soil attributes, the presence of moderate spatial dependence is considered enough to ensure a reliable estimation of spatial variability through the semivariogram adjustment. Ichami et al. (2020), when adjusting the semivariogram to study the variability of organic carbon in the soil under grain cultivation, obtained a moderate spatial dependence for this edaphological attribute, by adjusting the exponential model. The authors considered the adjustment of the respective model adequate to estimate the variability of organic carbon in the soil.

Kriging

The lower homogeneity in the isolines in AFS maps, when comparing to FOR, are probably associated with the intensive management practices carried out in this first area, as also verified by Silva et al. (2016). These authors evaluated the spatial variability of soil fertility under an agroforestry system in Seropédica (RJ) and also found a lack of uniformity in the pattern of distribution of variables in space. They found a certain similarity in the spatial distribution pattern between some variables, allowing an integrated management of the fertility of this soil, based on such information.

The higher values of Ca and Mg in AFS compared to the native forest can be explained by the application of dolomitic limestone in AFS, which, in addition to neutralizing the acidic ions in the soil, provides considerable amounts of these two basic cations. This liming reduces the problems of leaching of these nutrients, which is still present in FOR, as also observed by Jemo et al. (2014) assessing soil fertility in north-central and southeastern Nigeria.

As well as Ca and Mg, the soil potential acidity (H+Al) in AFS area is irregular, although it is superior (mostly) to the FOR. This must also be explained by the liming practice carried out without taking into account variations in space. In the study developed by Santos et al. (2014), the spatial distribution of some soil chemical attributes was assessed through semivariogram fitting and kriging, among them the acidity and contents of exchangeable Al. These authors observed an irregular distribution in the area for exchangeable aluminium due to an inefficiency in correcting soil acidity. These authors recommended the application of limestone according to the spatial predictions established.

For available phosphorus (P), it was observed a certain segregation in the AFS area with part of the area being occupied by a concentration range between 0.355 and 1.52 mg dm^{-3} and another part being occupied by a predominant concentration range between 1.52 and 2.69 mg dm^{-3} (Figure 2-F). As with liming, phosphate fertilization in the agroforestry area was probably inefficient in supplying equally the area that clearly presents considerable variations of this nutrient over the soil.

This shows that even in AFS, problems with P supply are still evident, mainly due to Fe and Al oxides, which are often associated with this nutrient, forming insoluble compounds and making P unavailable for plants. This is common in tropical soils, which are rich in oxides, which makes it necessary to submit them to an appropriate fertilizing and liming activity (Brady and Neil 2013), even the agroforestry system playing the role of supplier of plant biomass for the soil (Thomazini et al. 2015). Bitencourt et al. (2016), in their study, also obtained traces of P distributed in the area in a segregated form, although the values of this nutrient were much higher in the cultivated area.

S.O.M. models in both areas were not able to be submitted to kriging, due to their low R^2 and extremely elevated SQR values, as well as unsuitable range in the model from FOR, denoting a possible segregation in this variable. When comparing the Organic Carbon stock of an alley agroforestry system (Alley cropping) in different spacing with a native forest, Cardinael et al. (2015) obtained different results to those found for the present study, regarding the distribution of organic matter in space. By adjusting the semivariogram and interpolating data by kriging, the authors were able to observe the great potential that agroforestry systems have for the accumulation of organic matter in the soil, contributing, among other aspects, to the increase in nutrient cycling.

However, it is not always possible to observe a variation in the content of organic matter depending on management practices. Panday et al. (2019) evaluated the spatial variability of organic matter and other attributes of a soil under an agroforestry system, in comparison with agricultural cultivation area and pasture area. These authors did not observe a considerable difference in the organic matter content in the area of AFS in comparison with the other management systems, corroborating to the results of the present study.

This highlights that, even though agroforestry plantations, in general, contribute to the increase of biomass on the soil, studies involving the spatial variability of soil attributes are important tools to subsidize cultivation and adaptive management practices, if necessary. These maps might be useful specially as base tools to a localized income application, allowing a more efficient nutrients management (Metwally et al. 2019).

Ordination Assessment

We observed a high relationship between pH and bases and a negative relationship between these variables to Al and m%, corroborating the results found for linear correlation as well as the behaviour observed for these variables in the kriging maps (Figure 3; Figure 4). Aquino et al. (2016) found similar results when assessing the spatial variability and relationship through PCA of soil fertility from agroforestry systems in Western Amazonia, with pH, bases and acidity attributes representing the behaviour of the agroforestry under study.

S.O.M. was highly associated with Ca and K, showing the importance of biomass deposition on the soil surface and organic matter production for nutrients availability, as found by some studies with agroforestry (Hossain et al. 2011; Dhanya et al. 2013), although this attribute could not be submitted to kriging due to the low quality of its semivaogram adjustment. These and principal components results reinforce the possibility of integrated management of these attributes, especially through localized application of acidity correctors, fertilizers and other incomes using the spatial variability of these fertility variables.

5. Conclusions

The spherical and Gaussian models are most recommended for adjusting soil fertility variables under agroforestry systems and native forest, under the conditions presented by the present study. The management practices adopted in AFS contributed to a greater homogeneity of organic matter, making this attribute present a similar behavior to FOR. In general, the variables studied can have their spatial variability estimated by semivariograms for later kriging, based on spatial dependence. Mostly, the kriging maps can be adopted as logistical maps for management and intervention practices in order to improve the soil fertility in the study areas, especially through localized application of fertilizers, lime and organic matter, which was corroborated by the results of principal components analysis.

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