Revista Ciência Agronômica, v. 55, e20228656, 2024
Centro de Ciências Agrárias - Universidade Federal do Ceará, Fortaleza, CE
www.ccarevista.ufc.br

Scientific Article
ISSN 1806-6690

Multivariate analysis applied to evaluate the spatial variability of a soil subjected to conservation management[1]

Anderson Gomide Costa[2]*, Carlos José da Silva[3], Caroline Souza da Fonseca[3], João Henrique Gaia Gomes[3], Marcos Gervasio Pereira[4]

ABSTRACT - Monitoring the spatial variability of soil attributes is an important tool in crop management. Multivariate statistical methods and geostatistics were jointly applied to evaluate the influence of different attributes on spatial variability in the soil. The aim of this research was to apply multivariate principal component analysis to map the spatial variability of the soil in an area subjected to different methods of conservation management and identify the most relevant physical and chemical attributes. Disturbed and undisturbed soil samples were collected and georeferenced at 99 different points in the study area at depths of 0.00 - 0.10 m and 0.10 - 0.20 m to measure the physical and chemical attributes of the soil; multivariate principal component analysis (PC) was then applied to the data. Geostatistics was applied to the PCs showing greater explanatory capacity, evaluating spatial dependence, and generating maps of spatial variability. The variance in the soil attributes was explained by the first eight PCs. Soil density, particle density and pH had the greatest influence on the spatial variability of the soil since they showed the highest correlation with the PC with the greatest explanatory power. The PCs that correlated with at least two of the soil attributes showed moderate (PC1 and PC6) and strong (PC2, PC4 and PC5) spatial dependence. The generated maps helped identify the joint influence of the variability of the most relevant attributes, making it possible to characterise regions under different methods of conservation management.

Key words: Physical and chemical attributes of the soil. Organic cultivation. Agroforestry system. Principal component analysis.

DOI: 10.5935/1806-6690.20240041
Editor-in-Article: Prof. Daniel Albiero - daniel.albiero@gmail.com
*Author for correspondence
Received for publication on 12/12/2022; approved on 22/09/2023
[1]This research was part of the master's thesis of Carlos José da Silva and was funded by the Coordination for Improvement of Higher Education Personnel (CAPES) and Carlos Chagas Filho Foundation for Research Support in the State of Rio de Janeiro (FAPERJ)
[2]Engineering Department, Technology Institute, Universidade Federal Rural do Rio de Janeiro, Seropédica-RJ, Brazil, acosta@ufrrj.br (ORCID ID 0000-0003-0594-8514)
[3]Technology Institute, Postgraduate Program in Agricultural and Environmental Engineering, Universidade Federal Rural do Rio de Janeiro, Seropédica-RJ, Brazil, carlosjose19621@gmail.com (ORCID ID 0000-0003-3346-4293), carol.c.r.l@outlook.com (ORCID ID 0000-0003-0480-1326), gaia.gomes.pgeaamb@gmail.com (ORCID ID 0000-0003-3870-7258)
[4]Soil Science Department, Agronomy Institute, Universidade Federal Rural do Rio de Janeiro, Seropédica-RJ, Brazil, mgervasiopereira01@gmail.com (ORCID ID 0000-0002-1402-3612)

INTRODUCTION

Conservation management, such as organic cultivation and agroforestry systems (AFSs), contribute to environmental sustainability, making the soil more resistant to erosion and less dependent on external inputs, and allowing the loss of organic matter, water and the physical and chemical quality of the soil to be controlled (FORTINI; BRAGA; FREITAS, 2019). According to data from the Brazilian Ministry of Agriculture, Livestock and Supply (MAPA), organic production in Brazil occupies an area of approximately 1.5 million hectares, with more than 26,800 units registered for this type of production (BRASIL, 2022).

Given the increasing pressure for public policies that encourage sustainable agriculture, and the expansion of the consumer market for organic products (MULLER *et al*., 2017; SAZVAR; RAHAMANI; GOVINDAN, 2018), improving and assessing the impact of management systems that are based on the reuse of organic waste is important for guaranteeing the environmental and economic viability of these methods. In this scenario, monitoring the attributes of soil quality is an important indicator of the productive potential and restrictions of the type of management employed (CHAVEIRO *et al*., 2022; MESFIN; HAILESELASSIE, 2022; PAGE; DANG; DALAL, 2020).

Techniques associated with geostatistics have been applied to evaluate the spatial variability of soil attributes, identify regions of low productivity in agricultural areas, characterise soil quality, and enable different methods of crop management (TORIYAMA, 2018; ZERAATPISHEH *et al*., 2022; ZHANG *et al*., 2022). In soils under conservation management, variability in the physical and chemical attributes of the soil can be influenced by a minimum of tillage in the planting rows, fertilisation using different products of organic origin, or by using organic matter from crop residue as ground cover (DALCHIAVON *et al*., 2012; VOLTR *et al*., 2021).

Individual soil attributes are normally evaluated using univariate analysis together with geostatistics to determine spatial dependence and generate maps of the variability of the attributes (GELAIN et al., 2021; GORAI; BHUSHAN; KUMAR, 2013). Although well-established, this type of analysis tends to be limited when interpreting how these attributes influence the soil when evaluated together.

Multivariate statistical methods have been applied as an alternative way of evaluating spatial variability based on the interaction of soil attributes (BELKHIRI; NARANY, 2015; BUSS *et al*., 2019; MARTINS *et al*., 2020). Burak, Passos and Andrade (2012), used geostatistics and principal component analysis to verify that attributes related to acid-base reactions had the most influence on the spatial variability of a soil cultivated with coffee, since these correlated with the principal component having the greatest explanatory power. Principal component analysis was also used by Trevisan *et al.* (2017) to evaluate the spatial variability of the physical properties of the soil and of rice production under different cover crops, making it possible to reduce the analysed variables to three principal components which were then used to generate management zones.

The aim of this research was to use multivariate principal component analysis to map the spatial variability of the soil in an area subjected to different methods of conservation management, and identify the physical and chemical attributes of the soil that most influenced this variability.

MATERIAL AND METHODS

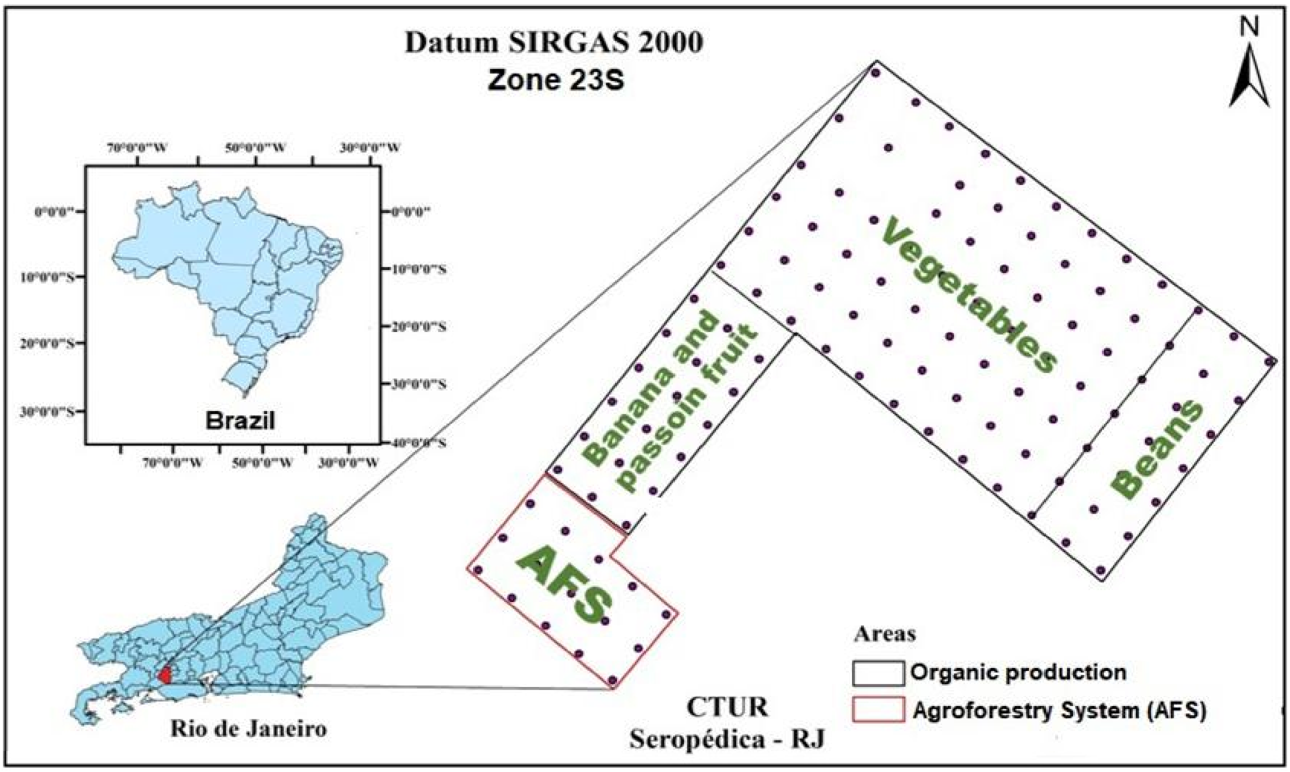
Characterisation of the experimental area

The experiment was conducted in an area of agroecological production located at the Federal Rural University of Rio de Janeiro (22°46’24” S and 43° 42’ 08” W, altitude 33 m). The area has a history of fourteen years organic cultivation, using fertiliser made exclusively from organic waste, with a minimum tillage system of soil preparation and crop management, including two annual mechanised operations (rotary hoe and tiller).

The area is approximately 0.44 ha in size (Figure 1) and was cultivated using agroecological systems for the production of various vegetables, including lettuce (*Lactuca sativa*. L), cabbage (*Brassica oleracea*), mustard (Sinapsis alba), chicory (*Cichorium endívia*), endive (*Cichorium intybus*), rocket (*Eruca sativa*), turnip (*Brassica rapa* L.), and radish (*Raphanus sativus*. L.). Beans (*Phaseolus Vulgaris*) were also grown in the area, and fruit trees, such as the banana (*Musa acuminata*) and passion fruit (*Passiflora edulis*), in addition to a region under an agroforestry system - AFS (producing gliricidia for animal feed, using leaves and crushed branches as top dressing).

The soil in the experimental area was classified as a typical Eutrophic Tb Haplic Planosol, formed geologically in the Paraíba do Sul complex from sedimentary parent material. The soil is classified as non-stony and non-rocky. The local relief is flat, imperfectly drained, with no apparent erosion. The primary vegetation is subtropical sub-deciduous forest, with the soil currently used for cultivating oil crops.

Figure 1 - Location of the study area characterised by one region with the organic cultivation of various crops (vegetables, fruit and beans) and one region under an agroforestry system



Georeferencing and analysis of the soil samples

The soil samples were acquired at a regular spacing of 7.0 m. The points were georeferenced using a Magellan Promak 2 GPS receiver, with a precision of ±5mm +5ppm, coupled to an Ashtech Proantenna external antenna. Five individual samples were collected from each sampling point to form a single composite sample.

Disturbed and undisturbed soil samples were collected at depths of 0.00 - 0.10 m and 0.10 - 0.20 m. To analyse the physical attributes of the soil, 99 undisturbed samples were collected at a depth of 0.00 - 0.20 m using a Kopeck ring. To analyse the chemical attributes, 99 disturbed samples were collected in the 0.00 - 0.10 m layer, and 99 disturbed samples in the 0.10 - 0.20 m layer.

As per the methodology proposed by Teixeira *et al*. (2017), the undisturbed soil samples were taken to the laboratory, oven-dried at 105 ºC and weighed to determine the bulk density (Ds) using the volumetric ring method. To determine particle density (Dp) using the volumetric flask method, the samples were crushed and passed through a 0.2 mm sieve to obtain the ADFE. The total pore volume (TPV) was determined as the ratio of bulk density (Ds) to particle density (Dp).

The disturbed soil samples were air-dried (ADFE), crushed, passed through a 2 mm sieve, and oven-dried at 105 °C to give oven-dried fine earth (ODFE). The following chemical analyses were carried out: pH at a soil to water ratio of 1:2.5; exchangeable calcium (Ca^{2+}), magnesium (Mg^{2+}), potassium (K^{+}), sodium (Na^{+}) and aluminium (Al^{3+}); available phosphorus (P); extractable hydrogen + aluminium (H+Al) (potential acidity).

Data analysis

Descriptive data analysis and principal component analysis were carried out using the PAST 4.03 Software. The descriptive analysis was carried out on the data collected in the 0.0 - 0.10 m and 0.10 - 0.20 m layers, analysing the maximum, minimum, and mean values, and the median, coefficient of variation, kurtosis, asymmetry and normality.

As described in Silva *et al*. (2010), the coefficient of variation (CV) was analysed considering low values as CV < 12%, medium values as 12% < CV < 60% and high values as CV > 60%. Skewness or degree of departure from the symmetry of the distribution (Cs) was evaluated observing that if Cs > 0, the distribution is skewed to the right; if Cs < 0, the distribution is skewed to the left; and if Cs = 0, the distribution is symmetric. Kurtosis (Ck), the degree of flattening of a normal distribution, was classified as mesokurtic (Ck = 0), platykurtic (Ck < 0), or leptokurtic (Ck > 0). Data normality was assessed using the Shapiro-Wilk test to ascertain whether the distribution was similar to a normal distribution.

Following the descriptive analysis, the data were normalised as described in Machado *et al*. (2020) to remove the effect of the different units of the variables. Multivariate principal component analysis (PCA) was carried out on the normalised data with the aim of explaining the correlation between the observable variables, and reduce the number of variables needed to describe the observed variance, the result of the spatialisation of the samples.

The percentage variance explained by the principal components (PCs) was evaluated to determine the number of principal components necessary to explain the variance in the data as a function of the spatialisation of the soil samples. The PCs that presented an accumulated explained percentage greater than 70% were selected as representative of the variance generated by the physical and chemical attributes (MACHADO *et al*., 2020).

After analysing the explained percentage, a correlation analysis was carried out between the original variables (soil attributes) and the most representative PCs. The PCs that presented the highest correlation coefficients with at least two soil attributes were selected for analysing the spatial variability using geostatistics.

The semivariograms were analysed, and the maps of spatial variability in the soil generated using the WGS+ 10 Software. The semivariograms associated with each PC were selected based on a performance evaluation of the following parameters: Nugget effect (Co), sill (Co+C), range (Ao), correlation coefficient (r^2), residual sum of squares (RSS), and spatial dependence index (SDI).

The spatial dependence index was classified as per Cambardella *et al*. (1994): strong spatial dependence ≥ 75%, moderate spatial dependence between 25% and 75%, and weak spatial dependence ≤ 25%.

After selecting the semivariograms, the data were interpolated using ordinary kriging to map the spatial variability of the PCs associated with the soil attributes collected at a depth of 0 - 0.20 m.

RESULTS AND DISCUSSION

A descriptive analysis of the data (Table 1) showed that the central tendency (mean and median) was similar for 73.7% of the attributes, indicating a distribution close to a central value. The attributes Ds, Dp and pH at a depth of 0 - 0.10 m had CV values of less than 12%, the variation being classified as low. The other soil attributes had a CV between 12% and 60%, and are therefore considered to have medium variation. At a depth of 0.10 - 0.20 m, only pH had a low CV value. The other attributes under evaluation were considered to have medium variation. The assessment of normality using the Shapiro-Wilk test showed that all the attributes had a p-value greater than 0.05, and were not considered to have a normal distribution.

Table 1 - Descriptive analysis of the physical and chemical attributes of the soil in the 0-0.10 m and 0.10-0.20 m layers

Var.	Und.	Min.	Max.	Mean	Med.	CV(%)	CK	ASM	SW
0 - 0.10 m (99 samples evaluated)									
Ds	$Mg.m^{-3}$	1.10	1.86	1.55	1.57	8.69	1.38	-0.86	0.95
Dp	$Mg.m^{-3}$	1.69	2.63	2.42	2.44	4.30	24.26	-3.47	0.73
TPV	%	23.00	52.0	35.94	35.00	14.23	0.88	0.57	0.97
pH	H_2O	4.39	7.30	6.08	6.18	7.75	2.73	-1.10	0.93
Ca^{2+}	$cmolc.kg^{-1}$	1.60	3.00	2.17	2.10	14.63	-0.08	0.82	0.92
Mg^{2+}	$cmolc.kg^{-1}$	0.20	2.50	1.37	1.40	41.39	-0.78	-0.31	0.96
Al^{3+}	$cmolc.kg^{-1}$	0.10	0.40	0.24	0.20	24.31	-0.09	0.71	0.73
H+AL	$cmolc.kg^{-1}$	1.00	4.20	3.41	3.55	14.01	5.88	-1.74	0.88
P	$Mg.kg^{-1}$	7.79	39.87	25.87	28.27	52.42	3.75	-0.40	0.95
Na^{+}	$cmolc.kg^{-1}$	0.01	0.02	0.01	0.01	33.31	-0.98	1.97	0.43
K+	$cmolc.kg^{-1}$	0.01	0.12	0.04	0.03	31.30	1.93	1.39	0.88

Continuation Table 1

0.10 – 0.20 m (99 samples evaluated)									
pH	H_2O	4.70	6.90	6.07	6.15	6.73	0.50	-0.70	0.97
Ca^{2+}	cmolc.kg^{-1}	0.80	2.60	1.58	1.60	22.11	0.14	0.03	0.98
Mg^{2+}	cmolc.kg^{-1}	0.40	3.40	1.52	1.40	35.29	2.05	1.11	0.93
Al^{3+}	cmolc.kg^{-1}	0.30	0.60	0.40	0.40	17.58	-0.36	0.21	0.82
H+AL	cmolc.kg^{-1}	1.48	3.00	2.07	1.98	20.21	-0.84	0.49	0.93
P	Mg.kg^{-1}	7.56	39.87	23.46	23.72	35.35	-1.08	0.04	0.97
Na^{+}	cmolc.kg^{-1}	0.01	0.03	0.01	0.01	34.57	4.28	2.23	0.46
K^{+}	cmolc.kg^{-1}	0.00	0.07	0.02	0.02	53.15	4.06	1.59	0.82

Variables (Var), minimum (Min), maximum (Max), median (Med), coefficient of variation (CV%), asymmetry (ASM), kurtosis (CK), Shapiro-Wilk (SW). *Significant at 5% by T-test for a normal distribution. Bulk density (Ds), Particle density (Dp), Total pore volume (TPV), Hydrogen potential (pH), calcium (Ca^{2+}), magnesium (Mg^{2+}), aluminium (Al^{3+}), potential acidity (H+Al), phosphorus (P), sodium (Na^{+}), and potassium (K^{+})

Still on data distribution, at a depth of 0 - 0.10 m, 55% of the attributes were skewed to the left (Ds, Dp, pH, Mg, H+Al and P) with the remaining 45% skewed to the right (TPV, Ca^{2+}, Al^{3+}, Na^{2+} and K^{+}). At a depth of 0.10 - 0.20, only pH was skewed to the left, the rest of the attributes being skewed to the right. This shows that at a depth of 0 - 0.10 m, the greatest concentration of data had values greater than the mean, stretching the distribution to the left, while at a depth of 0.10 - 0.20 m there is a concentration of data with values below the mean, stretching the distribution to the right. Most of the data presented a leptokurtic distribution.

The mean values for the chemical attributes of the soil were classified as per the Liming and Fertilisation Manual of the state of Rio de Janeiro (FREIRE *et al*., 2013). The pH was considered moderately high, the levels of calcium (Ca^{2+}) were medium, magnesium (Mg^{2+}) was considered good, aluminium (Al^{3+}), phosphorus (P) and potassium (K^{+}) were considered low. Exchangeable acidity (H + Al) at 0.00 - 0.10 m was considered medium, while at 0.10 - 0.20 m it was considered low.

When principal component analysis was applied to the soil attributes, the first eight principal components had an accumulated explained percentage (EPac) of 74.27%, and were considered representative for explaining the total variability of the data (EPac > 70%).

As shown in Table 2, PC1 alone explained 14.99% of the total variability of the data, the soil attributes that showed the highest correlations with this PC being Ds, Dp and pH in the 0 - 0.10 m layer, and pH in the 0.10 - 0.20 m layer. PC2, which explained 13.32% of the total variability, had the highest correlation with Ca^{2+} in the 0 - 0.10 m and 0.10 - 0.20 m layer, and Mg^{2+} in the 0 - 0.10 m and the 0.10 - 0.20 m layers. PC4 (EP% = 9.03%) was correlated with Dp, TPV and pH in the 0.10 - 0.20 m layer. Finally, PC5 (EP% = 7.80%) was correlated with H + Al and P in the 0.10 - 0.20 m layer, while PC6 (EP% = 6.92%) was correlated with potential acidity (H + Al) in the 0 - 0.10 m layer and Na^{+} in the 0.10 - 0.20 layer. PC3, PC7 and PC8 presented fewer than two attributes associated with the highest correlation coefficient, and were disregarded when analysing spatial variability.

Soil attributes that showed a correlation with a specific principal component may have been influenced by the same aspects related to management in the different regions of the experimental area. Analysing the attributes correlated with PC1, the component with the greatest explanatory power shows the relationship between Ds and TPV to be inversely proportional, so that the higher the bulk density, the smaller the total pore volume. pH, also correlated with PC1, influences the trend towards soil acidification, especially in regions of high rainfall. As such, it contributes to the basic character of the exchange complex and favours an increase in the Al^{3+} and H^{+} cations, which increase the acidic nature of the soil. The base cations (Ca^{2+} and Mg^{2+}) associated with acidity, when present in low levels, show a strong correlation in PC2.

In order to assess the spatial variability generated jointly by at least two of the soil attributes, of the eight representative PCs, those with at least two soil attributes with the highest associated correlation power (PC1, PC2, PC4, PC5 and PC6) were selected for the spatial dependence analysis.

The models for each PC were selected based on the coefficient of determination and the spatial dependence index (Table 3). Spatial dependence for PC2, PC4 and PC5 was classified as strong, while for PC1 and PC6, spatial dependence was classified as moderate. The classifications show that the principal components are influenced by the intrinsic properties of the soil, which are correlated.

Table 2 - Explained percentage of variance using principal components (PC), and correlation between the original variables and the principal components

PC	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Autov	2.85	2.53	1.93	1.72	1.48	1.31	1.22	1.07
EP (%)	14.99	13.32	10.15	9.03	7.80	6.92	6.43	5.63
EPAc (%)	14.99	28.31	38.46	47.49	55.29	62.21	68.64	74.27
Correlation of the attributes in the 0.00 - 0.10 m layer								
Ds	0.88*	0.05	0.09	-0.22	-0.20	0.18	0.15	-0.02
Dp	0.46	0.17	0.03	0.51*	0.16	0.01	0.44	-0.05
TPV	-0.71*	0.03	-0.08	0.51*	0.31	-0.20	0.07	-0.01
pH	0.60*	-0.10	0.39	0.44	0.18	-0.03	-0.12	0.19
Ca^{2+}	-0.06	0.79*	0.03	-0.08	0.14	0.02	-0.34	-0.03
Mg^{2+}	0.07	-0.81*	0.06	0.05	-0.20	-0.21	0.23	0.12
Al^{3+}	-0.45	-0.30	0.27	-0.10	-0.12	0.40	0.13	0.16
H+AL	-0.04	0.19	0.21	-0.05	-0.12	0.53*	-0.20	-0.55*
P	0.08	0.21	0.31	-0.32	0.33	-0.07	0.56*	-0.25
Na^{+}	0.07	0.22	0.67*	-0.37	0.19	0.07	-0.02	0.34
K^{+}	0.20	-0.06	-0.08	-0.42	0.48	-0.04	0.16	0.17
Correlation of the attributes in the 0.10 - 0.20 m layer								
pH	0.53*	0.11	0.17	0.58*	0.11	0.06	-0.28	0.06
Ca^{2+}	-0.04	0.57*	-0.30	0.12	-0.26	0.15	0.17	0.43
Mg^{2+}	-0.02	-0.64*	0.41	-0.06	0.18	-0.09	-0.40	-0.12
Al^{3+}	-0.49	-0.13	0.16	0.27	0.03	0.54	0.23	0.14
H+AL	-0.08	0.20	0.16	-0.19	-0.54*	-0.39	-0.15	0.22
P	-0.11	0.04	-0.37	-0.17	0.62*	-0.08	-0.18	0.10
Na^{+}	-0.23	0.33	0.37	0.13	-0.16	-0.50*	0.21	-0.38
K^{+}	-0.38	0.25	0.70*	0.10	0.06	-0.07	-0.01	0.21

Principal components (PC), Explained percentage (EP), Accumulated percentage (EPac), Bulk density (Ds), Particle density (DP), Total pore volume (TPV), Hydrogen potential (pH), calcium (Ca^{2+}), magnesium (Mg^{2+}), aluminium (Al^{3+}), potential acidity (H+Al), sodium (Na^{+}), potassium (K^{+}), and phosphorus (P). Correlation greater than ± 0.50 (*)

Table 3 - Parameters of the semivariogram generated from the principal components associated with the attributes of the physical and chemical analysis of the soil in the 0-0.20 m layer

Variable	Model	Co	Co+C	Ao(m)	R²	RSS	SDI	Class
PC1	Spherical	1.738	3.691	136.30	0.79	0.299	53%	Moderate
PC2	Exponential	0.346	3.416	21.50	0.94	0.268	90%	Strong
PC4	Spherical	0.097	1.80	9.90	0.16	0.121	95%	Strong
PC5	Gaussian	0.155	1.515	6.50	0.79	0.038	90%	Strong
PC6	Exponential	0.606	1.371	17.10	0.81	0.054	56%	Moderate

Nugget Effect (Co), Sill (Co+C), Range (Ao), Correlation Coefficient (R²), Residual Sum of Squares (RSS), Spatial Dependence Index (SDI)

Despite the SDI being classified as strong, the low coefficient of determination (R^2 = 0.157) when modelling PC4, shows that even the best fit model (spherical) had limitations for these data, which suggests that the maps of spatial variability for these parameters may not be representative.

Another aspect to be considered is the range of the semivariogram, which varies depending on the spatial interaction of the soil processes that affect each property based on the sampling scale being used. As this parameter represents the maximum distance between samples for determining soil properties with a good degree of representativeness (LONDERO *et al*., 2020), it was found that the ranges generated by the models were generally greater than 7.0 m (the distance used for each sampling point), showing that the distance between the collected samples was sufficient for assessing spatial dependence. PC5 had a range of less than 7.0 m, which indicates that for assessing H + Al and P in the 0.10 - 0.20 m layer, the distance between the sampling points should be reduced.

Parameters associated with the semivariograms, such as R^2 and range, can be better adjusted based on an analysis of the spatial variability in different directions. In this case, an analysis taking into account the anisotropic nature of the data can improve the characteristics of the semivariogram parameters (GUEDES *et al*., 2008; PARK; AHN; LEE, 2013).

The map of spatial variability (Figure 2A) shows that the AFS (to the south) and the fruit-growing area (centre-south) had the highest PC1 values compared to the area of organic vegetables and legumes (to the east). It was therefore concluded that the soil attributes Ds, TPV and pH, which are better correlated with this component, had a greater influence on the variability of the soil in these areas. As the root systems of the crops in the AFS and fruit-growing areas are deeper, the soil porosity tends to increase, contributing to the greater influence of these parameters (LENCI *et al*., 2018). Differences in these attributes between areas become more obvious when analysing the spatial variability based on two classes (Figure 2B).

The map of spatial variability of the other attributes generated from PC2 (Figure 3A), which is associated with Ca^{2+} and Mg^{2+}, showed an obvious difference between the AFS (to the south) and the area of organic cultivation (centre-east), particularly the fruit-growing area (centre-south). The map generated by PC5 (Figure 3B) showed lower values related to the area of organic fruit cultivation, indicating that the soil attributes associated with this component (H + AL and P in the 0.10 - 0.20 m layer) has less influence in this region. Finally, the variability map generated from PC6 (Figure 3C), and which is associated with the variability of H + AL at a depth of 0.00 - 0.10 m and Na+ at a depth of 0.10 - 0, 20 m, showed that these attributes had a different effect on the area of organic vegetable cultivation.

The analysis of spatial variability based on the principal components enabled at least two soil attributes to be assessed at one time, defining the most important physical and chemical attributes of the soil, mapping spatial variability, and analysing the joint influence of these attributes in regions under different methods of

Figure 2 - Map of spatial variability for PC1 associated with the soil attributes Ds, Dp and pH in the 0 - 0.10 m layer, and pH in the 0.10 - 0.20 m layer, in an area under organic cultivation and an agroforestry system. (A) zones of spatial variability divided into four classes; (B) zones of spatial variability divided into two classes

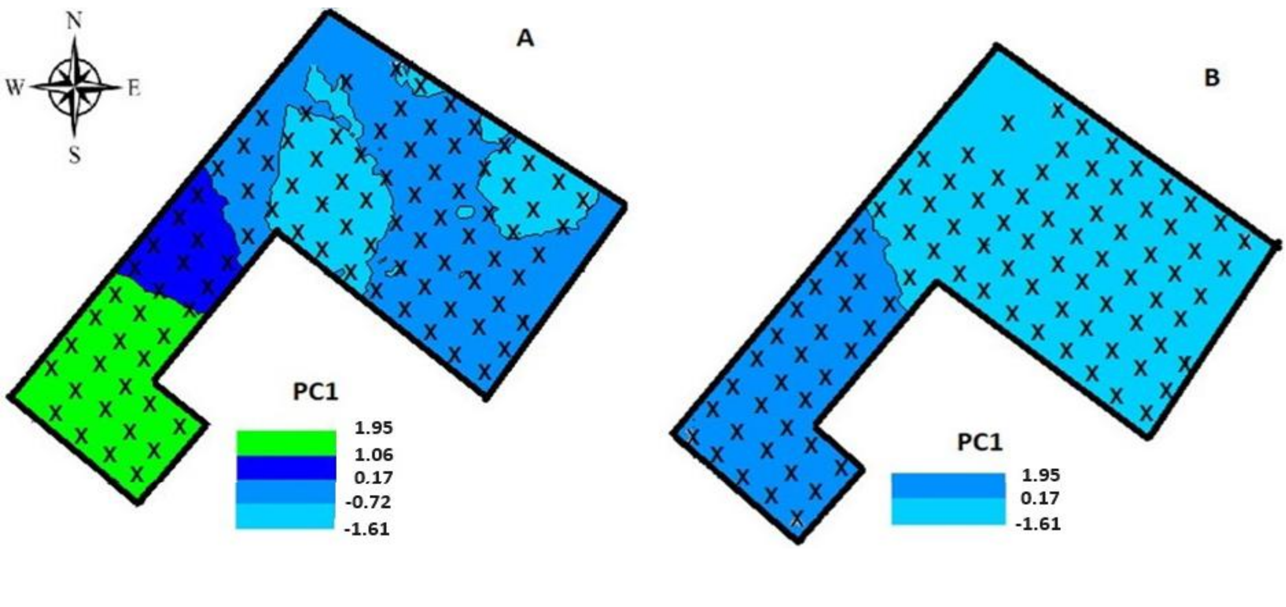
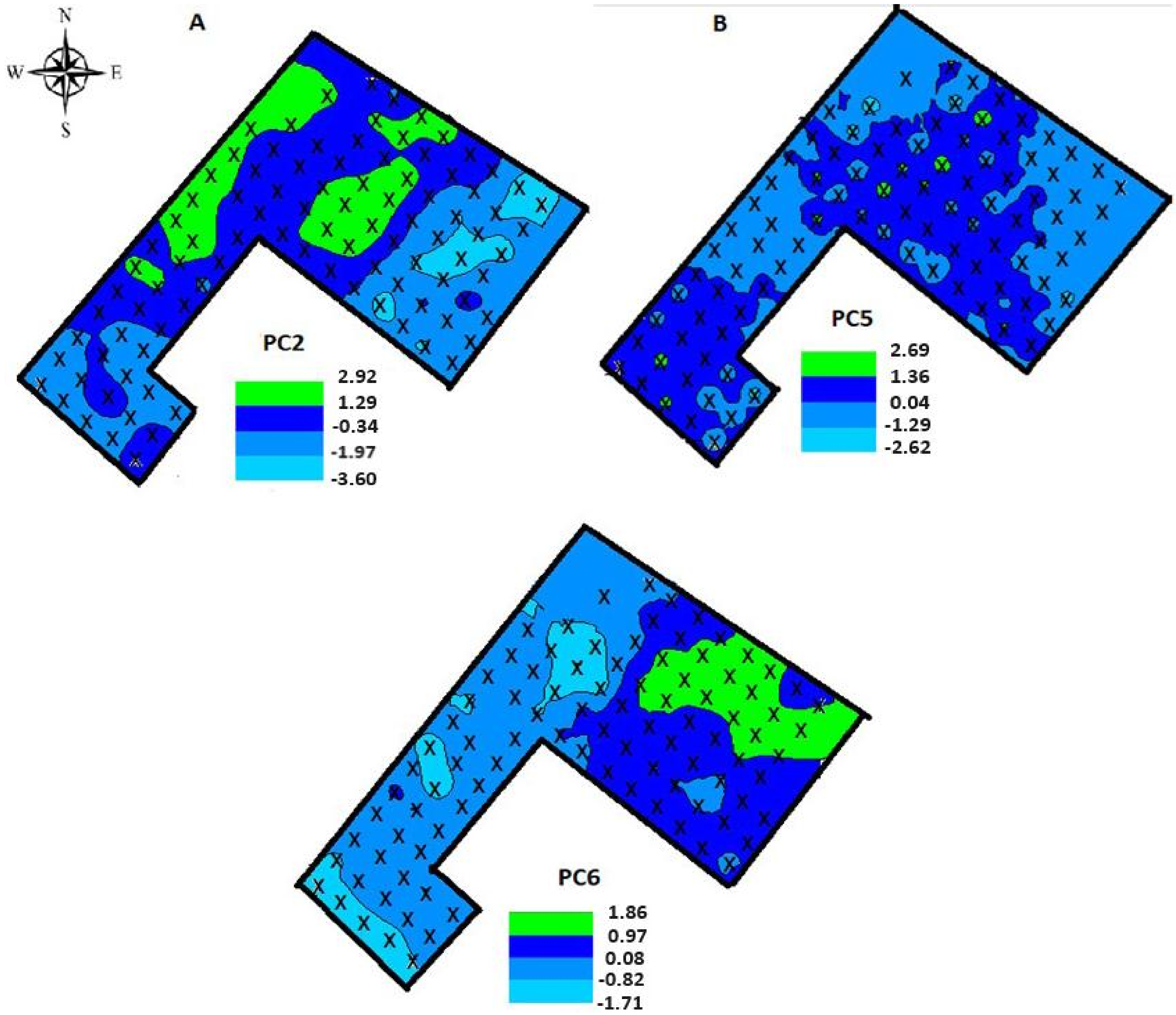


Figure 3 - Map of spatial variability in an area under organic cultivation and an agroforestry system: (A) map for PC2 associated with the soil attributes Ca^{2+} and Mg^{2+} in the 0 - 0.10 m and in the 0.10 - 0.20 m layer; (B) map for PC5 associated with the soil attributes H + AL and P in the 0.10 - 0.20 m layer; and (C) map for PC6 associated with the soil attributes H+Al in the 0.10 - 0.20 m layer and Na^{+} in the 0.10 - 0.20 m layer



conservation management. The maps of spatial variability of the principal components can be used as an aid to manage the area under evaluation, and are especially important in helping to define strategies for the localized correction of soil fertility and methods of soil preparation based on the associated attributes.

CONCLUSIONS

1. The spatial variability of the soil attributes could be explained by eight principal components, which presented an accumulated explained percentage of 74.23%, with five principal components (PC1, PC2, PC4, PC5 and PC6) showing a correlation with at least two of the soil attributes, demonstrating that multivariate analysis allows for a broad and interactive characterisation of the influence of the variability of the soil attributes;
2. By evaluating the correlation with the principal components that showed the highest explanatory percentage, it was possible to identify the soil attributes that had the most influence on soil variability as a function of the different methods of conservation management, showing that this is an efficient way

of indicating which soil attributes have the greatest influence on its variability;

3. The maps generated from the principal components made it possible to characterise the spatial variability of the soil when influenced by more than one attribute at the same time, thereby characterising the different methods of conservation management.

ACKNOWLEDGEMENTS

The authors would like to thank the Coordination for the Improvement of Higher Education Personnel (CAPES), the Carlos Chagas Filho Foundation for Research Support in the State of Rio de Janeiro (FAPERJ) and the Universidade Federal Rural do Rio de Janeiro for the funding and infrastructure to carry out this research.

REFERENCES

BELKHIRI, L.; NARANY, T. S. Using multivariate statistical analysis, geostatistical techniques and structural equation modeling to identify spatial variability of groundwater quality. **Water Resources Management**, v. 29, n. 6, p. 2073-2089, 2015.

BRASIL. Ministério da Agricultura e Abastecimento. **Folder Produtos Orgânicos**. 2022. Availabe in: https://www.gov.br/agricultura/pt-br/assuntos/sustentabilidade/organicos/arquivos-publicacoes-organicos/folder-organico_web.pdf. Acess at: december 03, 2022.

BURAK, D. L.; PASSOS, R. R.; ANDRADE, F. V. Variabilidade espacial de atributos químicos do solo sob cafeeiro Conilon: relação com textura, matéria orgânica e relevo. **Bragantia**, v. 71, p. 538-547, 2012.

BUSS, R. N. *et al*. Spatial and multivariate analysis of soybean productivity and soil physical-chemical attributes. **Revista Brasileira de Engenharia Agrícola e Ambiental**, v. 23, p. 446-453, 2019.

CAMBARDELLA, C. A. *et al*. Field-scale variability of soil properties in central Iowa soils. **Soil Science Society of America Journal**, v. 58, p. 1501-1511, 1994.

CHAVEIRO, A. *et al*. Qualidade física e química do solo em sistema de plantio direto cultivado com hortaliças: uma revisão. **Research, Society and Development**, v. 11, n. 9, p. e32711931564, 2022.

DALCHIAVON, F. C. *et al*. Variabilidade espacial de atributos da fertilidade de um Latossolo Vermelho Distroférrico sob Sistema Plantio Direto. **Revista Ciência Agronômica**, v. 43, n. 3, p. 453-461, 2012.

FORTINI, R. M.; BRAGA, M. J.; FREITAS, C. O. Impacto das práticas agrícolas conservacionistas na produtividade da terra e no lucro dos estabelecimentos agropecuários brasileiros. **Revista de Economia e Sociologia Rural**, v. 58, n. 2, p. e199479, 2020.

FREIRE, L. R. *et al*. **Manual de calagem e adubação do Estado do Rio de Janeiro**. Seropédica: Editora Universidade Rural, 2013. 430 p.

GELAIN, E. *et al*. Variabilidade espacial e correlação dos atributos do solo com produtividade do milho e da soja. **Nativa**, v. 9, n. 5, p. 536-543, 2021.

GORAI, T.; BHUSHAN, M.; KUMAR, S. B. Application of geostatistical techniques in spatial variability mapping of soil fertility: a review. **International Journal of Advances in Agricultural Science and Technology**, v. 1, n. 1, p. 100-111, 2013.

GUEDES, P. C. L. *et al*. Anisotropia no estudo da variabilidade espacial de algumas variáveis químicas do solo. **Revista Brasileira de Ciência do Solo**, v. 32, n. 6, p. 2217-2226, 2008.

LENCI, L. H. V. *et al*. Aspectos fitossociológicos e indicadores da qualidade do solo em sistemas agroflorestais. **Nativa**, v. 6, p. 745-753, 2018.

LONDERO, R. *et al*. Dependência espacial da fertilidade do solo sob plantio direto e suas relações com a produtividade da soja. **Caderno de Ciências Agrárias**, v. 12, p. 1-8, 2020.

MACHADO, T. A. *et al*. Quality of tomatoes under different transportation conditions by principal component analysis. **Revista Ceres**, v. 67, p. 448-453, 2020.

MARTINS, R. N. *et al*. Site-specific nutrient management zones in soybean field using multivariate analysis: an approach based on variable rate fertilization. **Communications in Soil Science and Plant Analysis**, v. 51, n. 5, p. 687-700, 2020.

MESFIN, S.; HAILESELASSIE, H. Evaluation of soil physico-chemical properties as affected by canopies of scattered agroforestry trees on croplands. **South African Journal of Plant and Soil**, v. 39, n. 2, p. 153-162, 2022.

MULLER, A. *et al*. Strategies for feeding the world more sustainably with organic agriculture. **Nature communications**, v. 8, n. 1290, p. 1-13, 2017.

PAGE, K. L.; DANG, Y. P.; DALAL, R. C. The ability of conservation agriculture to conserve soil organic carbon and the subsequent impact on soil physical, chemical, and biological properties and yield. **Frontiers in Sustainable Food Systems**, v. 4, p. 31, 2020.

PARK, J. S.; AHN, I. Y.; LEE, E. J. Spatial Distribution Patterns of the Antarctic Hair Grass Deschampsia antarctica in Relation to Environmental Variables on Barton Peninsula, King George Island. **Arctic, Antarctic, and Alpine Research**, v. 45, n. 4, p. 563-574, 2013.

SAZVAR, Z.; RAHAMANI, M.; GOVINDAN, K. A sustainable supply chain for organic, conventional agro-food products: the role of demand substitution, climate change and public health. **Journal of Cleaner Production**, v. 194, p. 564-583, 2018.

SILVA, S. D. A. *et al*. Variabilidade espacial de atributos químicos de um Latossolo Vermelho-Amarelo húmico cultivado com café. **Revista Brasileira de Ciência do Solo**, v. 34, p. 15-22, 2010.

TEIXEIRA, P. C. *et al*. **Manual de métodos de análise de solo**. Brasília, DF: Embrapa Solos, 2017. 573 p.

TORIYAMA, K. Development of precision agriculture and ICT application thereof to manage spatial variability of crop growth. **Soil Science and Plant Nutrition**, v. 66, n. 6, p. 811-819, 2018.

TREVISAN, R. G. *et al*. Variability of physical properties of soil and rice grown under cover crops in crop-livestock integrated system. **Bragantia**, v. 76, p. 145-154, 2017.

VOLTR, V. *et al*. The soil organic matter in connection with soil properties and soil inputs. **Agronomy**, v. 11, n. 4, p. 779, 2021.

ZERAATPISHEH, M. *et al*. Spatial variability of soil quality within management zones: Homogeneity and purity of delineated zones. **Catena**, v. 209, p. 105835, 2022.

ZHANG, J. Z. *et al*. Hybrid machine learning model with random field and limited CPT data to quantify horizontal scale of fluctuation of soil spatial variability. **Acta Geotechnica**, v. 17, n. 4, p. 1129-1145, 2022.