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Multivariate technique for determination of soil pedoenvironmental indicators in Southern Amazonas

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ABSTRACT. The use of statistical techniques to evaluate soil attribute behaviour is an important tool for choosing the most adequate form of soil management. Thus, the aim of this study was to jointly assess the physical and chemical attributes and the magnetic susceptibility characteristics of three environments and to use multivariate statistics to define which attributes have the greatest potential as environmental change indicators. The study was conducted in three areas: one with archaeological black earth (and planted maize); one with pasture; and one of the forest. Sixty-four (64) deformed and non-deformed soil samples each were collected within these areas, with a 70 x 70 m grid spaced every 10 meters at depths of 0.0-0.2 and 0.4-0.6 m, to determine the chemical attributes (fertility), as well as the physical attributes (texture) and magnetic susceptibility. The data were analyzed through multivariate statistics. The archaeological dark earth areas have different behaviours between pastures and forests: chemical attributes have greater interaction in archaeological dark earth due to the high fertility of the anthropic horizons. The attributes that may indicate environmental changes are calcium, potential acidity and clay for archaeological dark earth, forest and pasture areas, respectively.

Keywords: main component, Amazonian, archaeological dark earth.

Técnicas multivariadas na determinação de indicadores pedoambientais de solos na região Sul do Amazonas

RESUMO. O uso de técnicas estatísticas a fim de avaliar o comportamento de atributos do solo é uma importante ferramenta na determinação de manejo e uso adequado de solos. Sendo assim, o objetivo deste trabalho foi avaliar conjuntamente os atributos físicos, químicos e a suscetibilidade magnética do solo na caracterização de três ambientes e definir quais atributos apresenta potencial no estudo de indicadores de mudanças ambientais, por meio de estatísticas multivariadas. O estudo foi realizado em três áreas, sendo uma área com terra preta arqueológica (TPA) (cultivada com milho), uma com floresta e uma com pastagem. Nestas áreas foram coletadas 64 amostras de solos deformadas e indeformadas em malhas de 70 x 70m com espaçamento regular de 10m nas profundidades de 0,0-0,2 e 0,4–0,6 m para determinação dos atributos químicos (fertilidade), físicos (textura) e suscetibilidade magnética. Os dados foram analisados submetendo-os a técnicas de estatísticas multivariadas. A TPA apresenta comportamento diferenciado da pastagem e floresta, sendo que os atributos químicos apresentam maior interação para TPA em razão da alta fertilidade de horizontes antrópicos. Os atributos possíveis indicadores de mudanças ambientais são o cálcio para TPA, acidez potencial para a floresta e argila para a pastagem.

Palavras-chave: componente principal, Amazônia, terra preta arqueológica.

Introduction

Soil behaviour can be studied by assessing several factors, such as the nutrient levels, which correspond to soil fertility (Silva, Lima, Xavier, & Teixeira, 2010a), and physical attributes that represent the soil structure's organization and the microorganisms that are responsible for mineralization processes and thus represent a potential nutrient supply source for plants.

The evaluation of these soil factors, when performed using univariate methods, increases the scale of the problem and becomes an expensive process (Silva et al., 2010a). An alternative is the use of multivariate analysis, which is an important tool for the exploratory data analysis of soil because it allows the grouping of samples according to similarity while still enabling the selection of the most important variables to discriminate between pre-selected groups (Benites, Moutta, Coutinho, & Balieiro, 2010). However, current research has increasingly reported on the need to develop indicators of global impacts for land use and occupation (Rockström et al., 2009). Such studies are even more necessary for areas with high environmental sensitivity, such as those found in the landscape of the Amazonian deforestation arc located in Southern Amazonas State.

Some multivariate statistical techniques can be applied to soil properties to establish the use of pedoenvironmental indicators; these techniques include principal component analysis (PCA), which aims to reduce the problem dimensionally and ease data interpretation. According to Barroso and Artes (2003), this analysis of factors is a statistical technique that aims to describe the dependence structure of a set of changeable variables and measure commonalities.

The goal of discriminant analysis (DA) is to identify the variables that discriminate groups and choose the most appropriate group to which they should belong based on their characteristics (Hair, Anderson, Tatham, & Black, 2005). Some researchers have used Quality Control Charts to evaluate the behaviour of attributes. This chart is one of the main tools used in statistical quality control and may be indicative of how variables behave in each studied management (Kume, 1993). The combined use of these techniques based on soil attribute behaviours can aid in decision-making, ideal land use and handling and may further indicate possible attributes that are undergoing major changes due to human interference.

The aim of this study was to jointly assess the soil's physical and chemical attributes and its magnetic susceptibility in three different environments and to use these data, by means of multivariate statistics, to define which attributes have great potential as indicators of environmental changes in Southern Amazonas.

Material and methods

The study was performed in farms located around road BR 230, in Manicoré City, Transamazônica, Amazonas State, Brazil. Soil sampling was conducted in areas with three different uses. One was forest, located at 7° 54' 44.5" S and 61° 31' 44.7" W, at an average altitude of 140 m (Figure 1); it is characterized as a Tropical Dense Rainforest that contains by 20- to 50-m-tall trees.

Another was on soil with an anthropic horizon, i.e., archaeological dark earth (ADE) sited at 7° 55' 02.1" S and 61° 31' 45.2" W, which is 102 m in altitude and had been under corn cultivation for 120 days. The last one was a pasture area at 07° 54' 42" S, 61° 31' 50" W and a 135 m mean altitude that had been under intensive pasturing with brachiaria (*Brachiaria brizanta*) at 1 animal unit per hectare capacity. Moreover, the soils were classified as Alitic Plinthic Red Argisols (Ultisols), except for the area with ADE, which was rated as Dystrophic Abrupt Red-Yellow Argisol (Ultisol) (Empresa Brasileira de Pesquisa Agropecuária [Embrapa], 2013).

These soils were derived from Rondonian granites from the Upper Precambrian. The Köppen classification for the region's climate is a rainy tropical type with a short dry period (*Am*), temperatures ranging between 25 and 27°C, and rainfall between 2,250 and 2,750 mm per year, with the greatest concentration of rainfall from October to June (Oliveira, Campos, Freitas, & Soares, 2015).

Seventy-square-meter grids were established in these areas surrounded by 0.49 ha. Soil samples were collected at the cross-points, which were at 10-metre intervals, for a total of 64 sampling points within each grid (Figure 1). Then, at each point, the collection of soil samples from 0.0 to 0.2 m and 0.4 to 0.6 m depths was performed.

Disturbed soil samples were collected for particle size analysis by the pipette melthod, which used a 0.1 mol L^{-1} NaOH solution as a chemical dispersant and mechanical stirring in a high-rotation apparatus for 15 minutes, according to the methodology proposed by Empresa Brasileira de Pesquisa Agropecuária (Embrapa, 2011). Using the ion exchange resin method, the exchangeable calcium (Ca^{2+}), magnesium (Mg^{2+}), potassium (K^{+}), available phosphorus (P), and potential acidity (H+Al) were determined (Raij, Andrade, Cantarella, & Quaggio, 2001). The pH was measured potentiometrically using a 1:2.5 ratio of soil and water (Empresa Brasileira de Pesquisa Agropecuária [Embrapa], 2011). The total carbon was quantified by Walkley-Black's method, and organic matter was estimated from the organic carbon content.

A Bartington MS2 coupled to a Bartington MS2B sensor was used to determine the magnetic susceptibility (MS) in fine air-dried soil samples (FADS). The evaluation was made at a low frequency (0.47 kHz) to obtain more accurate results because it was a single reading (Bartington Instruments [Bartington], 2013).

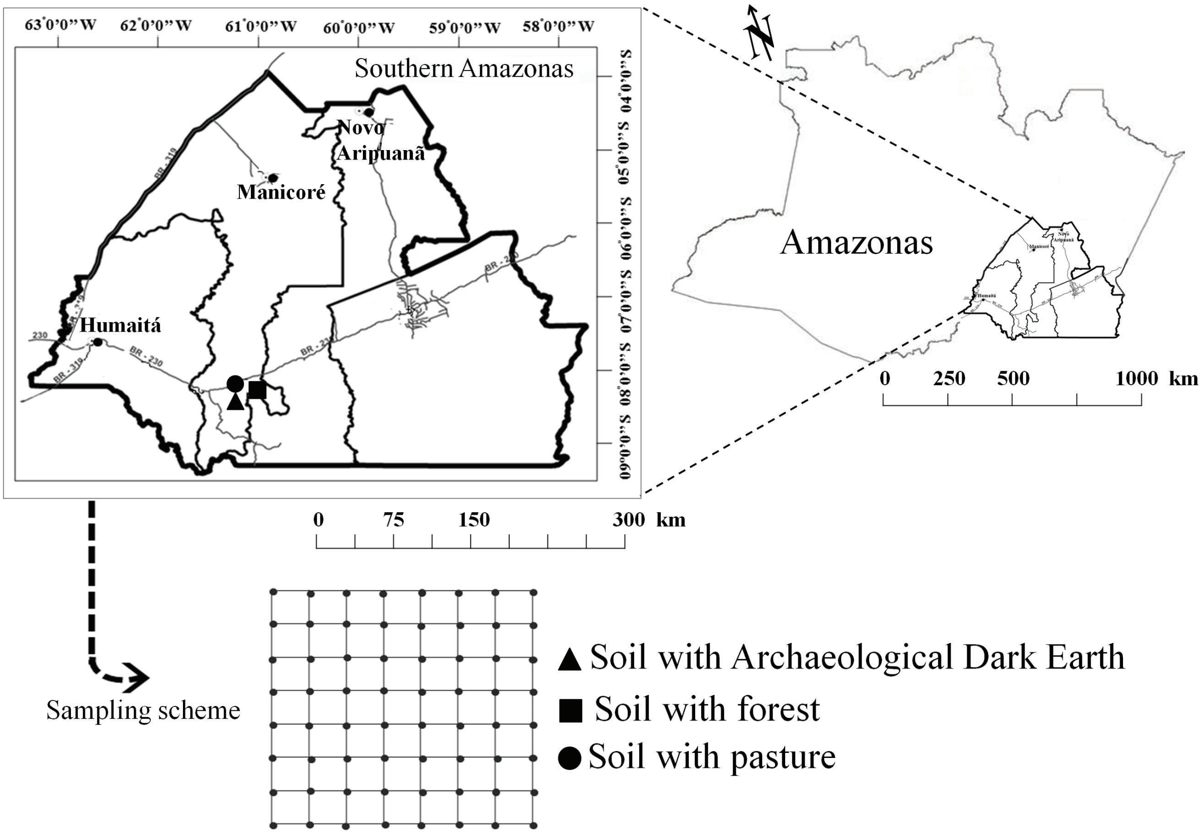


Figure 1. Location map and soil sampling scheme for the studied areas in Southern Amazonas.

To consider the multivariate structure of the data, statistical techniques were used to verify similarities among the land management practices in an attempt to group them in terms of physical and chemical attributes. A "scree-plot" graph of eigenvalues was created to determine the number of components that should be excluded. Such a graph orders the eigenvalues according to the main components, ultimately plotting the variance percentage by each attribute. Notably, this analysis of components should explain over 70% of the total variance (Hair et al., 2005), and these constitute the chosen response variables for principal component analysis (PCA).

Knowing the components to be used, principal component analysis was performed to obtain a smaller set of variable linear combinations that would preserve most of the information provided by the original ones (Silva et al., 2010b). Such analysis accounts for the simultaneous qualitative interactions among those attributes whose original values had been normalized to a mean of 0 and a variance equal to 1. The criteria for choosing the number of components were an eigenvalue greater than 1.00 and a synthesized cumulative variance greater than 70% (Hair et al., 2005).

Subsequently, factor analysis was performed, which allowed the relationships between variables to be explained as a limited number of new variables by extracting the principal components calculated from the correlation matrix among variables. The Orthogonal Varimax Rotation method was used to facilitate interpretation. This method transforms the factor coefficient such that the correlation values among factors and *n* original variables come closer to zero or 1 (Hair et al., 2005).

Recently, Control Chart analysis has been applied to better understand how the soil attribute variability is at all collected points. According to Kume (1993), a control chart is one of the main tools used for statistical quality control and may be indicative of how the variables behave in each area studied.

To compare the area profiles by using a combination of all variables, discriminant composed by a data classification matrix was performed for further analysis. From this analysis, it was possible to define how different the areas are because they are represented in a graph where the boundaries can be observed. The graph axis (x and y) represent the canonical variables, which are new multivariate variables created from the original set of variables and attributes. All statistical analyses were performed using the Statistica software version 7.0.

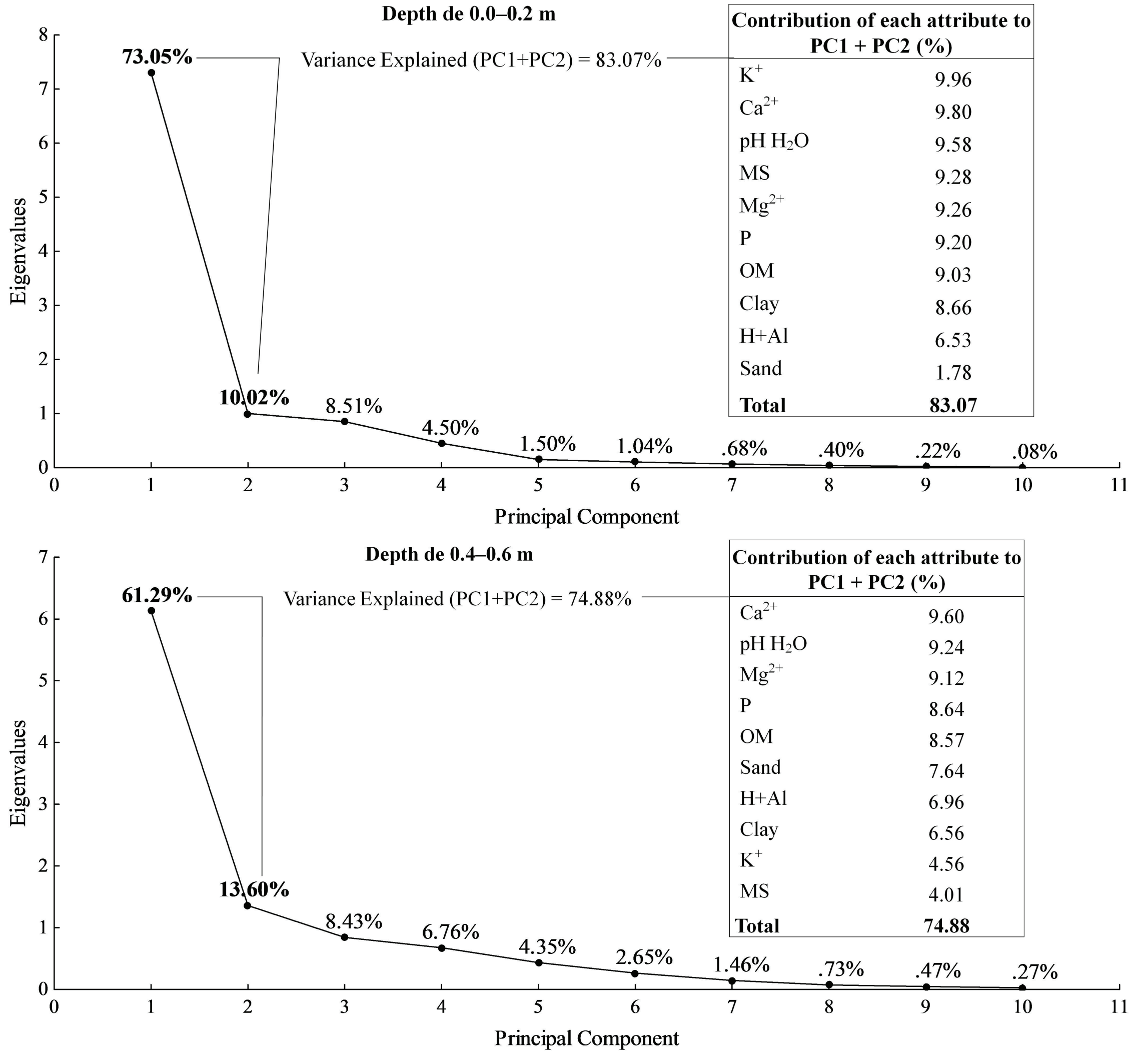
Results and discussion

The scree plot (Figure 2) shows that it is possible to use only the first two principal components because they explain over 70% of the total variance (Hair et al., 2005) and can graphically represent the discriminant power of soil attributes and the contribution of each variable in the total variance.

In the first and second retained components, each environmental attribute's importance shows the most significance, with 83.07 and 74.88% of the explained variability at depths of 0.0-0.2 and 0.4-0.6 m, respectively. The attributes had the following order of significance for their components: K^+ (9.96%), Ca^{2+} (9.80%), pH in H_2O (9.58%), MS (9.28%), Mg^{2+} (9.26 %) and P (9.20%) at 0.0 to 0.2 m depth (Figure 2A); and Ca^{2+} (9.60%), pH in H_2O (9.24%), Mg^{2+} (9.12%), P (8.64%) and OM (8.57%) at 0.4 to 0.6 m (Figure 2B). For these attributes, greater impacts or alterations may occur when the area is subjected to some form of anthropogenic management.

The eigenvalues confirm that the first and second main components were needed to explain the total variance because they presented high eigenvalues (7.30 and 1.00 at a depth of 0.0 to 0.2 m; 6.12 and 1.35 at a depth of 0.4-0.6 m), thus justifying the use of principal component analysis 1 (PC1) and principal component analysis 2 (PC2). According Kaiser (1958), the PCs with eigenvalues greater than 1 (one) can be used for a two-dimensional ordering of access and variables, thereby enabling biplot graph construction.

Variable correlations and principal component graphic representation (Table 1 and Figure 3) allowed the characterization of the variables that were most favoured in the environmental formation and differentiation.



Contribution of each attribute to PC1 + PC2 (%)	
K^+	9.96
Ca^{2+}	9.80
pH H_2O	9.58
MS	9.28
Mg^{2+}	9.26
P	9.20
OM	9.03
Clay	8.66
H+Al	6.53
Sand	1.78
Total	**83.07**

Contribution of each attribute to PC1 + PC2 (%)	
Ca^{2+}	9.60
pH H_2O	9.24
Mg^{2+}	9.12
P	8.64
OM	8.57
Sand	7.64
H+Al	6.96
Clay	6.56
K^+	4.56
MS	4.01
Total	**74.88**

Figure 2. Data set variation ratio explained by principal component (PC) and contribution of each variable in the total variance by "scree plot" method.

Table 1. Correlation among each principal component and the studied variables.

Variables	Principal component --Depth 0.0 – 0.2 m--- PC1	 PC2	 --Depth 0.4 – 0.6 m-- PC1	 PC2
Sand	-0.420577	0.034579	-0.850816★	0.199056
Clay	0.930401★	-0.016233	0.747539★	0.311334
pH H_2O	-0.978538★	0.019005	-0.960924★	-0.015644
Potential acidity	0.804035★	-0.079144	0.798272★	0.241429
Organic matter	-0.948272★	-0.057533	-0.329314	0.865057★
Phosphorus	-0.958909★	0.012626	-0.928323★	-0.047597
Potassium	-0.080809	-0.994790★	0.293114	0.608593
Calcium	-0.989511★	0.026008	-0.977922★	0.058434
Magnesium	-0.962230★	-0.016517	-0.934860★	0.194632
MS	-0.963315★	0.001161	-0.631510★	-0.047930

★Most significant values; PC1: principal component 1; PC2: principal component 2; PC3: principal component 3. MS: magnetic susceptibility

The variables that were most strongly correlated with the ADE area at a depth of 0.0 to 0.2 m were pH in H_2O, OM, Ca^{2+}, Mg^{2+}, P and MS (Table 1 and Figure 3A), which appeared in the third and fourth quadrants with a small angle to the abscissa. The ADE soils have higher OM contents, which gives them greater fertility. High levels of P are also a striking feature of the ADEs. Cunha et al. (2009) reported P contents of 116 mg kg^{-1} in ADE areas under the forests of archaeological sites in Amazonas State; 290.5 mg kg^{-1} under ADE cropped areas; and 4.7 mg kg^{-1} in non-anthropogenic areas. The incorporation of organic waste, especially fish bones, turtle shells, animal or even human bones, which are rich in P, contributed to the high content in ADEs (Lima, Schaefer, Mello, Gilkes, & Ker, 2002).

The Ca^{2+} and Mg^{2+} values are also high in ADEs as observed by Barros, Lima, Canellas, and Kern (2012), which justifies their connection to this environment. This behaviour is due to either the incorporation of calcium-rich bones from the Pre-Columbian period or a higher Ca^{2+} from exchange surfaces, which results in less leaching. Campos, Santos, Mantovanelli, and Soares (2012a) found Ca^{2+} and Mg^{2+} higher values in ADEs for non-anthropogenic soils, thus affirming a strong correlation of these attributes to ADE (Table 1).

MS is also highly related to ADE area at 0.0 to 0.2 m of depth (Table 1 and Figure 3A). The OM presence favours the conditions that are required for iron reduction, which promotes increased susceptibility.

Pasture and forest areas are featured by greater bond to clay and potential acidity (H+Al) (Table 1 and Figure 3A). The potential acidity values of forest areas were greater across the environments, probably due to the higher leaching from intense rainfall with drainage systems (Campos, Ribeiro, Souza Júnior, Ribeiro Filho, & Oliveira, 2010; Campos, Ribeiro, Souza Júnior, Ribeiro Filho, & Almeida, 2012b).

In the subsurface layer (0.40-0.6 m), a behaviour similar to the surface layer (0.0 to 0.2 m) can be observed. The subsurface variables that were strongly correlated with ADE were sand pH in H_2O, OM, Ca^{2+}, Mg^{2+}, P and MS (Table 1 and Figure 3B). In contrast, the pasture area was characterized by a closer link to clay (Figure 5B), in accordance with the smallest angle relative to the abscissa's axis, probably due to the presence of a clay-like soil. The forest has a strong connection with the H+Al (Figure 3B), as stated by Campos et al. (2012b); this condition is due to the increased leaching promoted by the intense rainfall associated with better drainage conditions in the Amazonian environment.

Based on these results, it can be stated that the forest and pasture environments are more similar or that they have more physical, chemical and MS homogeneous behaviours (Table 1 and Figure 3). However, the ADE presents as a unique environment that has peculiar chemical, physical and MSs for this type of environment (Figure 3A and B).

The factor analysis (Table 2) indicates that 73.69% of the data variability is explained by the first factor and that 10.24% is explained by the second factor; thus, 83.93% of the data variability is explained by the first two factors. This shows that of the 10 variables, two factors needed to be used, with 64 observations in the original set, resulting in a dimensional reduction of the original variables with an explanation loss lower than 20% (16.07%).

Table 2. Factorial analysis of soil attributes at the evaluated depths with factors (Factors 1 and 2) corresponding to the studied environments in Southern Amazonas.

Attributes	---Depth 0.0-0.2 m--- Factor 1	 Factor 2	--Depth 0.4-0.6 m-- Factor 1	 Factor 2
Sand	0.526836★	0.205837	0.830345★	0.267486
Clay	-0.927258★	0.031663	-0.764111★	0.266531
pH H_2O	0.978019★	-0.021800	0.959871★	0.048330
Potential acidity	-0.798974★	0.084820	-0.811210★	0.200701
Organic matter	0.947510★	0.094369	0.248974	0.918742★
Phosphorus	0.955780★	-0.002876	0.927550★	0.036452
Potassium	-0.027139	0.981456★	-0.478394	0.514503★
Calcium	0.989056★	-0.013465	0.969478★	0.139332
Magnesium	0.961184★	-0.020344	0.915273★	0.265287
MS	0.960728★	0.008044	0.632019★	0.046771
Relative variance	73.69%	10.24%	61.81%	13.87%

★Most discriminant values; MS: Magnetic susceptibility.

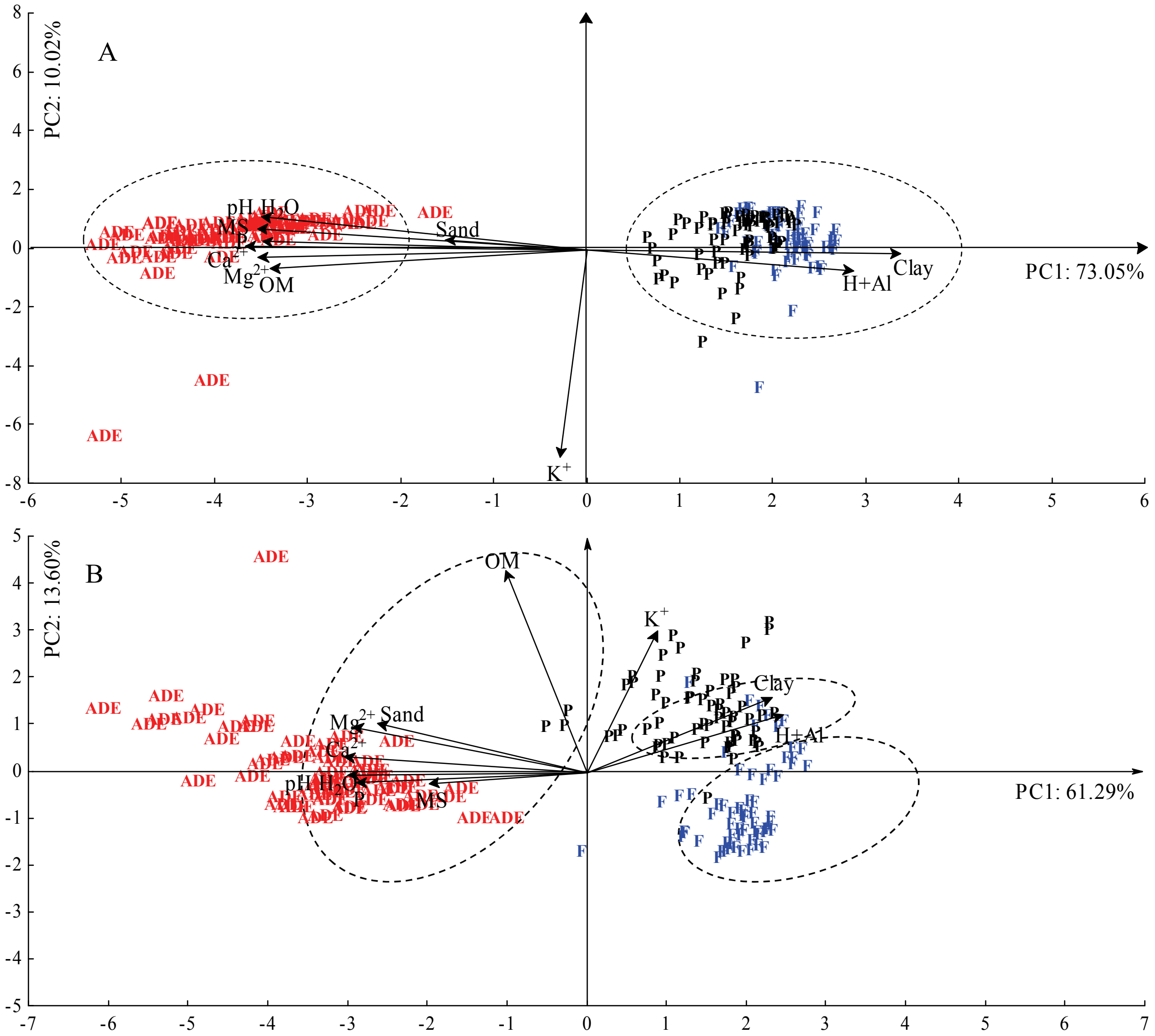


Figure 3. Principal component analysis of soil attributes in the studied environments. A = 0.0 – 0.2 m depth; B = 0.4 – 0.6 m depth; ADE= archaeological dark earth; P= pasture; F= forest.

In factor analysis, the weighting that defines which variables are the most important indicate that the variables that form factor 1 have high factor loadings (Table 2). These variables explain the higher percentage of variation and are the highest contributors to changes in soil characteristics as a function of land use. However, only potassium has a low discriminatory power among the studied attributes, which indicates that there is no difference in this attribute among the three environments in the first layer, as shown for Factor 2.

Clay and H+Al are directly proportional to the other attributes, which means that when the clay and H+Al contents increase, the other attributes decrease and vice-versa. Barreto, Lima, Freire, Araújo, and Freire (2006) observed a relation between potential acidity and soil pH. These authors observed that the higher the pH is, the lower the potential acidity is in the forest. At the 0.4–0.6 m depth, it can be noted that there is a very similar behaviour among the attributes, in which the OM had a lower discriminating power and was expressed in Factor 2 together with K^+. Thus, the higher the OM content is, the lower the K^+ discriminant power is.

A Control Chart of attribute variability was designed for each environment to evaluate each attribute's performance in the variability of all attributes together (Figure 4). The analysis enables clearly visualizing the boundaries between environments, showing their specific variability. However, ADE differs from pasture and forest at depths in the subsurface layer, where the variability in MS is smaller or where the attributes are more homogeneous. This analysis facilitates the interpretation of human interference on surface horizons, which differs from that observed for adjacent soils.

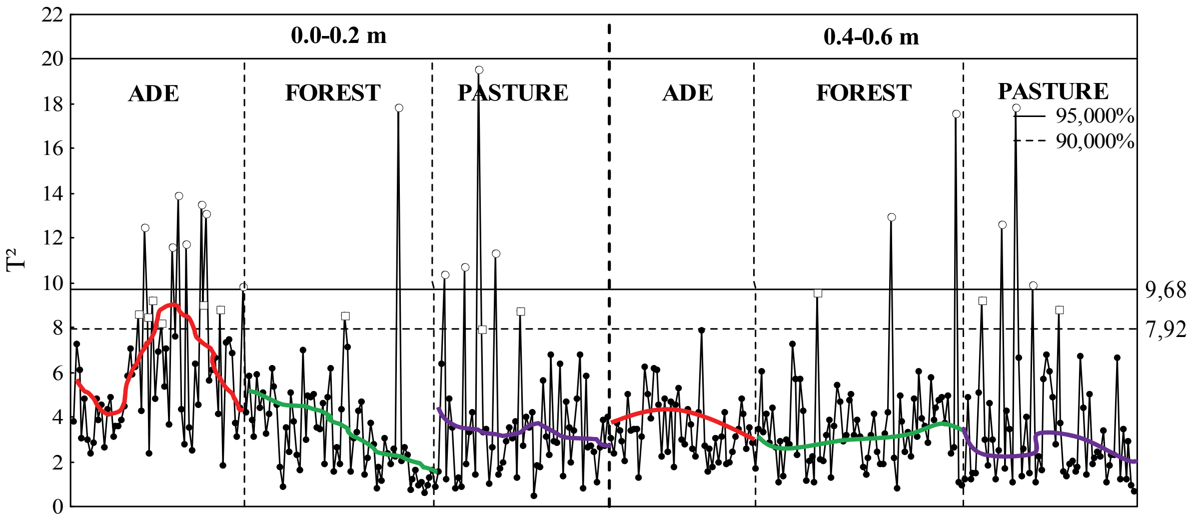


Figure 4. Control Chart of attribute variability in each studied environment in Southern Amazonas.

It should be noted that ADE has the highest data variability, followed by forest and pasture. This finding demonstrates the influence of anthropogenic transformation in soils with anthropic horizons (ADEs). Archaeological evidence indicates that ancient human activities in Amazonian habitats significantly transformed the landscape within neighbouring settlements, especially in the late prehistoric period. A remarkable record of this is the soil areas altered by prehistoric men, which feature a dark colour, archaeological material remains (ceramic fragments and lithic artefacts) and high Ca^{2+}, Mg^{2+}, Zn, Mn, P and C contents (Kern et al., 2009).

As mentioned above, ADE differs in that it is highly fertile. This behaviour is directly linked to greater data variability. In this sense, to verify the relationship between the existing variability among environments and their chemical, physical and MS, we applied a complementary technique using discriminant analysis, which has efficiently matched the results for all areas (Figure 5). By discriminant analysis, it was found that 51.62% of the studied relationship variability was explained in the first two roots (Figure 5) at the 0.0-0.20 m depth. The first canonical root (1 Can) explained 49.33%, and the second (Can 2) explained 2.29%. At the depth of 0.40-0.60 m, the first two roots explained 32.74% of the variance, with 29.09% in the first canonical root (Can 1) and 3.64% in the second (Can 2), totalling 32.73% of the variability among studied relationships.

The discriminant analysis results show that Can 1 is responsible for separating ADE from the other areas because ADE has soil with better physical and chemical qualities and has more distant characteristics of other environments. This separation is in accordance with the results of both the principal component analysis (Figure 5) and clustering analysis (Figures 3 and 4). Because the soil with anthropic horizon presents a higher fertility and higher OM content in relation to forest and pasture, this may have been the factor that most influenced the attribute characterization and MS of each area.

Through discriminant analysis, the most powerful attributes to discriminate between environments are pH in H_2O, H+Al, OM and Ca^{2+} at both depths (Table 3). These results demonstrate that these chemical properties may be the most important and contribute the most to area discrimination.

Table 3. Canonical Discriminant Analysis values, highlighting each studied variable weight in Southern Amazonas.

Attributes	--Depth of 0.0-0.2 m--		-Depth of 0.4-0.6 m-	
	Can 1	Can 2	Can 1	Can 2
Sand	0.06287	-0.49534	-0.34401	-0.64447
Clay	-0.19757	-0.50629	-0.22099	-0.46587
pH H_2O	0.80518*	-0.85966*	-1.14584*	-0.21075
Potential acidity	0.92197*	0.55627	-1.15091*	0.61098
Organic matter	-1.01512*	-1.89896*	0.96410*	-1.32450*
Phosphorus	0.01017	-0.46156	0.01965	-0.16534
Potassium	-0.23310	0.37203	0.19983	0.23770
Calcium	1.02901*	1.86653*	-1.02969*	0.83193
Magnesium	0.39721	0.09631	0.11768	0.06386
MS	0.25995	-0.04610	-0.05913	0.00575

* Main characterization of canonical relationships; MS: Magnetic susceptibility.

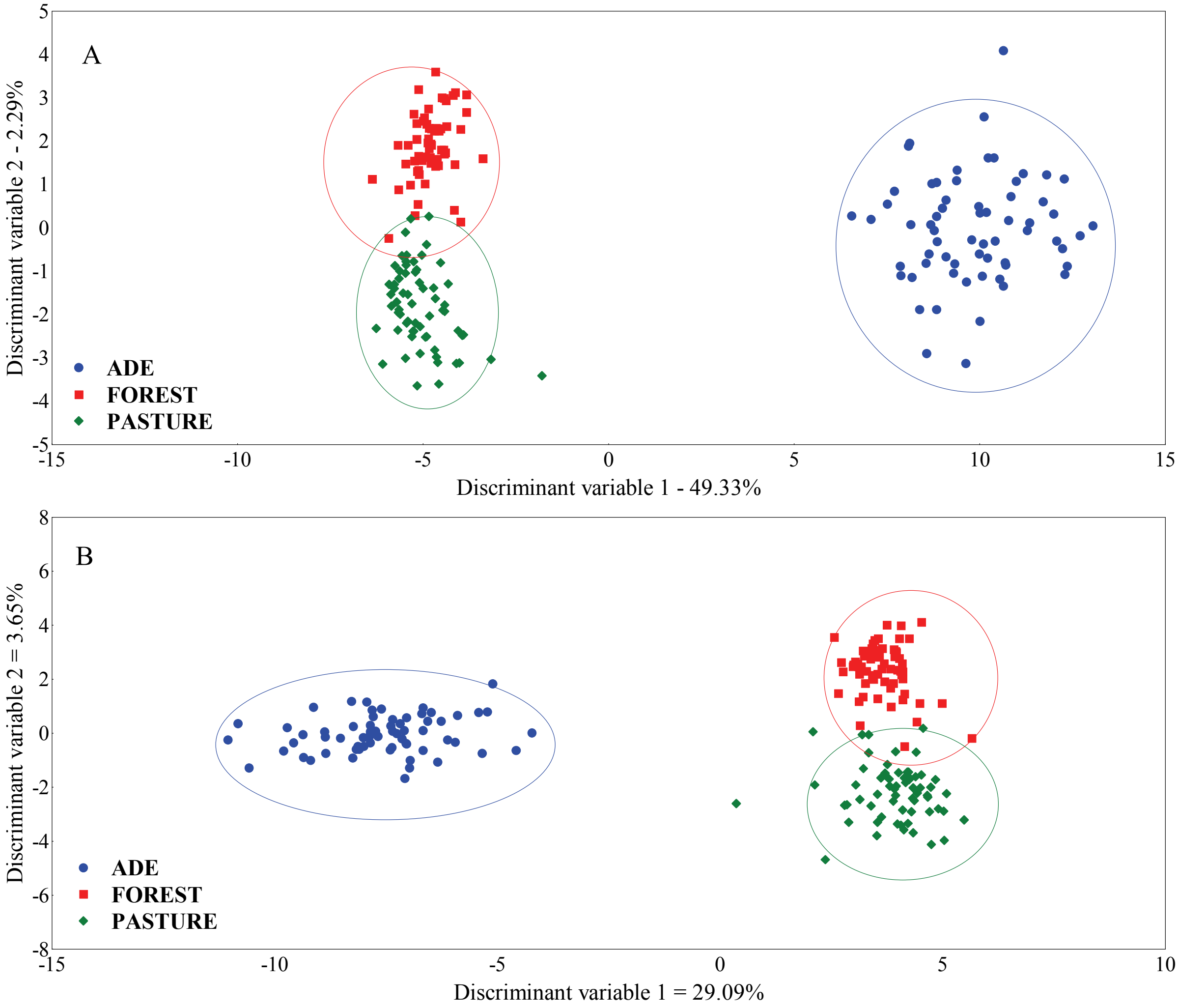


Figure 5. Area clustering by Canonical Discriminant Analysis based on studied attributes in Southern Amazonas. A = 0.0–0.2 m depth; B = 0.4–0.6 m depth. ADE= archaeological dark earth.

In contrasting environments, Table 4 shows that the highest F values are found in ADE area compared to other areas, especially pasture, which demonstrates that ADE differs significantly from the other soils. In contrast, pasture areas and forest have similar characteristics, as observed by their smaller F values, which had no significant difference for both depths.

Table 4. Multivariate analysis contrasting the studied areas in Southern Amazonas.

Managements	Depth of 0.0 – 0.2 m	Depth 0.4 – 0.6 m
	Value of F	Value of F
ADE x Pasture	687.8156***	417.1080***
ADE x Forest	664.7170***	401.0062***
Pasture x Forest	41.5622	65.8633

(***) All values are significant at $p < 0.001$.

This behaviour can be explained by the higher soil fertility and the anthropic horizon presence, as shown by Campos et al. (2012a), who conducted a physical and chemical characterization of soils with anthropic and non-anthropogenic horizons. The authors found that soils with anthropic horizons have better physical and chemical qualities than do soils without the presence of an anthropic horizon, which is common in this region.

In this regard, while assessing Figures 3, 4 and 5 in terms of the main component, it can be seen that the ADE area lies in the third and fourth quadrants and has a greater distance from the forest and pasture areas. The forest is in the same quadrant as the pasture area, demonstrating that these environments have similar features. Within this context, evaluating these areas by discriminant analysis, a similar behaviour is noted; additionally, it shows which connections exist between the areas. Pasture overlaps the forest area, thus demonstrating a greater homogeneity between these environments.

Therefore, in this sense, we can highlight that Ca^{2+}, clay and H+Al are closely linked to ADE, pasture and forest areas, respectively. These attributes may undergo major alterations when the areas are subjected to human actions; thus, the attributes may be possible indicators of environmental changes. An attribute that has been related to a particular environment can provide a measure of environmental change or impact if the components or attributes in the soil are found to have been switched. The use of soil attribute identifiers from different environments is a key tool for driving the practices that reduce depletion to acceptable levels because the pH in H_2O, H+Al, OM and Ca^{2+} contribute greatly to distinguishing the environments, which demonstrates the chemical attributes that are responsible for differentiation among the three environment.

Conclusion

Forest and pasture areas present similar behaviours and attributes, which differ from those of archaeological dark earth areas (ADE) that have greater fertility from anthropic horizons in Amazonian soils.

The soil attributes that are most suitable to use as pedoenvironmental indicators are calcium, potential acidity and clay for dark archaeological, forest and pasture soils, respectively.

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