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Carbon stock variability and aggregate stability in soils of Amazon, Brazil

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Abstract

Converting natural ecosystems into agro-ecosystems often reduces soil organic carbon content by decreasing carbon input, as well as by increasing erosion losses and organic matter decomposition rate. This study aimed at evaluating carbon stocks, soil aggregate stability, and spatial variability of some other attributes in soils of Southern Amazonas state. The study was carried out on areas with archaeological dark earth (ADE), under rainforest, pasture, agroforestry environments, sugarcane, and cassava. We collected disturbed and undisturbed soil samples from 64 points in a regular spacing of 10 m at 0.0-10 cm depth. From these samples, we determined the stock of organic carbon (STOC), organic carbon (OC), organic matter (OM) content, soil aggregate stability (SAS), and soil bulk density (SBD). Data analysis included univariate, multivariate, and descriptive statistics. The STOC was higher in ADEs and the adjusted semivariograms pointed out a greater spatial variability for soils under pasture and cassava crop. Kriging maps of principal component analysis scores proved a positive correlation between the studied variables and terrain slope, with higher values for lower lands.

Keywords: Organic Carbon; Multivariate Analysis, Geostatistics, Soil Management, Soil Quality.
Abbreviations: CO_2_carbon dioxide, AM_Amazonas, USDA_United States Department of Agriculture.

Introduction

Soils under natural vegetation have a balanced carbon stock because of a steady relationship between input and output caused by its sources and decomposition as well as microbial respiration. Given that, soil carbon contents are virtually constant over time (D'Andréa et al., 2002; Costa et al., 2006). Soil organic matter (OM) is critical to a global carbon cycle, once it is the main triggering agent of negative electrical charges, which are responsible for nutrient and water retentions, aggregation of soil particles, besides serving as substrate and contributing to the maintenance of soil biological diversity (Silva et al., 2004). In this sense, OM is the largest terrestrial reservoir of carbon (C), bearing about twice the amount of C in the atmosphere and plant biomass (Bruce et al., 1999; Swift, 2001).

Intensive farming and soil disturbance are responsible for soil organic matter removal, which is one of the main agents of aggregate formation and stabilization (Tisdall and Oades, 1982; Castro Filho et al. 1998). Roth et al. (1991) reported that bare soil crops have decreased aggregate stability, promoting soil surface sealing, reducing water infiltration and thereby promoting runoff and erosion. Improper crop handling mineralizes soil organic carbon, which is transferred to the atmosphere as CO_2. Furthermore, proper farming techniques make the system to sequester C from the atmosphere, which is an important regional and global strategy to offset CO_2 emissions from fossil fuel consumption and mitigate climate changes (Cerri et al., 2006).

Several studies show that there is a correlation between the content of soil organic carbon and aggregate stability in water. Moreover, the influence of organic matter on soil aggregation is a dynamic process, in which beneficial effects are associated with intensifying microbial activity, resulting in products important to the aggregate formation and stability (aggregating agents). However, these beneficial effects are a result of the joint action of microorganisms, fauna, and vegetation (Rozane et al., 2010).

In this context, the knowledge of carbon stock and spatial variability is crucial especially to improve management practices and assess agriculture effects on environmental quality (Cambardella et al., 1994). Nowadays, much attention has been given to global warming, emissions of greenhouse gases, and environmental conditions by means of studies focused on soil carbon stocks and turnovers (Bernoux et al., 1998). This is because the organic material serves as a ubiquitous reservoir of carbon in soil.

Therefore, we should understand the mechanisms that lead to significant increases in carbon stocks for Archaeological Dark Earths (ADEs), as well as other cropped lands in the Amazon area. This knowledge can serve as basis for management techniques that reduce greenhouse gas emissions and promote increased carbon sequestration into the soil (Teixeira, 2007). Given the above, this study aimed at assessing the carbon stocks, aggregate stability, and their respective spatial variability in soils from the Amazonian region that are under different management systems.

Results and discussion

Comparison between areas using classical statistics

The results of the mean test showed significant differences among the management systems (Table 1). OM, STOC and OC were higher in ADE (68.19 g dm^{-3}; 35.15 mg h^{-1}; 39.55 g kg^{-1}); while GMD, MWD, and SBD were lower, what corroborates with finding of Oliveira et al. (2015a). This can explains the ADE's high fertility compared to neighboring soils. As reported by other authors, such as Lehmann et al. (2003) and Glaser (2007), ADEs are usually of superior natural fertility, with high contents of P, Ca, Mg, Zn, Mn, and stable OM. Moreover, Cunha et al. (2007) stated that such fertility is strongly connected to molecular characteristics of the alkaline soluble fraction of the organic matter or humic acid. These same authors found that the A horizon of anthropogenic soils, found in the Amazon soils, have higher total carbon content compared to non-anthropogenic ones.
The lowest SBD was measured in soils under cassava and in ADE (1.16 and 0.89 kg dm^{-3}, respectively). It is because cassava field had been harrowed the year before. Yet for ADE, it is related to high OC content. Steinbeiss et al. (2009) stated that lower soil bulk densities may be attributed to elevated amounts of OC. In contrast, SBD was higher in areas under agroforestry, pasture, and rainforest. However, Islam and Weil (2000) did not observe such findings; these authors found SBD averages significantly greater in cultivated areas, compared to forest soils. Regarding the aggregate stability (Table 1), we observed that soils under sugarcane and pasture have higher values of GMD and WMD. These increased aggregate sizes might be due to increased pressures exerted on these soils by mechanization and animal trampling. Portugal et al. (2010), studying aggregate stability in soils under different uses and compared to woods, found high aggregates stability in surface layers.

Comparison between areas using multivariate statistics

By knowing the variation of physical properties among management systems, we established a factor analysis (Table 2). This procedure enabled determining the properties with higher factor loadings by the varimax method. By this method, we could establish which properties had discriminatory power for all management systems. Table 2 shows that the first two factors explained 91% of the total variance, and all soil properties had high factor loadings. SBD, OM, OC, and STOC were the most relevant variables to estimate Factor 1, which explained 64% of the total variance. Differently, GMD and WMD were related to Factor 2, which explained 27% of the total variance. It can highlight that all studied variables have a high factor loading, which explains the high correlation between the variables and management systems.

In this sense, we performed a principal component analysis (PCA) (Fig 1) that enabled a better evaluation of groups of variables interrelated with the managements, and thereby making possible interpretation, spatial distribution delineation, and correlation with geomorphological properties (Burak et al., 2012). The PCA explained 91.16% total variance for the first two components, and showed an interaction between variables and studied managements. OM, OC, and STOC are directly related to the areas with ADE; while SBD, GMD, and WMD to others. This finding evinced ADE's high fertility against low fertility of nearby lands. Therefore, these soil properties may be more sensitive to environmental changes and, thus, being able to respond environmental changes than other properties.

The PCA defined the grouping of areas, highlighting the ADE environments from the rest. The rainforest, as a natural environment, was also highlighted from the others; however, it was very close to cropped areas. Meanwhile, agroforestry area, as a recovery environment, had widely different characteristics from sugarcane, pasture, and cassava, since the recovery time was not enough to establish a new balance (Oliveira et al., 2015b). Thus, agroforestry was presented as a transitional environment between natural forest and farmed environments (Fig 1), as observed by Oliveira et al. (2015a). Despite having different soil types, the cultivated areas (sugarcane, cassava, and pasture) are closer to homogeneity, which can be explained because all these soils underwent intensive managements, causing changes in their attributes. It is noteworthy that SBD, GMD, and WMD are related to forest, sugarcane, cassava, agroforestry, and pasture areas, being indicatives of greater values of soil density (Table 1).

The fact that soils under sugarcane, cassava, agroforestry, pasture, and natural vegetation have a closer link to SBD, GMD, and WMD (Fig 1) is due to managed areas, such as pastures, have higher aggregation stability because of soil compaction by cattle trampling pressure. On the other hand, the effect of grazing on soil aggregation is assigned to grass root growth and activities (Silva and Mielniczuk 1998; Liu et al., 2005). Additionally, such aggregation in grazing areas may be related to wetting and drying cycles, since those areas have poor ground cover, being mostly exposed to sunlight (Portugal et al., 2010).

Soils with sugarcane cultivation have, in general, a higher percentage of aggregates, as found by Souza et al. (2005). These authors assessed sugarcane-harvesting systems in a Red-yellow Latosol (Oxisol) from Ribeirão Preto, SP, Brazil; they checked that harvesting without burning and partial incorporation of crop residues provided higher WMD values up to 30 cm depth. For the soils with sugarcane and cassava in this study, the increase in aggregate size may come from pressures exerted by agricultural machinery (Oliveira et al., 2013).

Spatial variability

Based on the knowledge of the interaction among OM, STOC, OC, WMD, GMD, and SBD with the studied management systems, we performed a spatial evaluation. Most soil properties in the studied management systems had values near mean and median (Table 3), pointing a near-normal distribution, which is considered acceptable in geostatistical studies (Gonçalves and Folegatti, 2002). However, some properties have values distant from zero, indicating asymmetric distribution, which is confirmed by high skewness values, showing that they are affected by extreme values.

Results of the Kolmogorov-Smirnov test indicated normality for some properties (Table 3). Nevertheless, some of them showed no normal distribution in the different soils. The VC presented low (VC <12%), medium (12% <VC> 24%) high values (VC> 24%), indicating low, medium and high variability, respectively. It is noteworthy to mention that OM, STOC, and OC showed high VC values in some areas, especially in the rainforest, indicating that these attributes have high variability and cannot be detected due to the distance between sampling points. Montanari et al. (2012), Oliveira et al. (2015a), Souza et al. (2004), and Wortmann et al. (2009) found low, moderate, and high VCs for a few chemical and physical attributes, indicating the influence of management in cropping systems.

The VC compares the variability between samples of different sample units; however, it neither evaluates the spatial variability of soil properties nor its spatial pattern. For this, the soil attributes selected in a factor analysis, which have high discriminatory power for the studied soils, underwent geostatistical analysis, and when presented spatial dependence, this behavior was expressed by adjusted semivariograms models (Fig 2).

By Fig 2, we can see that both spherical and exponential models were predominant for the soil attributes, and the same trend was observed for scaled semivariogram adjustments. The adjustment of the models to the variables explains their behavior. According to Isaaks and Srivastava (1989), exponential models (observed in sugarcane and agroforestry) are better adjusted to erratic phenomena, on a small scale; while spherical ones (observed in ADE, pasture, rainforest, and agroforestry) describe properties with high spatial continuity or even less erratic, in a short distance; i.e., transitions between values are less abrupt. In soil science, the predominant models are the spherical (Carvalho et al., 2002). As well, McBratney and Webster (1983), Bertolani and Vieira (2001), and Siqueira et al. (2010) highlighted both spherical and exponential models as most frequently used in soil and environmental sciences. Oliveira et al. (2013; 2014; and 2015a,b) and Aquino et al. (2014 and 2015) found spherical and exponential models for soils studied in the Amazon, justifying the adjustments found in this experiment.

Some soil properties had no structural and spatial correlation, characterized by a pure nugget effect model (PNE), especially for ADE and rainforest, which presented PNE for GMD (Fig 2). As the studied variable is spatially independent, the C_0 (nugget effect) is equal to $C_1 + C_0$ (sill). The PNE may occur due to either measurement errors or existence of small-scale variability beneath sampling grid, once spacing between samples is greater than required to detect spatial dependence (Cambardella et al., 1994; Zanão Júnior et al., 2010). Changing the soil properties in cases of intense management system use provides high spatial variability. Differently, for natural environments or forests, nutrient cycling irregularity raises the spatial variability of soil properties.

The SDD, expressed by the relationship between nugget effect (C_0) and sill (C_0+C) (Cambardella et al., 1994), was classified as moderate for almost all semivariogram adjustments (Fig 2), indicating moderate spatial dependence. This spatial dependence would be possibly due to soil homogeneity for all managements.

The range of scaled semivariograms showed that soils under pasture and cassava have weaker spatial dependence and stronger spatial variability, with ranges of 28 and 31, respectively (Fig 2). In this sense, range values are essential for experimental planning and evaluation, since they can assist in defining the sampling procedures (McBratney and Webster, 1983; Souza et al., 2009). As indicated by Aquino et al. (2015) and Oliveira et al. (2015b), higher spatial variability is linked to soil intensive use and management, causing changes in its properties. Silva Junior et al. (2012), studying chemical attributes of soils under conversion and different management systems in northern Pará (Brazil), stated that soil chemical characteristics are changed in accordance with adopted plant species and management. Moreover, uneven fertilization and liming become sources of variability (extrinsic factor) (Burak et al., 2012).

We carried out geostatistical analyses using the scores ascribed to samples from the first two PCs, which accounted for the largest share of data variation (Fig 3). Regarding the adjustments of the scaled semivariograms, PCA exhibited a similar behavior. Exponential models adjusted to sugarcane and agroforestry, as well as spherical models adjusted to ADE, pasture, rainforest, and agroforestry followed the same order of adjustments of the scaled semivariograms. In addition, the ranges of semivariograms adjusted to scores showed similar values to adjustments made in the scaled semivariograms, demonstrating satisfactory fittings for the studied managements. These findings provide basis for further studies on soil mapping and characterization, as these environments are representative of the Amazon region and little research has been carried out on this issue.

Based on the adjustments of the semivariograms with the PC 1 and 2, we drew up Kriging maps (Fig 4). These maps represent a set of selected attributes in the analysis of factors, which means that, through the isolines represented on the maps, we can set variability boundaries for each variable assessed.

The kriging maps showed correlation between both components in each management. Interestingly, there was a similarity between isoline tracing and land slope outlines. Such performance was already expected, since soil properties normally follow land slope distribution pattern (Fig 4). Burak et al. (2012) found a relationship between soil properties and relief; these authors stated that chemical attributes' spatial variability indicates greater continuity of spatial dependence in forest and cassava areas, where there is more influence of relief and surface water flows.

It is clear the influence of land slope in the rainforest area, in which we found larger values in lowlands. On the other hand, in soils under cassava, sugarcane, pasture, and with ADE such connection was not found. In these locations, we can observe homogeneous zones of nutrient content that do not vary exclusively with relief variations. Canellas et al.

(2000), studying a soil sequence along a 500-m slope and average declivity of 5%, found higher organic carbon levels in upper positions (upper third). These authors also attributed the redistribution of more soluble fractions of organic matter (fulvic acids) within less elevated regions and higher slope (middle third) to the water dynamics.

Materials and methods

Experiment location

The sample collection was performed in farms located in southern Amazonas state, within the vicinity of Santo Antônio do Matupi village, region of Manicoré and Humaitá, Amazonas-Brazil. Six areas with different land managements were mapped as following: natural environment or forest (Amazonian rainforest), anthropic horizon or archaeological dark earth (ADE), brachiaria pasture (*Brachiaria brizantha*), agroforestry management, sugarcane and cassava crops (Fig 5).

Experimental areas

The forest area is located at 7º54'44.5" S, 61º31'44.7" W, and 140-m altitude. The local vegetation consists of dense rainforest with an average canopy height of about 20–50 m. An adjacent area with ADE, which is sited at 07º55'02.1" S, 61º31'45.2" W, and 102-m altitude, which is under corn cultivation for around 120 days. The pasture area is under extensive grazing (1 animal unit per hectare) with brachiaria (*Brachiaria brizantha*) for 10 years, and is situated at 07º54'42" S, 61º31'50" W, and 135 m altitude. All these areas are within the county of Manicoré, AM, Brazil. Local soils were classified according to criteria established by the Brazilian Society of Soil Science and Soil Taxonomy as Plinthic Red Argisols (Ultisols, USDA Soil Taxonomy) (Embrapa, 2013; Soil Survey Staff, 1999) with alithic character except for soils within the ADE area, which were sorted as abruptic dystrophic Red-yellow Argisols (also Ultisols, USDA Soil Taxonomy) (Embrapa, 2013; Soil Survey Staff, 1999).

The agroforestry area is located at 7º28'29" S, 63º02'07" W, and at an average elevation of 63 m, which has been grown with coffee, cocoa, palm trees, andiroba, among others for 20 years. The sugarcane crop area is located at 7º54'38" S, 63º14'22" W, and 70-m average altitude, which has been carrying burnt sugarcane farming for about 10 years. The cassava plantation is situated at the geographical coordinates of 7º50'24" S, 63º15'01" W, and elevation of 73 m; the area has been cultivated for 10 years continuously. Local soils were limed, fertilized, and harrowed only in the second year of cultivation; during the evaluation, the area was in the fourth month of cultivation. The three areas mentioned above are located in Humaitá, AM, Brazil (Fig 1). Local soils were classified as Plinthic Alithic Haplic Cambisol (Inceptsol, USDA Soil Taxonomy) (Embrapa, 2013; Soil Survey Staff, 1999). Chemical and physical characterization of these management systems can be found in Oliveira et al. (2015a). Regarding the source material, soils in Manicoré are developed from granites of the Rondoniano Mobile Belt, with ages ranging from the Upper Precambrian (Brasil, 1978). Yet the soils in Humaitá are from old alluvial sediments, which are chronologically from Holocene (Brasil, 1978).

The local climate, according to Köppen's classification, is of the rainy tropical type, with a short dry period (Am), temperatures ranging between 25°C and 27°C, and rainfall varying from 2,250 and 2,750 mm, which is concentrated from October to June (Brasil, 1978).

Soil-sampling and evaluation of soil attributes

Soil sampling points were distributed over a 70 x 70 m grid set throughout these areas, covering 0.49 ha. As shown in Fig 1, soil samples were collected at regular spacing of 10 meters, totaling 64 samples per grid. These points were previously georeferenced using a Garmin Etrex GPS unit (South American '69). The samples were taken within 0.0 and 0.10 m depth.

In these samples, we carried evaluations on total carbon, using the Walkley-Black method modified by Yeomans and Bremner (1988). We also estimated organic matter based on the organic carbon (OC). The following equation was used to convert organic carbon into amounts of organic matter:

$OM = 1.724 \times OC$

Where, OM = organic matter content in the soil

OC = content of organic carbon at 0.10 cm depth (g kg^{-1})

The organic carbon stock in the soil was quantified using the expression proposed by Veldkamp (1994):

$STOC = (OC \times SBD \times t)/10$

Where, STOC = stock of organic carbon at 0.10 cm depth (Mg ha^{-1}), OC = organic carbon content at 0.10 cm depth (g kg^{-1}), SBD = soil density at at 0.10 cm depth (kg dm^{-3}), t = thickness of soil layer (in case 0.10 meters).

The undisturbed soil samples, collected by volumetric ring, were saturated with water by capillary action up to reach two thirds of the ring height (Embrapa, 2011). The soil bulk density (SBD) was calculated by the ratio between the mass of the soil, dried at 105 °C for 24 hours, and the cylinder volume (Embrapa, 2011). In addition, we also collected soil with preserved structure, at the same locations, for aggregate stability determination as proposed by Kemper and Chepil (1965). The results were expressed as percentage of aggregates retained on sieves of >2.0; 2.0-1.0; and <1.0 mm meshes, geometric mean diameter (GMD), and weighted mean diameter (WMD).

Statistical analysis

Given the multivariate data structure, we used multivariate statistical techniques to verify similarities among the different soils in an attempt to group them by attributes. We performed an analysis of factors that enables relating a set of variables to be explained in terms of a limited number of new variables; therefore, we opted to use the principal component extractions (Jeffers, 1978), which were calculated from the correlation matrix among variables. We also used the orthogonal rotation method (varimax) to facilitate interpretation (Hoffmann, 1992).

The factor analysis was complemented by the principal component one (PCA) for a smaller set of linear combinations of variables selected from the factor analysis, which preserved most of the information provided by the original variables (Silva et al., 2010). This analysis makes it possible to assess how soil attributes interact qualitatively at

Table 1. Mean test for soil attributes in areas under different land managements in the Amazon region.

Managements	Atributos					
	OM	STOC	TOC	GMD	WMD	SBD
	g dm^{-3}	mg ha^{-1}	g kg^{-1}	mm	mm	kg dm^{-3}
ADE	68.19A	35.15A	39.55A	1.78E	2.57E	0.89D
Pasture	27.47B	20.88B	15.93B	2.79A	3.13A	1.31A
Forest	18.66C	14.11D	10.82C	2.27C	2.83C	1.30A
Agroforestry	20.58C	15.58D	11.94C	2.04D	2.76CD	1.31A
Sugarcane	30.48B	22.28B	17.68B	2.55B	3.08AB	1.27AB
Cassava	27.69B	18.53BC	16.06B	2.29C	2.97B	1.16C

* means followed of uppercase letters in the same column do not differ by the Tukey's test, at 5% significance. ADE = Archaeological Dark Earth; OM = organic matter; STOC = stock of total organic carbon; TOC = total organic carbon; GMD: geometric mean diameter; WMD: weighted mean diameter; SBD: soil bulk density

Table 2. Factors extracted by principal component analysis, emphasizing soil attributes with loadings above 0.7 (in modulus) for soils under the different managements in the Amazon region.

Attributes	Factor 1	Factor 2
Soil bulk density	**0.830025**	0.048216
Geometric mean diameter	0.510731	**-0.827941**
weighted mean diameter	0.499256	**-0.833724**
Organic matter	**-0.964096**	-0.251749
Total organic carbon	**-0.964096**	-0.251749
Stock of total organic carbon	**-0.880088**	-0.356391
Eigenvalues	**3.832561**	**1.636677**
% total variance	**63.87602**	**27.27795**
Cumulative Eigenvalue	3.832561	5.469239
% Cumulative	63.8760	**91.1540**

Table 3. Descriptive statistics of properties with high discriminatory power for soils under different managements in the Amazon region.

Statistics	OM	STOC	TCO	GMD	WMD	SBD
	g dm^{-3}	mg ha^{-1}	g kg^{-1}	mm	mm	kg dm^{-3}
Archaeological Dark Earth - Red Ultisol						
Mean	68.19	35.15	39.55	1.78	2.57	0.89
Median	68.00	35.27	39.44	1.74	2.58	0.88
Variance	183.33	52.70	61.68	0.13	0.07	0.01
SD	13.54	7.26	7.85	0.36	0.26	0.08
CV (%)	20.00	21.00	20.00	20.00	10.00	9.00
Asymmetry	-0.27	-0.42	-0.27	0.35	-0.37	-0.43
Nt	0.10*	0.09^{ns}	0.10*	0.11*	0.07^{ns}	0.09^{ns}
Pasture - Red Ultisol						
Mean	27.47	20.88	15.93	2.79	3.13	1.31
Median	27.00	20.20	15.66	2.84	3.17	1.29
Variance	13.94	10.69	4.69	0.17	0.03	0.01
SD	3.73	3.27	2.17	0.42	0.19	0.12
CV (%)	14.00	16.00	14.00	15.00	6.00	9.00
Asymmetry	0.43	0.45	0.43	-2.49	-2.79	0.65
Nt	0.12*	0.11*	0.12*	0.13*	0.15*	0.13*
Forest - Red Ultisol						
Mean	18.66	14.11	10.82	2.27	2.83	1.30
Median	20.50	15.72	11.89	2.35	2.88	1.31
Variance	43.34	25.40	14.58	0.16	0.05	0.01
SD	6.58	5.04	3.82	0.40	0.23	0.08
CV (%)	35.00	36.00	35.00	18.00	8.00	6.00
Asymmetry	-0.28	-0.33	-0.28	-0.40	-0.62	-0.62
Nt	0.16*	0.14*	0.16*	0.12*	0.11*	0.09^{ns}
Agroforestry – Haplic Cambisol						
Mean	20.58	15.58	11.94	2.04	2.76	1.31
Median	20.50	15.42	11.89	2.09	2.88	1.31
Variance	10.15	5.01	3.42	0.51	0.28	0.01
SD	3.19	2.24	1.85	0.71	0.53	0.09
CV (%)	15.00	14.00	15.00	35.00	19.00	7.00
Asymmetry	0.79	0.50	0.79	-0.35	-3.37	0.13
Nt	0.17	0.10	0.17	0.10	0.19	0.06
Sugarcane – Haplic Cambisol						
Mean	30.48	22.28	17.68	2.55	3.08	1.27
Median	30.50	22.13	17.69	2.62	3.11	1.28
Variance	39.11	18.26	13.16	0.12	0.02	0.01
SD	6.25	4.27	3.63	0.34	0.14	0.09
CV (%)	21.00	19.00	21.00	13.00	5.00	7.00
Asymmetry	-0.05	-0.10	-0.05	-0.48	-0.68	-0.22
Nt	0.11*	0.08^{ns}	0.11*	0.12*	0.12*	0.13*
Cassava – Haplic Cambisol						
Mean	27.69	18.53	16.06	2.29	2.97	1.16
Median	28.00	17.63	16.24	2.32	3.00	1.16
Variance	22.95	9.63	7.72	0.14	0.03	0.01
SD	4.79	3.10	2.78	0.38	0.18	0.07
CV (%)	17.00	17.00	17.00	17.00	6.00	6.00
Asymmetry	0.51	0.97	0.51	-0.56	-0.72	0.11
Nt	0.12*	0.12*	0.12*	0.09^{ns}	0.11*	0.07^{ns}

SD= standard deviation; CV= coefficient of variation; Nt = normality test at 5 % probability by the Kolmogorov-Smirnov test; OM = organic matter; STOC = stock of total organic carbon; TOC = total organic carbon; GMD: geometric mean diameter; WMD: weighted mean diameter; SBD: soil bulk density.

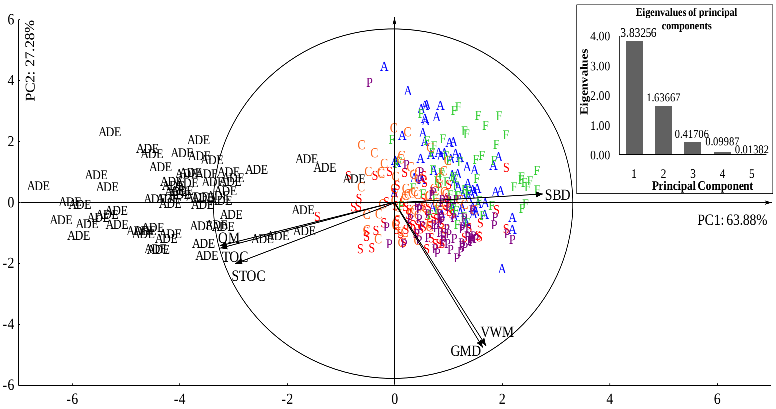

Fig 1. Principal component analysis of the soil attributes with high discriminatory power. ADE = Archaeological Dark Earth (colours black); P = pasture (colours purple); F = forest (colours green); A = agroforestry (colours blue); S = Sugarcane (colours red); C = Cassava (colours orange); OM = organic matter; STOC = stock of total organic carbon; TOC = total organic carbon; GMD: geometric mean diameter; WMD: weighted mean diameter; SBD: soil bulk density.

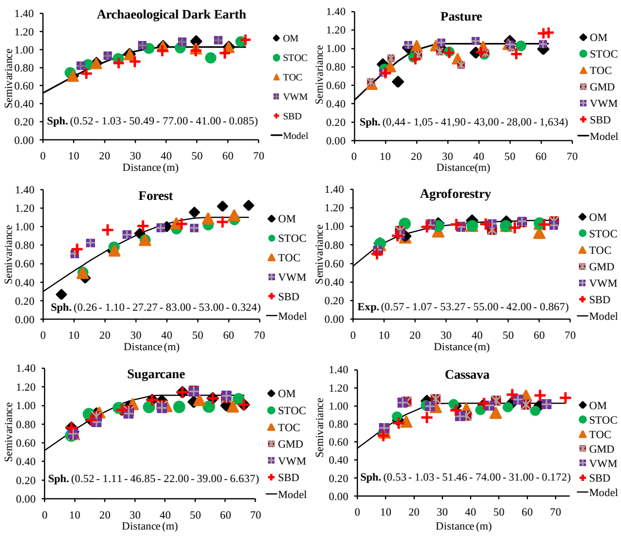

Fig 2. Scaled semivariograms adjusted to the attributes with high discriminatory power for soils under different managements in the Amazon region. Sph= spherical; Exp= exponential; [model (nugget effect – sill – SDD – R^2 – range and residue)]. SDD = spatial dependence degree; R^2= determination coefficient; OM = organic matter; STOC = stock of total organic carbon; TOC = total organic carbon; GMD: geometric mean diameter; WMD: weighted mean diameter; SBD: soil bulk density.

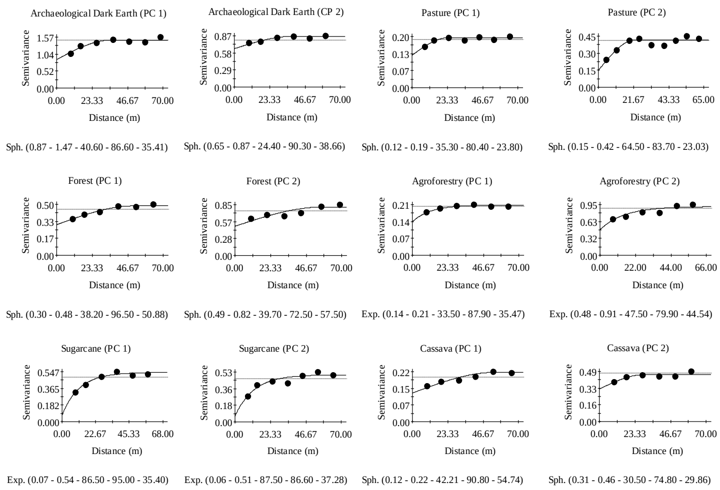

Fig 3. Semivariograms adjusted to the principal components (PC1 and PC2) of the attributes with high discriminatory power for soils under different managements in the Amazon region. Sph= spherical; Exp= exponential; [model (nugget effect – sill – SDD – R^2 – range)]. SDD = spatial dependence degree; R^2= determination coefficient.

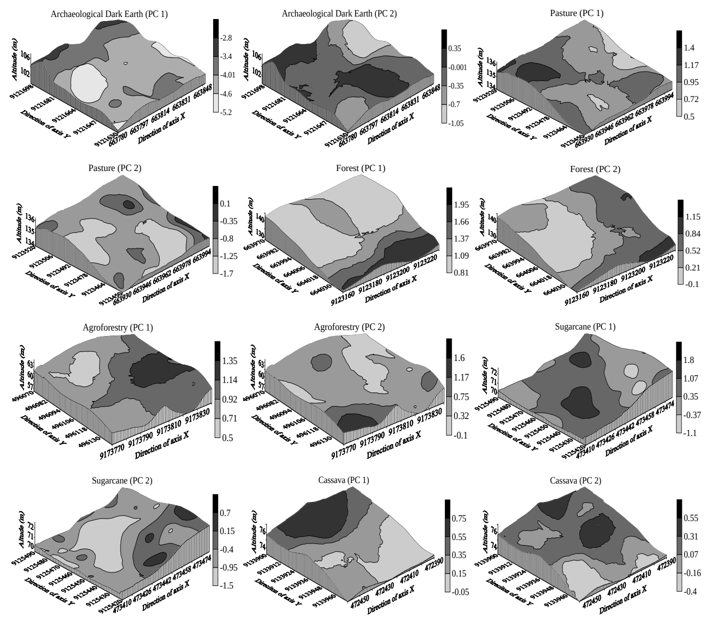

Fig 4. Spatial distribution of sample scores corresponding to PC1 of the attributes with high discriminatory power for soils under different managements in the Amazon region. Darker colors = larger values; lighter colors = lower values

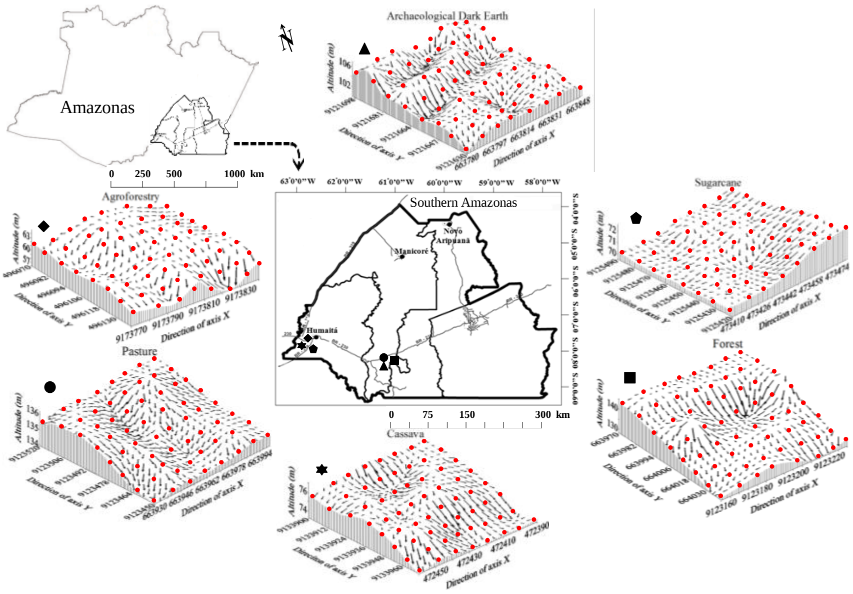

Fig 5. Location of the study areas and soil-sampling diagram. Arrows indicate direction of water flow.

a given time, whose original values were normalized to a mean of 0 and a variance of 1, in order to compose PCA variables. The criterion for choosing the number of components was to select those with eigenvalues above 1, which are able to synthesize a cumulative variance above 70% (Hair et al., 2005). From these data, kriging maps can be designed, making use of the principal components (PCs).

Once recognized the interaction between soil attributes and types, we performed a data exploratory analysis calculating mean, median, standard deviation, variance, variation coefficient (VC), skewness, and normality through the Kolmogorov-Smirnov normality test. The VC (%) was calculated based on Warrick and Nielsen (1980), which classifies VC values smaller than 12% as low, between 12 and 24% as medium, and above 24% as high.

We measured spatial dependence through modeled semivariograms, using geostatistical analysis (Isaaks and Srivastava, 1989). The experimental semivariogram was estimated, under intrinsic hypothesis, as in equation 1:

$$\hat{y}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_1 - Z(x_1 + h)]^2 \qquad (1)$$

In which: γ(h) - semivariance value for a distance h; N(h) - number of pairs involved in semivariance calculation; $Z(x_i)$ - Z attribute value at x_i; $Z(x_i+h)$ - Z attribute value at an h distance from x_i.

The scaled semivariogram was built on parameters of experimental semivariograms of soil properties, which were scaled through division of semivariances by statistical variance (Isaaks and Srivastava, 1989). In this study, semivariograms were scaled to reduce them to the same scale, facilitating comparisons among different variables. In addition, this study aimed at representing several semivariograms simultaneously to understand similarity patterns and spatial variability causes (Ceddia et al., 2009).

Spherical (Equation 2) and exponential (Equation 3) models were fitted to the scaled experimental semivariograms, which were identified within the figures as *Sph* and *Exp* (C_0 - C_1+C_0 - [(C_0/ (C_0+C_1)] x100 - R^2 - a - residue):

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

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

In which: C_0 = nugget effect; C_0 + C_1 = sill; h = distance between experimental observations; a = spatial dependence range; [(C_0/ (C_0+C_1)] x100 = spatial dependence degree; R^2= determination coefficient.

The classification proposed by Cambardella et al. (1994) was used to measure spatial dependence degree (SDD) of each variable. In this method, SDD values smaller than 25% are considered strong, from 25 to 75% moderate, and above 75% poor spatial dependence.

Variability boundaries were defined jointly for all variables, based on the isoline maps. For that, we employed PC1 and PC2 sample scores to build spatial distribution maps, using the Surfer 8.0 software (Golden Software Inc., 1999).

Conclusion

The carbon stock is higher in areas of archeological dark Earth (ADE). The semivariograms adjusted to the land managements pointed out higher variability in areas under pasture and cassava cultivation. The maps of score isolines of principal component analysis showed that the studied soil attributes are related to the slope; however, it is not an intrinsic condition, and other factors such water flows can be related to the values of the studied variables.

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