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Fuzzy logic and geostatistics in studying the fertility of soil cultivated with the rubber tree[1]

Lógica fuzzy e geoestatística no estudo da fertilidade do solo cultivado com seringueira

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ABSTRACT - Knowledge of the spatial variability of soil attributes is an aid to soil management. The aim of this study was to apply fuzzy logic and geostatistics in defining the spatial variability of soil fertility, in soil cultivated with the rubber tree. Soil samples from the 0-0.20 m and 0.20-0.40 m layers were collected in a stratified random sampling grid, with a shortest distance of 6 m, for a total of 60 points. The chemical attributes were P, K, Ca, Mg, BS, CEC and V. The spatial dependence of the attributes was determined, and the maps were constructed using ordinary kriging interpolation. The interpolated values were transformed into degrees of pertinence (FI), with the lower and upper limits previously defined, using an increasing model. The nutrient P displayed values in both layers below the recommended lower limit (< 20 mg dm^{-3}). The rules of inference indicated that the total area shown in the fuzzy maps of soil fertility requires the application of correctives and fertiliser, as it has an FI < 0.50 and a percentage area > 50%. This methodology reduced the number of maps for interpreting soil fertility in the area, enabling visualisation of the spatial and gradual variability of the needs of the region.

Key words: Soil management. Map of fertility. Fuzzy logic.

RESUMO - O conhecimento da variabilidade espacial de atributos do solo auxilia no seu manejo. Com este trabalho objetivou-se aplicar a lógica fuzzy e geoestatística para definir a variabilidade espacial gradual da fertilidade do solo cultivado com seringueira. Amostras de solo nas camadas de 0-0,20 m e 0,20-0,40 m de profundidade foram coletadas em uma malha com amostragem aleatória estratificada, com a menor distância de 6 m, totalizando 60 pontos. Os atributos químicos foram: P, K, Ca, Mg, SB, CTC e V. Determinou-se a dependência espacial dos atributos e construiu-se os mapas por interpolação por krigagem ordinária. Os valores interpolados foram transformados em graus de pertinência (IF), com os limites inferiores e superiores previamente definidos, com o modelo crescente. O nutriente P, nas duas camadas, apresentou valores abaixo do limite inferior (< 20 mg dm^{-3}) recomendado. As regras de inferências indicaram que a totalidade da área apresentada nos mapas fuzzy de fertilidade necessita de aplicação de corretivo e de adubação por apresentar IF < 0,50 e porcentagem da área > 50%. Esta metodologia reduziu o número de mapas na interpretação da fertilidade do solo na área, permitindo visualizar a variabilidade espacial e gradual das necessidades na área.

Palavras-chave: Manejo do solo. Mapa de fertilidade. Lógica difusa.

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INTRODUCTION

The rubber tree (*Hevea brasiliensis* L.), native to the Amazon region, has aroused great interest for cultivation in tropical areas, achieving high rubber production when improved clones are used together with adequate crop management (ROQUE *et al*., 2006).

Knowledge and understanding of soil fertility is of paramount importance for the rational management of agricultural crops. Several studies have been carried out along the lines of precision agriculture, in which maps are constructed of the spatial distribution of crop production, and the physical, chemical and biological attributes of the soil, correlating them for a better interpretation of their relationship in the production process.

Soil attributes often do not reveal a purely random variation throughout the terrain, but show a spatial correlation (GOMES *et al*., 2007). For this reason, geostatistics has been used as an important tool in data analysis in order to model and study the structure of spatial dependence of soil attributes through adjustment of experimental semivariograms. Vieira *et al*. (2012) studied and correlated dendrometric variables of the rubber tree with physical attributes of the soil, and found a moderate degree of spatial dependence.

Fuzzy logic is a mathematical tool that has been used in interpreting soil fertility. It is known as fuzzy set theory, which deals with information of an imprecise or vague nature, as opposed to Boolean logic (classic logic), which treats the real world as having only two classes: true or false (FARIAS; DIMURO; COSTA, 2010).

Bressan *et al*. (2006) proposed a fuzzy classification system to infer the risk of weed infestation, together with the construction of area maps, considering their spatial dependence. Silva and Lima (2009) with the coffee crop, and Souza *et al*. (2009) with pasture, applied fuzzy logic to the chemical attributes of the soil, determining their respective degrees of pertinence in relation to reference values, and also constructing thematic maps using geostatistic techniques, which allowed gradual changes in the classes of soil fertility to be visualised on the maps, defining zones of gradual transition, rather than classifying the information into precisely defined classes, making it more representative of natural behaviour throughout the soil.

Lima *et al*. (2016) used geostatistical techniques to construct maps of the spatial and temporal distribution of soil requirements for nitrogen, phosphorus, potassium and liming, as well as of production in coffee. Fuzzy logic was applied to the thematic maps, defining zones of low, medium and high requirements for the application of inputs, together with spatial continuity.

The use of fuzzy logic allows the classification and presentation of different chemical attributes on a single map based on their degree of pertinence relative to reference values, identifying gradual zones for the management of a given area. In areas cultivated with the rubber tree, there is no information on the use of this methodology to represent soil fertility. The aim of this study therefore, was to apply fuzzy logic to observing the gradual variation in levels of soil fertility in an area cultivated with the rubber tree at the initial stage of development, using geostatistical techniques to construct a final map of the area for both sampling layers.

MATERIAL AND METHODS

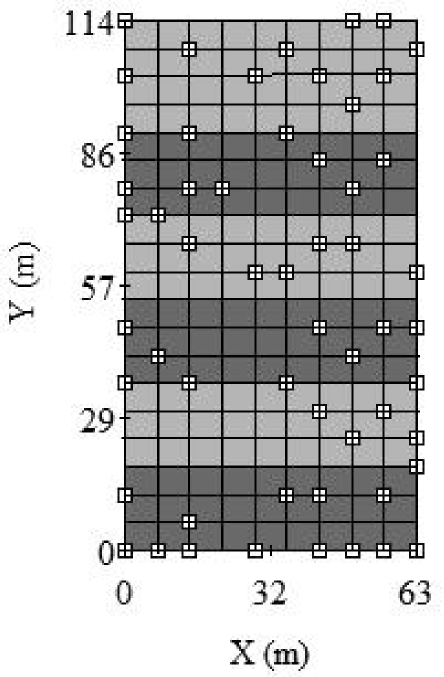
The study area is located in the north of the State of Espirito Santo, Brasil, in the town of Nova Venécia, in a Oxisol of a clayey texture cultivated with the rubber tree (clone Fx 3864). The region has a warm climate classified as tropical hot, Am, according to Köppen, with high temperatures from November to March. The average annual precipitation is 1400 to 2200 mm, according to Silva, Lima and Bottega (2011), with the temperature ranging from 24 to 26 ^{o}C. The granulometric fractions of the soil in the 0-0.20 m layer are 474.3 g kg^{-1} clay, 124.1 g kg^{-1} silt, 288.4 g kg^{-1} fine sand and 105.9 g kg^{-1} coarse sand, and in the 0.20-0.40 m layer 495.6 g kg^{-1} clay, 119.0 g kg^{-1} silt, 279.0 g kg^{-1} fine sand and 106.4 g kg^{-1} coarse sand.

In January 2013, the soil was prepared for planting the rubber tree seedlings using a subsoiler with three rods mounted on the hydraulic lift system of a tractor and working at a depth of 0.50 m, in passes in the area 7.0 m apart. After liming in the row, the area was harrowed and then ploughed at the same depth as the subsoil. The seedlings were manually deposited in the furrows at a spacing of 3.0 m, the rubber trees being grown at a spacing of 7.0 m (between rows) x 3m (in the row).

Formulation 20-00-20 NPK fertiliser (0.05 kg) was used when planting, and at intervals of 30 days for one year, applying 5 L of water to each plant. Ammonium sulphate (0.01 kg) was applied to the soil around the holes 10, 30 and 60 days after planting. For the first two months after planting, water (5 L) was applied twice a week. This practice was repeated during months of low precipitation. From one year after the seedlings were planted, 0.10 kg of the same formulation was applied to the soil every 60 days.

Eighteen months after planting the seedlings, a sampling grid (Figure 1) was constructed at a spacing of 7.0 x 6.0 m, using a stratified random distribution of the points in the area, for a total of 60 cells, considering

Figure 1 - Distribution of the stratified random sampling points in the area cultivated with the rubber tree



3.0 to 4.0 planting rows per cell. Each tree was selected by lot from those in the cell, taking into account planting failures, so that the smallest distance between neighbours in the cell was 6.0 m, and the largest 15.0 m, giving a total of 60.0 points. Soil samples were collected from the 0-0.20 m and 0.20-0.40 m layers, 0.50 m from each tree. The UTM coordinates of the centre point of the sampling grid are 357594.87 (m) and 7931631.22 (m), DATUM WGS84 (FUSO 24S).

The chemical attributes of the soil used in the study to characterise soil fertility were P, K, Ca, Mg, BS (base sum = Ca + Mg + K), CEC (pH 7) = [BS+(H+Al)] and V [base saturation = (BS/CEC)*100], determined as per the methodology recommended by Embrapa (2011). After the attributes were determined in the laboratory, a descriptive analysis of the data was carried out by measuring position and dispersion; normality of the data was tested by the Kolmogorov-Smirnov test ($p \leq 0.05$), since data with a normal distribution better define the sill of the semivariogram in spatial analysis.

Geostatistical analysis was applied to each chemical attribute of the soil in order to verify the existence and, in which case, to quantify the degree of spatial dependence of the attributes, by fitting theoretical functions to the experimental semivariogram models based on the stationarity assumption of the intrinsic hypothesis, as per equation 1:

$$\gamma(h) = \frac{1}{2N} * \sum_{i=1}^{N(h)} [Z(xi) - Z(xi+h)]^2 \quad (1)$$

where: *N(h)* is the number of experimental pairs for observations *Z(xi)*, *Z(xi+h)*, separated by a vector *h*.

For each chemical soil attribute, the theoretical semivariogram models, such as the spherical, exponential and Gaussian, were tested in fitting the experimental semivariogram, defining the following parameters: nugget effect (C_0), sill (C_0 + C), structural variance C) and range (a) of spatial dependence. The criterion for choosing the theoretical model was based on the residual sum of squares, R^2 (determination of coefficient) and the significant correlation coefficient ($p \leq 0.05$) between the observed values and those estimated by cross-validation, as described by Lima *et al*. (2016).

The theoretical semivariograms that were defined were staggered by the variance of the data, with the aim of standardising the scale of semivariance and identifying chemical attributes with the same pattern of spatial distribution.

The degree of spatial dependence (DSD) for each attribute was classified as per Cambardella *et al*. (1994), as weak, moderate and strong, for the ranges: (DSD) ≥ 75.0%, 25.0% ≤ DSD < 75.0%, and DSD < 25% respectively, determined according to equation 2:

$$DSD = \left(\frac{C_0}{C_0 + C}\right) * 100 \quad (2)$$

Once spatial dependence was shown, and the semivariogram models defined by cross-validation for each attribute, the thematic maps were constructed by ordinary kriging.

For each attribute, fuzzy logic (FL) was used to classify the values interpolated by ordinary kriging, generated as files with the .grd extension using the GS+ software (ROBERTSON, 1998). These values were transformed into degrees of pertinence (IF) using a spreadsheet, creating a fuzzy set (FS) following intervals for the moderate class of soil fertility proposed by Prezotti *et al*. (2007) in the rubber tree crop (Table 1).

The function of association chosen in classifying the continuous data was the linear function, used by Bonisch *et al*. (2004), Silva and Lima (2009) and Souza *et al*. (2009) in the study of soil fertility, according to equations 3, 4 and 5, for a data set with increasing values:

$$MF_A(Z) = 0 \text{ Se } z < p \quad (3)$$

$$MF_A(Z) = z\text{-}p/q\text{-}p \text{ Se } p \leq z < q \quad (4)$$

$$MF_A(Z) = 1 \text{ Se } z \geq q \quad (5)$$

Table 1 - Criteria for classifying the degrees of pertinence of the chemical attributes of the soil: phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), base sum (BS), cation exchange capacity (CEC at pH 7) and base saturation (V)

Attributes Level Classes				
Attributes	Unity	Low (< p)	Average (p ≤ z ≤ q)	Hight (z ≥ q)
P	mg dm^{-3}	< 20.0	20.0 – 30.0	> 30.0
K	mg dm^{-3}	< 60.0	60.0 – 150.0	> 150.0
Ca	cmol$_c$ dm^{-3}	< 1.5	1.5 – 4.0	> 4.0
Mg	cmol$_c$ dm^{-3}	< 0.5	0.5 – 1.0	> 1.0
SB	cmol$_c$ dm^{-3}	< 2.0	2.0 – 5.0	> 5.0
CTC	cmol$_c$ dm^{-3}	< 4.5	4.5 – 10.0	> 10.0
V	%	< 30.0	30.0 – 50.0	> 50.0

z: observed attribute value; *p*: lower limit of the average class e *q*: upper limit of the average class (CF class)

where: MF_A is the degree of pertinence (FI) by which an element Z (interpolated) is included in the fuzzy set (FS); *p* is the lower limit and *q* the upper limit of the FS class included in set A.

The combined effect of the attributes was measured using FS functions of map algebra. Equal weight was attributed to all the representations, i.e. the attributes were considered to contribute equally to soil fertility. Thus, the fuzzy output operation, the fertility map for the 0-0.20 and the 0.20-0.40 m layers respectively, became the average considering all the fuzzified maps (SILVA; LIMA, 2009; SOUZA *et al*., 2009).

Fuzzy inference systems are nonlinear models that describe the input-output relationship of a real system, using a family of IF-SO linguistic constructs and fuzzy logic inference mechanisms (FARIAS; DIMURO; COSTA, 2010).

For the conditions of fertility in the area, the linguistic terms *not-fertilise* (NF) and *fertilise* (FE) were adopted. To evaluate the output (defuzzification), rules of inference were used to define fertility in the area, in which the terms can either be included or not in a given condition of fertility; four decision rules were defined (Table 2).

RESULTS AND DISCUSSION

Table 3 shows the results of the descriptive analysis of the chemical attributes of the soil sampled in the 0-0.20 m and 0.20-0.40 m layers, in an area cultivated with the rubber tree at the initial stage of development. In the 0-0.20 m layer, asymmetry can be seen on the left for all attributes except P and CEC. Whereas in the 0.20-0.40 m layer the attributes P, Mg and BS show positive asymmetry. The Kolmogorov-Smirnov test ($p \leq 0.05$) confirms a normal distribution for the chemical attributes of the soil in the two layers.

Considering the intervals shown in Table 1, according to Prezotti *et al*. (2007), all the chemical attributes of the soil are at the maximum value for the respective intervals, with the exception of P in the two layers, since they show values of < 20 mg dm^{-3}, the minimum value for the interval. Therefore, the fuzzification rule was only considered for the nutrients K, Ca, Mg, BS, CEC and V%, in both layers.

The variability of the data was quantified by the coefficient of variation (CV), following the classification of Pimentel-Gomes and Garcia (2002), and classified as low (CV <10%) for CEC (1,2) (layer 1 and 2); moderate

Table 2 - Rules of inference for soil fertility in the area

If [% area (PA) v. fuzzy index (FI)]		So
PA > 50%	FI > 0.50	NF
PA < 50%	FI < 0.50	NF
PA < 50%	FI > 0.50	FE
PA > 50%	FI < 0.50	FE

PA: percentage area; FI: fuzzy index (degree of pertinence), NF: *not-fertilised* and FE: *fertilised*

Table 3 - Descriptive analysis of the chemical attributes of soil cultivated with the rubber tree

Attributes		M	Md	Min	Max	S	Ks	Kc	CV (%)
P1	(mg dm^{-3})	9.4	8.5	4.0	18.1	4.12	0.63	-0.80	43.8
K1	(mg dm^{-3})	88.2	92.0	57.0	117.0	15.34	-0.55	-0.12	17.4
Ca1	($cmol_c$ dm^{-3})	2.0	2.1	1.1	2.9	0.47	-0.38	-0.31	22.9
Mg1	($cmol_c$ dm^{-3})	0.6	0.7	0.2	1.0	0.17	-0.40	-0.15	27.1
BS1	($cmol_c$ dm^{-3})	2.7	2.8	2.1	3.3	0.30	-0.42	-0.34	11.0
CEC1	($cmol_c$ dm^{-3})	9.2	9.2	8.1	10.6	0.64	0.39	-0.52	6.9
V1	(%)	29.8	31.0	18.0	36.0	5.06	-0.97	0.26	16.9
P2	(mg dm^{-3})	6.1	5.1	1.7	14.8	3.67	0.99	0.04	59.7
K2	(mg dm^{-3})	85.0	85.7	59.0	104.0	11.36	-0.18	-0.22	13.4
Ca2	($cmol_c$ dm^{-3})	1.5	1.6	0.5	2.5	0.45	-0.37	-0.37	28.8
Mg2	($cmol_c$ dm^{-3})	0.4	0.5	0.2	0.7	0.15	0.00	-0.76	33.4
BS2	($cmol_c$ dm^{-3})	2.2	2.2	1.6	3.0	0.28	0.71	0.56	12.8
CEC2	($cmol_c$ dm^{-3})	8.9	9.0	8.2	9.8	0.36	-0.24	0.31	4.1
V2	(%)	25.0	25.0	11.0	41.0	6.70	-0.03	-0.39	26.9

M: average: Md: median; Min: low value; Max: maximum value; S: standard deviation; Ks: skewness; Kc: kurtosis; CV: coefficient of variation; 1: 0-0.20 m layer; and 2: 0.20-0.40 m layer

(CV between 10% and 20%) for K (1,2), BS (1,2) and V1; high (CV between 20% and 30%) for Ca (1,2), Mg1 and V2; and very high (CV >30%) for P (1,2) and Mg2. Silva and Lima (2009) found a CV of 35.6% for BS, 10.2% for CEC and 26.9% for V in a study of soil fertility cultivated with coffee. The high CV for nutrient P is due to poor technical evaluation when planting the rubber trees, i.e. the nutrient was not applied until sampling, 18 months after planting the seedlings.

The geostatistical analysis of the chemical attributes is shown in Table 4, with the models and components of the staggered theoretical semivariograms fitted to the experimental data.

The semivariograms, staggered by the variance of the respective chemical soil attributes in the 0-0.20 m and 0.20-0.40 m layers, are shown in Figure 2. For any one attribute in layers 1 and 2, the same fit to the spherical (SPH) and exponential (EXP) models can be seen. The adjustments show values for R^2 greater than 70%, i.e. most of the variability in the estimated values of semivariance is explained by the models. For all attributes, the correlation between the observed values and those estimated by cross-validation was significant ($p \leq 0.05$).

In Figure 2, it can be seen for the two layers of soil that Ca, Mg and BS show the same pattern of spatial distribution, the same adjustment model (SPH), and similar ranges, indicating regions in both layers with the highest and lowest concentrations of these nutrients in the soil. This is related to the effect of soil preparation and applying the inputs to the rows at a smaller distance than between rows.

In the 0-0.20 m layer, a strong DSD is found for all attributes, with values less than 25.0%, except for P and K, which present a moderate DSD, with values between 25.0% and 75.0%. In the 0.20-0.40 m layer, P and Ca show a strong DSD (<25.0%), while for the other attributes the DSD is moderate.

The DSD represents the random percentage distribution of the sample data for a given attribute. Thus, irrespective of the adjustment of a theoretical model to the experimental data indicating spatial dependence within the total area under study, there are regions in the area with similar values. The attributes Ca1, V1 and P2 display low randomness, with a DSD of 1.0%. For the attribute CEC2, 56.4% of the variation in the samples is random; therefore, however close the sampling units, this variability will be present (OLIVEIRA *et al*., 2009).

The range (a) defines the distance at which the sample points display spatial dependence. The attributes K (40.0 m), BS (68.0 m) and V (86.0 m) have the highest range values in the 0-0.20 m layer in relation to the 0.20-0,40 m layer, showing greater spatial continuity in the area due to the type of liming and fertilisation adopted.

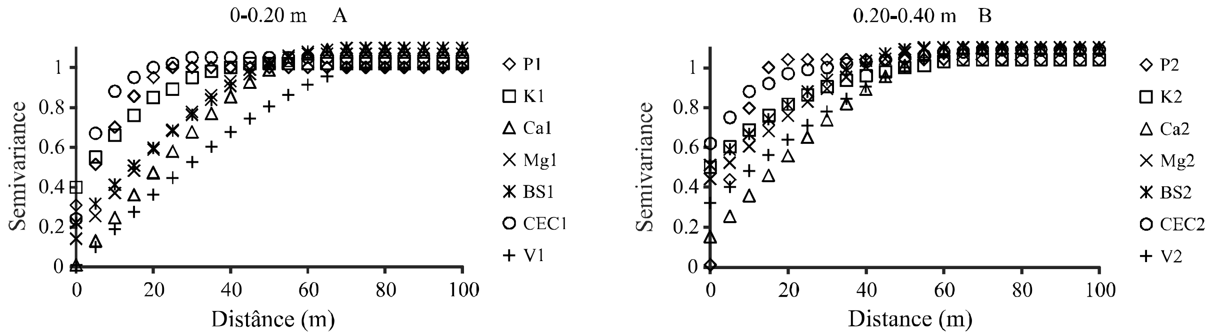
The range dimension influences the number of neighbouring points used to estimate values for non-sampled sites by the method of ordinary kriging

Table 4 - Parameters and models of the staggered semivariograms for the chemical attributes of the soil in the two layers

Attributes	Model	C_0	C_0+C	a (m)	R^2	DSD (%)
P_1	SPH	0.31	1.00	25.0	96.0	31.0
K1	EXP	0.40	1.04	40.0	72.0	30.0
Ca1	SPH	0.01	1.09	68.0	90.0	1.0
Mg1	SPH	0.14	1.07	60.0	92.0	13.1
BS1	SPH	0.22	1.10	68.0	93.0	20.0
CEC1	EXP	0.24	1.07	25.0	86.0	22.4
V1	SPH	0.01	1.04	86.0	92.0	1.0
P2	SPH	0.01	1.05	18.0	80.0	1.0
K2	EXP	0.50	1.09	26.0	90.0	45.9
Ca2	SPH	0.15	1.11	68.0	90.0	13.5
Mg2	SPH	0.44	1.11	60.0	99.0	39.6
BS2	SPH	0.51	1.11	56.0	84.0	45.9
CEC2	EXP	0.62	1.10	60.0	67.0	56.4
V2	SPH	0.32	1.11	72.0	87.0	28.8

1: 0-0.20 m layer; 2: 0.20-0.40 m layer; SPH: spherical model; EXP: exponential model; C_0: nugget effect; C_0+C: sill; a: range; R^2: determination coefficient; and DSD: degree of spatial dependence

Figure 2 - Staggered theoretical semivariograms for the chemical attributes of the 0-0.20 m (A) and 0.20-0.40 m (B) layers



interpolation. Roque *et al*. (2006), in the 235 clone of the rubber tree, found ranges adjusted to the exponential model, of 58.9 m for V in the 0-0.20 m layer. In different experiments there were variations in range for the same attributes and the same soil layer (0-0.20 m), in Oxisol. A study by Silva and Lima (2009) shows values of 9.0, 16.0 and 16.0 m for BS, CEC and V respectively in soil cultivated with coffee. Souza *et al*. (2009) found ranges of 26.0 m for K, 30.0 m for BS, 44.0 m for CEC and 58.0 m for V in an area of pasture. In an area cultivated with black pepper, Lima *et al*. (2010) determined ranges of 15.7 m for P, 7.0 m for K and an absence of spatial dependence for Ca, BS, CEC and V. This variation in range occurs due to the management adopted in each area, the rate and period of application of fertilisers and correctives, the size of the adopted sampling grid, and the intrinsic characteristics of the soil, such as texture and mineralogy.

The FS maps, with their respective degrees of pertinence (fuzzy index) (FI) for Ca, Mg, K, BS, CEC and V, are shown in Figures 3, 4 and 5. It can be seen that spatialisation of the degrees of pertinence of the chemical attributes Ca1, Ca2, Mg2, K2, BS1, BS2, V1 and V2 display an FI < 0.50 in 100% of the area (PA), and so by the rule of inference (Table 2) the area should be fertilised (FE). Mg1 and K1 with PA $> 50\%$ and FI < 0.50 should be fertilised (FE); CEC1 and CEC2 with PA $> 50\%$ and FI > 0.50 should not be fertilised (NF).

According to Moraes and Moraes (2008), although the rubber tree has low nutritional requirements, low values of P, Ca and Mg can lead to the formation of thinner bark, and laticiferous vessels, and stems of smaller diameter during the production stage.

Figure 3 - Maps of the fuzzy set of degrees of pertinence (FI) for the attributes Ca1, Ca2, Mg1 and Mg2 in the two layers of soil

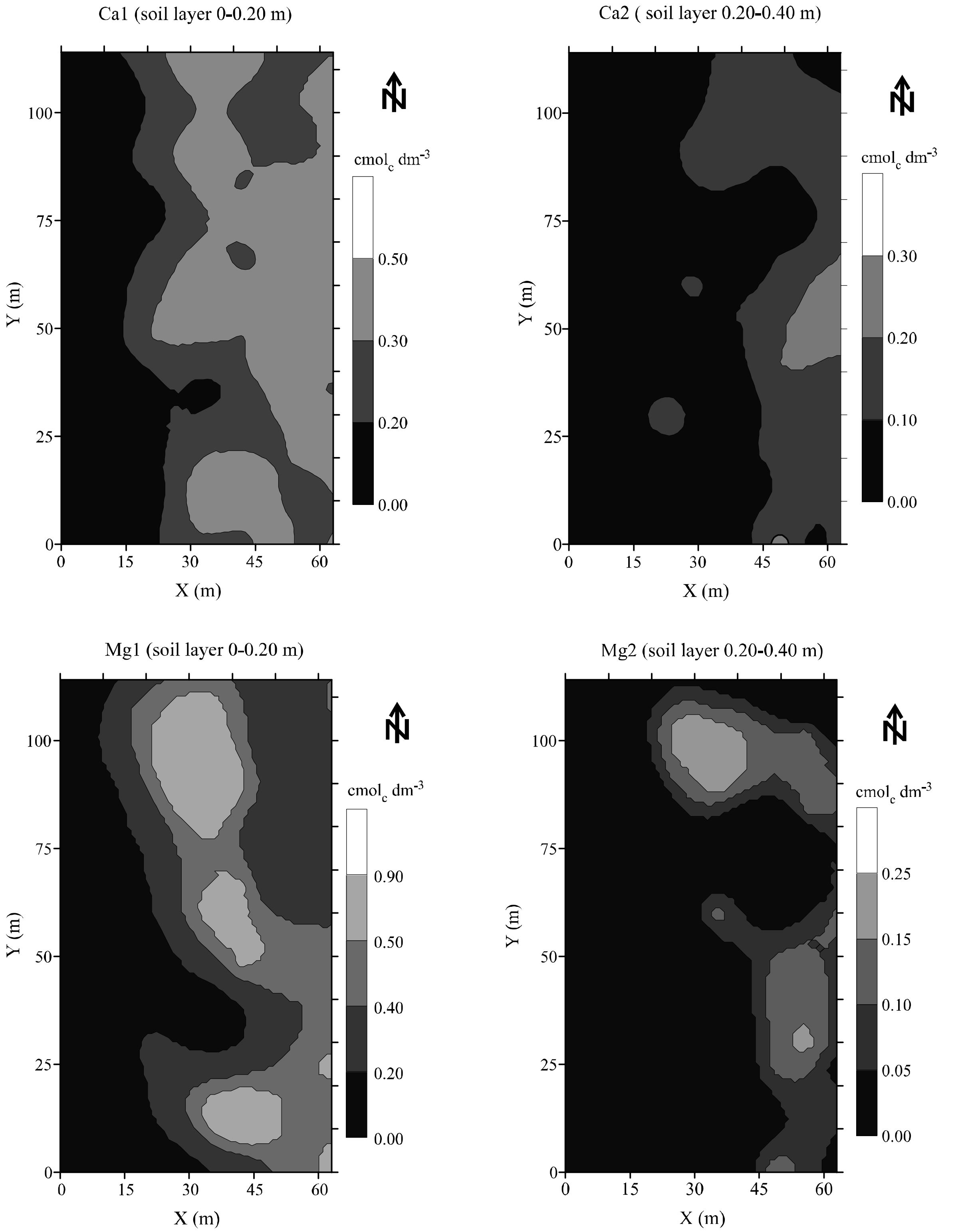


Figure 4 - Maps of the fuzzy set of degrees of pertinence (FI) for the attributes K1, K2, BS1 and BS2 in the two layers of soil

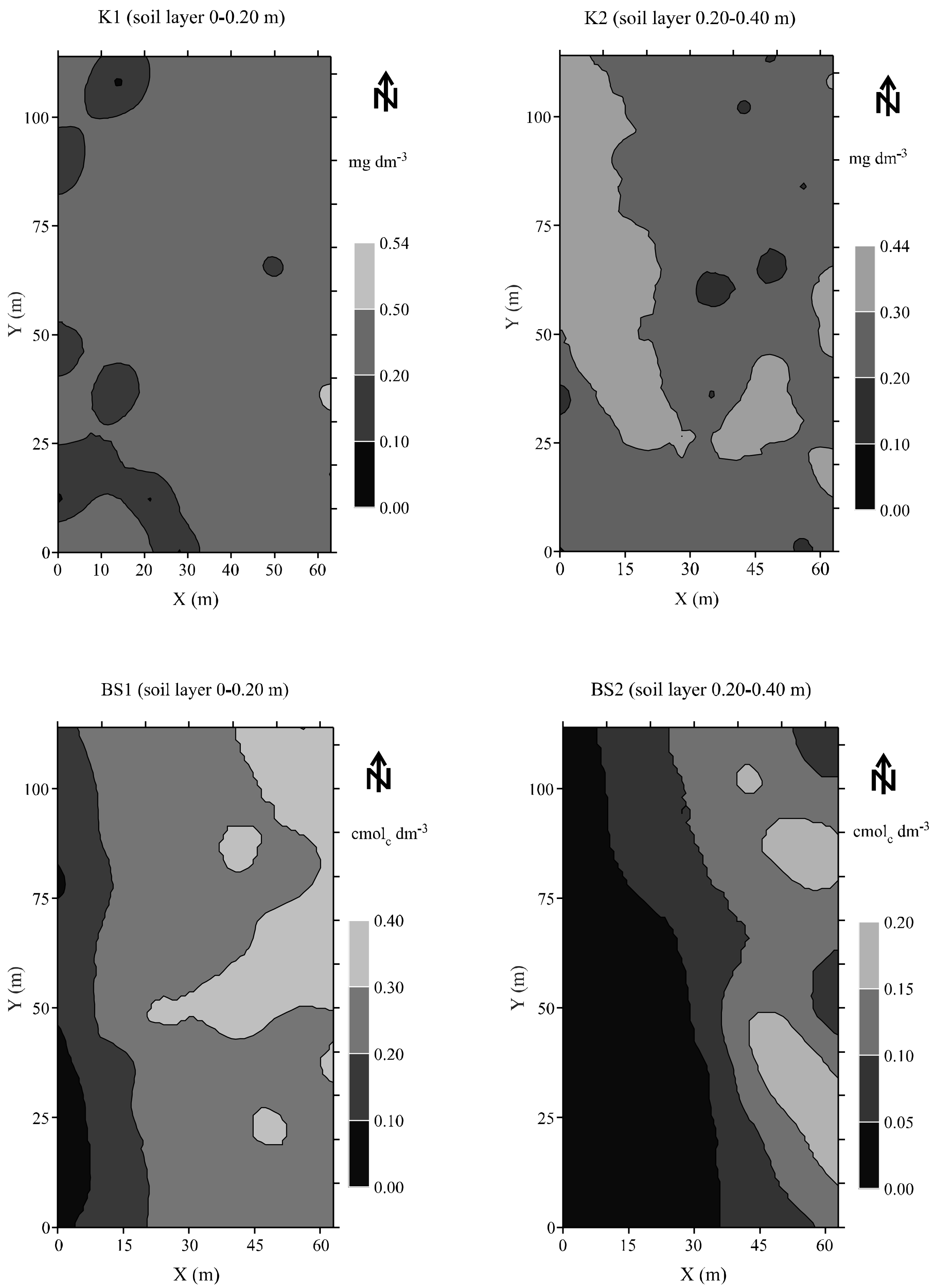
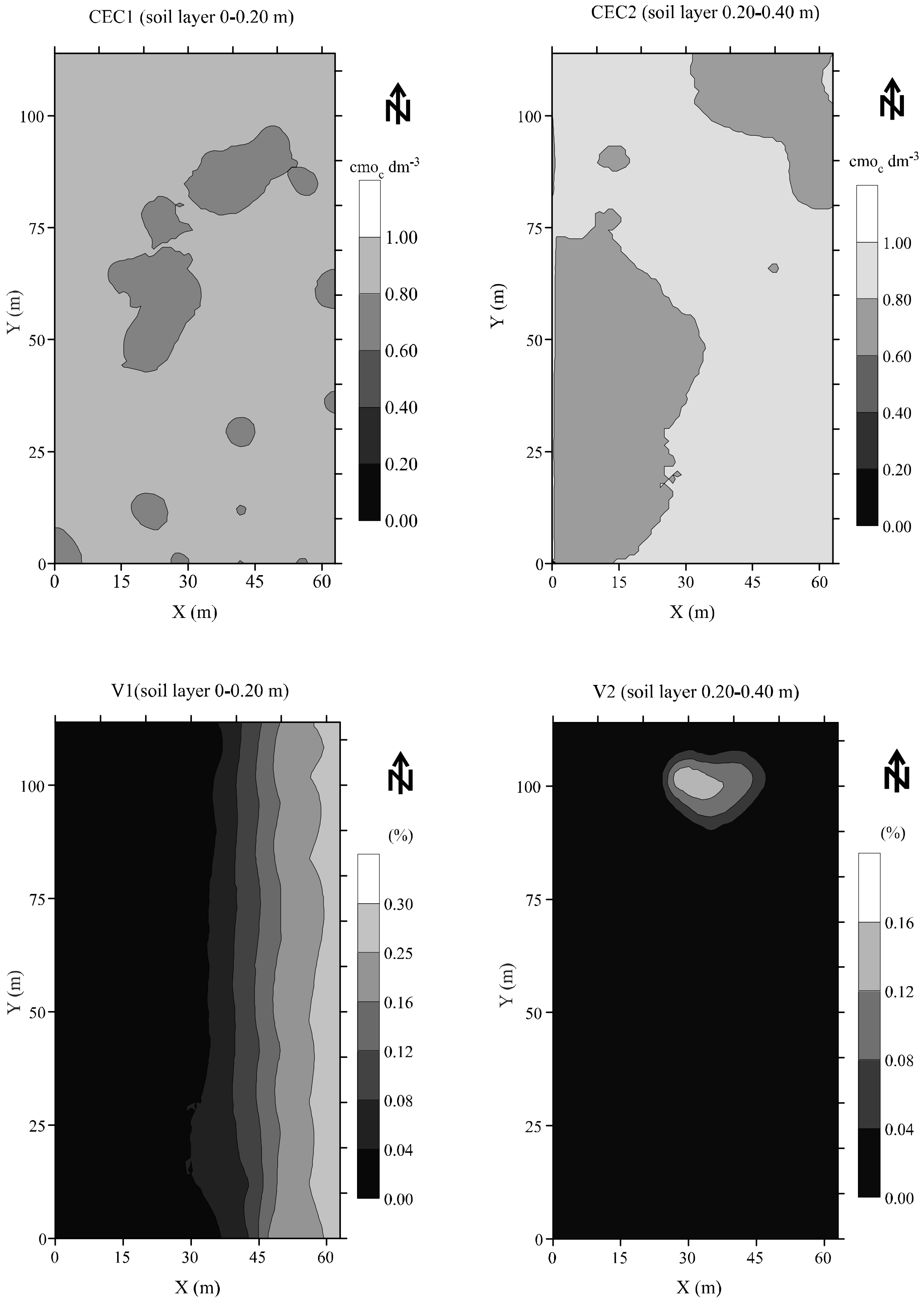


Figure 5 - Maps of the fuzzy set of degrees of pertinence (FI) for the attributes CEC1, CEC2, V1 and V2 in the two layers of soil



The individual attribute maps show a need for fertiliser, as the FIs fall into a minimal range in the soil and are limiting to plant development, especially the macronutrients K, Ca and Mg, with the exception of CEC1 and CEC2. In relation to CEC, in this study it should be noted that the contributions of H+Al are 68.5% and 75.3% for layers one and two respectively; this shows that most charges in the soil are not occupied by the essential cations Ca, Mg and K, but by toxic cations such as H and Al, thereby indicating non-true fertility.

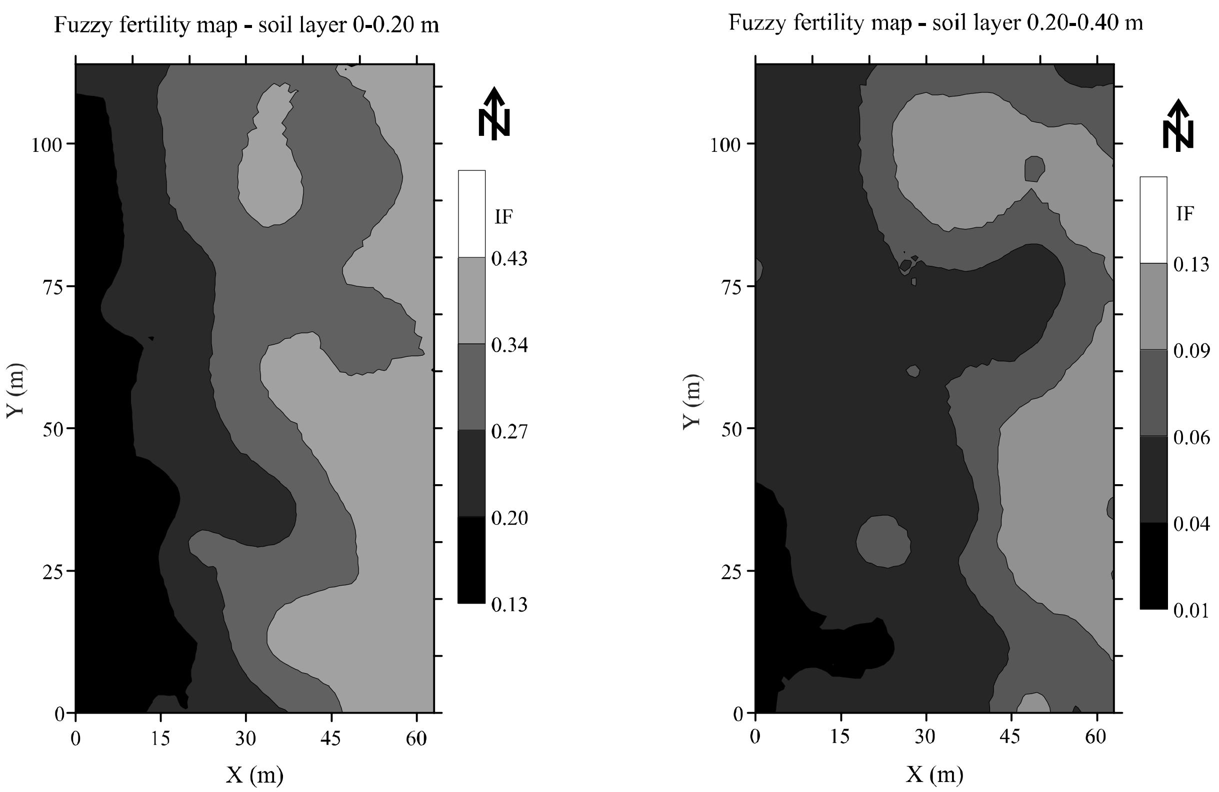
One observation to be made is in relation to the values found for K1 and K2 (Table 2); if Boolean logic is considered, it appears that concentrations in the area are not a limiting factor for indicating good soil fertility, i.e. the soil is of moderate fertility. Employing fuzzy logic, in layer one, a larger concentration is included in PA > 50% of the area with fertility less than or equal to 50% (FI = 0.50) of the range defined as of moderate fertility (60.0 to 150.0 mg dm^{-3}), and in layer two, 100% of the area with fertility less than 44% (FI = 0.44), indicating the need for fertiliser.

The need for liming is strongly linked to the low FI found in the two layers of soil for the basic cations (Ca, Mg and K); this is the first management practice recommended for a rubber tree plantation in the initial state of development. This should be followed by the application of the nutrient phosphorus (P), based on the low average values found in the two layers of soil.

Figure 6 shows the fuzzy maps for moderate fertility determined by map algebra for the two layers of soil, indicating the degrees of pertinence (FI) of fertility in the area cultivated with the rubber tree, eighteen months after planting the seedlings.

It can be seen that for layers one and two the area has 100% PA < 0.50 FI (one hundred percent of the area with the mean degree of pertinence of the chemical attributes smaller than 0.50) and, by the adopted rules of inference for defuzzification, the area shows the need for the application of correctives and production fertiliser. The left side of the area (Figures 3, 4 and 5) shows a region with a pronounced deficit of Ca, Mg, and consequently of BS and V, which reflected in the final map of soil fertility (Figure 6).

Figure 6 - Fuzzy maps of fertility of the area in the two layers of soil



CONCLUSIONS

1. All chemical attributes show spatial dependence in the two layers of soil;
2. The joint analysis of fuzzy logic (LF) and geostatistics allowed the spatial and gradual variability of soil fertility for each nutrient to be visualised on the maps, for the rubber tree in the initial stage of development;
3. The total area in the two layers presented an FI (fuzzy index = degree of pertinence) of less than 0.50, indicating a need for fertiliser (FE) in more than 50% of the area;
4. The joint use of fuzzy logic and geostatistics allowed the levels of soil fertility to be shown on a single map for each layer, defining regions with higher and lower requirements for fertiliser in the area, in order to rationalise management.

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