

MANAGEMENT ZONES DEFINITION USING SOIL CHEMICAL AND PHYSICAL ATTRIBUTES IN A SOYBEAN AREA

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ABSTRACT: Several equipments and methodologies have been developed to make available precision agriculture, especially considering the high cost of its implantation and sampling. An interesting possibility is to define management zones aim at dividing producing areas in smaller management zones that could be treated differently, serving as a source of recommendation and analysis. Thus, this trial used physical and chemical properties of soil and yield aiming at the generation of management zones in order to identify whether they can be used as recommendation and analysis. Management zones were generated by the Fuzzy C-Means algorithm and their evaluation was performed by calculating the reduction of variance and performing means tests. The division of the area into two management zones was considered appropriate for the present distinct averages of most soil properties and yield. The used methodology allowed the generation of management zones that can serve as source of recommendation and soil analysis; despite the relative efficiency has shown a reduced variance for all attributes in divisions in the three sub-regions, the ANOVA did not show significative differences among the management zones.

KEYWORDS: Precision agriculture, spatial variability, fuzzy clustering, management zones, autocorrelation, cross-correlation.

DEFINIÇÃO DE UNIDADES DE MANEJO USANDO ATRIBUTOS QUÍMICOS E FÍSICOS DO SOLO EM UMA ÁREA DE SOJA

RESUMO: Diversos equipamentos e metodologias vêm sendo desenvolvidos para tornar a agricultura de precisão disponível, especialmente considerando o alto custo de sua implantação e de amostragem. Uma possibilidade interessante é definir a área em unidades menores de produção que podem ser tratadas de maneira diferente, servindo como fonte de recomendação e análise. Assim, o presente estudo utilizou propriedades físicas e químicas do solo e de produtividade visando à geração de unidades de manejo, a fim de identificar se estas podem ser usadas como recomendação e análise. Unidades de manejo foram geradas pelo algoritmo Fuzzy C-Means, e sua avaliação foi realizada por meio da redução da variância e realização de testes de comparação de médias. A divisão da área em duas unidades de manejo foi considerada adequada, e as médias apresentaram-se distintas da maioria das propriedades do solo e produtividade; a metodologia utilizada permitiu a geração de unidades de manejo que podem servir como fonte de recomendação e análise do solo. Apesar de a eficiência relativa demonstrar que houve redução da variância para todos os atributos na divisão em três sub-regiões, a ANOVA não apresentou diferenças significativas entre as unidades de manejo.

PALAVRAS-CHAVE: Agricultura de precisão, variabilidade espacial, agrupamento fuzzy, zonas de manejo, autocorrelação, correlação cruzada.

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INTRODUCTION

The continued growth of precision agriculture technology (PA) promoted the emergence of machines equipped with sensors and equipment aiming at reducing costs and improving performance of production processes as well as allowing more detailed analysis of both soil and plants (chlorophyll meter, penetrometer, electrical conductivity meter, yield monitors, meters of vegetation index, among others).

According to KHOSLA et al. (2008), who conducts a research related to PA viability, there are some unknowns from producers that ultimately hinder its use in a more expressive way. Among the questions asked by the researcher, there are included some as: 1) Is it possible to determine the spatial variability of attributes in a less costly way? 2) Is the PA economically feasible? These questions are the focus of much research worldwide, aiming not only at answering them, but developing techniques and procedures that make affirmative answers to these questions. Thus, new forms of research on how to apply this technology study on lower sampling costs associated with sample size and the definition of management zones (TAYLOR et al., 2007; ROUDIER et al., 2008; RODRIGUES JR. et al., 2011; SUSZEK et al., 2012) emerges for making practical and economic PA.

A research to define management zones aims at dividing producing areas in smaller management zones should be treated differently, serving as a source of recommendation and analysis. Yield data, physical and chemical data of soil, electrical conductivity, topography and combination of them are routinely used to define these sub-regions, in addition to the use of statistical modeling of such attributes (RODRIGUES JR. et al., 2011).

For PEDROSO et al. (2010), there are several techniques to define management zones proposed in literature, and XIANG et al. (2007) make a division among techniques, considering two approaches: 1) Using empirical methods, which use frequency distribution of yield to divide the plot, usually in three or four management zones (SUSZEK, et al., 2012); 2) By means of cluster analysis methods such as K-means and Fuzzy C-means.

Quite feasible and obtaining satisfactory results (SUSZEK, et al., 2012), empirical techniques (normalized and standatized yield) make use of crop yield data for definition of management zones and assume that this figure corresponds to crop response, i.e., it does not aim at identifying those attributes affecting the yield, this is a later stage of the process. They also consider that techniques become more accurate the larger it is the number of used crops.

Clustering methods are highly suggested for defining management zones (YAN et al., 2007; ILIADIS et al., 2010) and include the use of several attributes such as electrical conductivity, slope and soil texture, nitrogen, among others and simultaneous use of these attributes. Although there is a possibility of any attribute can be related to crop yield, for DOERGE (2000), the ideal one is using predictable spatial information sources correlated with yield.

The most commonly used clustering methods to define management zones correspond to the K-means algorithm (RODRIGUES JR. et al., 2011; ORTEGA & SANTIBÁÑEZ, 2007) and Fuzzy C-Means (YAN et al., 2007). Both are differentiated by the robustness and are also set up according to Fuzzy C-Means method, which incorporated the theory of Fuzzy logic to the division algorithm.

In order to enable the use of PA technology and evaluate aspects that can influence the process of soybean nutrition, this study aimed at defining management zones using physical and chemical data of soil and soybean yield data to define sub-regions which can be taken as a source of recommendation and optimized sampling. For this, the Fuzzy C-means clustering technique implemented in software SDMZ (Software for Definition of Management Zones) was used.

MATERIAL AND METHODS

The study was carried out in a 19.8 ha commercial farming area, in Serranópolis do Iguaçu/PR, under the following geographical coordinates: 25°26'49"S and 54°04'59"W and 280 m average altitude (Figure 1). The area delimitation and sampling points' sites were obtained with a GPS receiver Trimble Geo Explorer XT 2005 and PathFinder software.

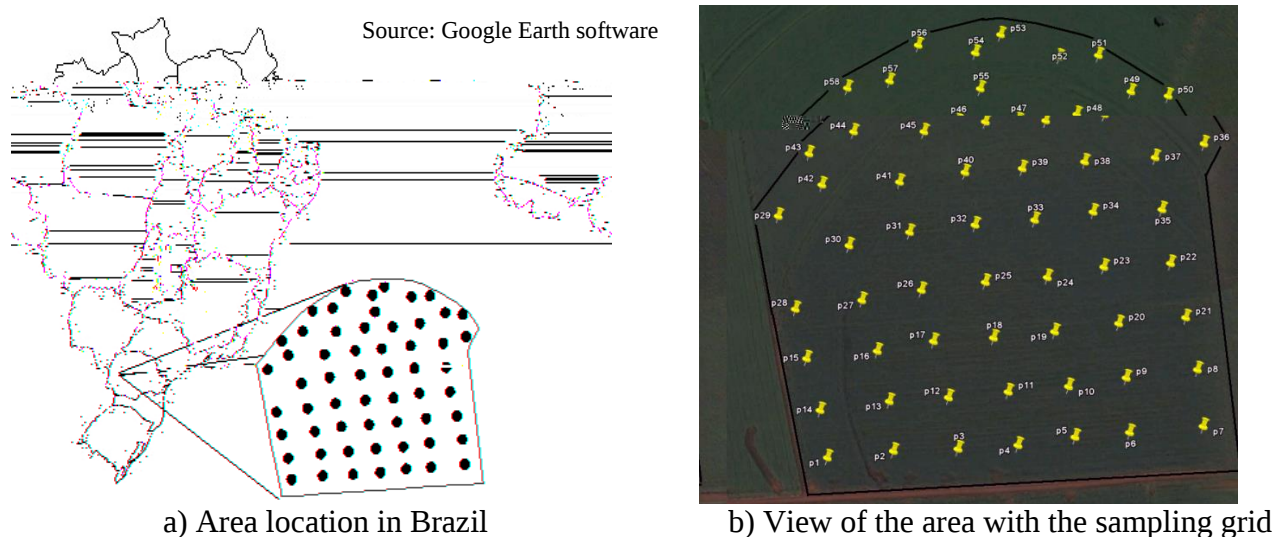


FIGURE 1. Visualization of the experimental area and experimental grid.

Fifty eight sampling points were defined ($2.93 \text{ points ha}^{-1}$, roughly equivalent to the $2.2 \text{ points ha}^{-1}$ suggested by FRANZEN & PECK, 1995) using an irregular grid (Figure 1), 30 m minimum distance and 497 m maximum distance, where data were collected on soybean yield, soil chemical parameters (C, pH, H + Al, Ca, Mg, K, Cu, Zn, Fe, Mn) and textural (silt, sand, clay) properties, in addition to water content and soil penetration resistance at the layers 0 to 0.1 m (SPR010), 0.1-0.2 m (SPR1020), 0.2-0.3 m (SPR2030) depth and average soil compaction at 0 to 0.3m (SPRAVG030) depth. The irregular grid was created considering the planting line.

Each sample point was represented by the total mass collected on two lines in a path of one meter and, as the spacing was 0.45 m, each sample point was represented by an area of approximately 0.9 m^2 (TAVARES-SILVA et al., 2012). The harvested product was referred to the threshing process and water content determination; subsequently yield values were corrected for 13% water content. Soil samples were collected with a hoe and shovel. They were packed in bags and sent for chemical analysis.

Four measurements of soil penetration resistance were performed from 0 to 0.30 m layer at each sampling point, by a Falker PGL 1020 electronic meter of soil penetration resistance.

Data were statistically analyzed by means of exploratory analysis, by calculating the mean, median, minimum, maximum, standard deviation and coefficient of variation (CV). The CV was considered low (homoscedasticity) when $CV \leq 10\%$, medium when $10\% < CV \leq 20\%$, high when $20\% < CV \leq 30\%$ and very high (heteroscedasticity) when $CV > 30\%$ (PIMENTEL & GARCIA, 2002). In order to evaluate the data normality at 5% probability, Anderson-Darling and Kolmogorov-Smirnov tests were performed, and those with normality for at least one of the tests were considered normal.

Usually, the definition of management unit aims at serving as a source of recommendation and analysis for several years (DOERGE, 2000). Therefore, stable and predictable sources of spatial information should be used, which are also correlated with yield. Non-stable sources of information can also be used to define management zones and adjust the amount of nutrients in a certain year. Thus, two approaches were used to generate management units: 1) statistics, where all the studied

attributes (not all that are considered stable) are used; and 2) agronomic, taking into account only the attributes of soil resistance to penetration and texture ones, considered as stable.

Aiming at evaluating the spatial correlation between the attributes and yield, the cross-correlation was used (BONHAM et al., 1995, Equation 1). It make possible to verify which attributes influenced positively or negatively on soybean yield, and if a sample is spatially autocorrelated.

$$I_{YZ} = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} * Y_i * Z_j}{W \sqrt{m_Y^2 * m_Z^2}} \quad (1)$$

where I_{YZ} - Degree of spatial association between Y and Z variables, ranging from -1 to 1, as it is followed: positive correlation $I_{YZ} \geq 0$ and negative correlation $I_{YZ} < 0$, - W_{ij} correspond to the ij element of spatial association matrix, calculated by $W_{ij} = (1/(1 - D_{ij}))$, so that, D_{ij} is the distance between i and j points; Y_i - transformed Y value at point i . The transformation is to have a zero average, by the formula: $Y_i = (Y_i - \bar{Y})$, where $\bar{Y}$ is the sample average of Y, Z_j variables - transformed Z variable at j point. Transformation occurs to have a zero average by the formula: $Z_j = (Z_j - \bar{Z})$, where $\bar{Z}$ the sample average of variable Z. W - corresponds to the sum of spatial association degrees obtained by the matrix W_{ij} , for $i = j$. m_Y^2 - Sample variance of the Y variable. m_Z^2 - corresponds to the sample variance of Z variable.

After the I_{YZ} calculation, the spatial correlation matrix was generated, which also presents the significance of the test in addition to the calculated index I_{YZ} , considering data permutation, where several correlation tests are performed by permuting values of one of the variables to be compared. It remains the points' sites and the values of a position are randomly replaced by one from another point. This technique requires a high computational degree. Under the hypothesis H_0 , Y_i random variables are independent and identically distributed and thus, all the permutations of Y_i values among areas are equally likely. Therefore, the p value of the test is given by Equation 2.

$$p \text{ valor} = \frac{\text{ContIf}(I^{(j)}) - I^{(1)}, j = 1, \dots, n}{n - 1} \quad (2)$$

where n is the number of permutations (default is 999 permutations) I - corresponds to the index calculated by the equation (1).

The null hypothesis is rejected with significance α if $p\text{-value} < \alpha$, i.e., H_0 is rejected with 0.05 of significance if $p\text{-value} < 0.05$.

For both studied situations (statistical and agronomic), matrices of spatial correlation were generated. In order to select the layers that will serve as input data for the Fuzzy C-Means algorithm, the following procedure was used:

1. Elimination of layers with spatial dependence and not significant at 95% significance;
2. From layers with spatial dependence, those with no correlation with soybean yield were removed.
3. The descending order was calculated, considering the degree of correlation with yield;
4. The redundant layers were eliminated (those which correlated with each other), preferring those with lower correlation with yield.

In order to draw the thematic maps, the sample data were interpolated and selected in the analysis of spatial correlation as self-correlated and influence on soybean yield. The surface was represented by 5 x 5 m polygons, representing 25 m². It was used the interpolation method of inverse distance, with an interpolation window of 10 neighbors.

The generation of management zones was performed by Fuzzy C-Means clustering technique (BEZDEK, 1981), which considers a data set $X = \{x_1, \dots, x_n\}$ where x_k corresponds to a feature vector $x_k = \{x_{k1}, \dots, x_{kp}\} \in R^p$ for all $k \in \{1, \dots, n\}$, and R^p is the p-dimensional space. It is aimed at finding a fuzzy pseudo partition which corresponds to a family of fuzzy sets of X c , which represents the data structure as best as possible and is denoted by $P = \{A_1, A_2, \dots, A_c\}$, satisfying

$\sum_{i=1}^c A_i(x_k) = 1$ and $0 \leq A_i(x_k) \leq 1$ where $K = \{1, 2, \dots, n\}$ and n represents the number of elements (lines) matrix X .

The algorithm is guided with parameters on the number of desired clusters (C), a distance measure that defines the allowable distance among points and centroids ($m = 1.3$) and error was used as a stopping criterion (10^{-4}). The position of each centroid is calculated considering the distance passed initially by the parameter (preferably to be $m = 1.3$). For each C , $v_1^{(t)}, \dots, v_c^{(t)}$ is calculated by (Equation 3) for $P^{(t)}$ partition, being $t \in \{1, \dots, n\}$ the iteration. The vector v_i corresponds to the clustering center and A_i is the data weighted average. The weight of x_k is the m -th power of its pertinence degree to the A_i fuzzy set.

$$v_i = \frac{\sum_{k=1}^n [A_i(x_k)]^m x_k}{\sum_{k=1}^n [A_i(x_k)]^m}$$

Calculation of the pertinence degree of x_k to the class A_i (Equation 4) is performed for each $x_k \in X$ and for all $i \in \{1, \dots, c\}$, if $\|x_k - v_i^{(t)}\|^2 = 0$.

$$A_i^{(t-1)}(x_k) = \frac{\|x_k - v_i^{(t)}\|^2}{\sum_{j=1}^c \|x_k - v_j^{(t)}\|^2}^{\frac{1}{m-1}} \quad (4)$$

where $\|x_k - v_i^{(t)}\|^2$ represents the distance between x_k and v_i .

As stopping criterion, $P^{(t)}$ and $P^{(t-1)}$ are compared, and if $|P^{(t)} - P^{(t-1)}| \leq \epsilon$, the algorithm is terminated and the classification is performed by considering the pertinence generated in the last iteration.

Since we worked on several data layers, data were normalized (Equation 5) (MIELKE & BERRY, 2007), whereas there can have different attributes measured and that influence on the clustering process.

$$P_{iNorm} = \frac{P_i - \text{Median}}{\text{Range}} \quad (5)$$

where P_{iNorm} is the normalized pixel value; P_i is the pixel value i to be normalized.

Eight thematic maps were generated, classified according to the division in management zones, considering respectively 2, 3, 4 and 5 sub-regions in the plot.

In order to carry out an evaluation, management zones were used for physical and chemical data and yield of soybean aiming at identifying if the generated zones are significantly different for each attribute. Two parameters were used in this evaluation:

1. Relative Efficiency (RE): evaluates whether there was reduction of total variance of the attribute evaluated with the division into management zones (Equation 6); it was considered an adequate clustering when $RE > 1$ so, the more efficient the higher RE;

$$RE = \frac{S_{AREA}^2}{S_{MZ}^2} \quad (6)$$

where S_{MZ}^2 is the sum of the variance in yield of each management unit, calculated separately, considering the proportion of the total area representing the management zone; S_{AREA}^2 - variance of yield related to the area.

2. Variance analysis: evaluates whether the management zones are associated with statistically different attributes, assuming that data have normal distribution and are internally independent in each sub-region.

RESULTS AND DISCUSSION

The attributes P, K and Zn were classified as heteroscedastic ($CV > 30\%$) and Fe, soil penetration resistance 0 to 10 cm (SPR_0_10), and sand as high CV. For other attributes, only pH could be classified as homoscedastic.

Ca, C, Cu, H+Al, Mg, Mn, yield, soil penetration resistance from 10 to 20 cm (SPR1020), from 20 to 30 cm (SPR2030), and average soil penetration resistance (SPRAVG030) (MPa), moisture, silt, and clay were classified with moderate CV. Cu, P, K and Zn presented some positive asymmetry, silt negative asymmetry and other attributes, symmetrical distribution. Only C and average SPR showed kurtosis classified as platikurtic, and Cu, P, K and Zn were classified as leptokurtic (Table 1). Only P attribute did not show normal distribution.

TABLE 1. Data descriptive statistics.

Attribute	Minimum	Mean	Median	Maximum	Range	SD	C V	Asymmetry	Kurtosis
Ca (cmol _c dm ⁻³)	4.71	6.21	6.19	8.02	3.31	0.70	11.2 (m)	0.02 (a)	-0.13 (A)
C (g dm ⁻³)	13.36	16.67	16.70	20.78	7.42	1.86	11.2 (m)	0.17 (a)	-0.93 (B)
Cu (mg dm ⁻³)	7.20	9.37	9.30	16.50	9.30	1.51	16.1(m)	1.96 (b)	7.74 (C)
Fe (mg dm ⁻³)	14.00	25.33	25.00	43.00	29.00	6.12	24.1(h)	0.60 (a)	0.14 (A)
P (mg dm ⁻³)*	6.70	20.48	17.70	57.30	50.60	10.41	50.8(vh)	1.18 (b)	1.75 (C)
H+Al (cmol _c dm ⁻³)	2.95	3.65	3.69	4.96	2.01	0.52	14.1(m)	0.55 (a)	-0.07 (A)
Mg (cmol _c dm ⁻³)	1.56	2.76	2.69	3.99	2.43	0.49	17.8 (m)	0.41(a)	0.09 (A)
Mn (mg dm ⁻³)	83.00	117.33	116.00	167.00	84.00	20.38	17.4 (m)	0.28(a)	-0.67 (A)
pH	4.90	5.65	5.70	6.20	1.30	0.29	5.1(l)	-0.17 (a)	-0.01(A)
K (cmol _c dm ⁻³)	0.18	0.38	0.35	1.14	0.96	0.18	46.3(vh)	2.32 (b)	6.34 (C)
Yield (t ha ⁻¹)	2.91	4.47	4.52	6.36	3.44	0.64	14.4 (m)	0.32 (a)	1.30 (A)
Zn (mg dm ⁻³)	3.10	5.59	5.20	11.70	8.60	1.91	34.2 (vh)	1.32 (b)	1.71 (C)
SPR010 (kPa)	2261	3988	3879	4560	3910	923	23.1 (h)	0.58 (a)	-0.09 (A)
SPR1020 (kPa)	3566.6	5115.3	5217.7	6509.0	2942.4	727.1	14.2 (m)	-0.08 (a)	-0.63 (A)
SPR2030 (kPa)	3451.9	4752.6	4757.6	6089.1	2637.2	636.4	13.4 (m)	0.21 (a)	-0.45 (A)
SPRAVG030(kPa)	3841.0	4874.1	4894.5	6115.0	2273.9	538.8	11.0 (m)	0.20 (a)	-0.80 (B)
Moisture (%)	10.180	13.22	12.93	17.58	7.40	1.81	13.7 (m)	0.39 (a)	-0.40 (A)
Clay	44.00	53.12	53.50	68.00	24.00	5.56	10.5 (m)	0.46 (a)	-0.34 (A)
Sand	9.00	14.38	14.00	23.00	14.00	3.09	21.5 (h)	0.47 (a)	-0.29 (A)
Silt	20.00	32.50	33.00	41.00	21.00	4.43	13.6 (m)	-0.93 (c)	1.13 (A)

SD - Standard deviation; N - number of sample elements; Symmetry: Symmetric (a); positive asymmetry (b) negative asymmetry (c) Kurtosis: Mesokurtic (A); Platikurtic (B) and leptokurtic (C); * Not Normal at 5% probability; coefficient of Variation (CV): low (l), medium (m), high (h) very high (vh); soil penetration resistance, from 0 to 10 cm (SPR010), from 10 to 20 cm (SPR1020), from 20 to 30 cm (SPR2030), and average soil penetration resistance (SPRAVG030).

Considering the classification proposed by COSTA & OLIVEIRA (2001) for soil chemistry, the attributes Ca, Cu, Mg and Mn presented high availability throughout the area (Table 2). C and Fe presented low availability at a sampling point, but in most sampling points (93% and 96.5%, respectively) could be classified as medium level of availability. Zn also presented with medium level in 84.2% of samples.

TABLE 2. Levels of interpretation of soil chemical properties with the percentage of the studied sampling points.

Attributes		Very low	Low	Medium	High	Very high
P (mg dm ⁻³)	Classification % found		≤ 3.0	3.1 - 6.0	6.1 - 9.0 7.0%	>9.0 93.0%
K (cmol _c dm ⁻³)	Classification % found		≤ 0.10	0.11 - 0.20 1.8%	0.21 - 0.30 40.3	>0.30 57.9
Ca (cmol _c dm ⁻³)	Classification % found		≤ 2.0	2.1 - 4.0	>4.0 100%	
Mg (cmol _c dm ⁻³)	Classification % found	<0.40	0.40 - 0.60	0.61 - 0.80	>0.80 100%	
C (g dm ⁻³)	Classification % found	<9.0	9.0 - 14.0 1.8%	15.0 - 20.0 93.0%	21.0-35.0 5.2%	>35.0
Cu (mg dm ⁻³)	Classification % found		< 0.8	0.8 - 1.7	> 1.7 100%	
Zn (mg dm ⁻³)	Classification % found		< 3.0	3.0 - 7.0 84.2%	>7.0 15.8%	
Fe (mg dm ⁻³)	Classification % found		< 15.0 1.8%	15.0 - 40.0 96.5%	> 40 1.8	
Mn (mg dm ⁻³)	Classification % found		< 15.0	15.0 - 30.0	>30.0 100%	

Source: COSTA & OLIVEIRA (2001)

Selected Layers

Statistic approach:

Using the spatial correlation matrix, Mg layer was selected to generate management zones, considering that:

1. Withdrew layers: Ca, C, Fe, P, H₂AL, Mn, SPR010, pH, K, due to non-significance of the spatial dependence. (Result matrix Figure 2);
2. Withdrew layers: average SPR, SPR1020, SPR2030, and silt, due to lack of correlation of them with soybean yield;
3. After ordering the remaining layers (Cu, Mg, moisture, Zn, clay, sand) in ascending order by degree of correlation with yield, redundant layers were eliminated.

YIELD	0.0038																			
CU	-0.0682	0.0877																		
MG	0.0830	-0.1488	0.1747																	
MOISTURE	-0.0364	0.1126	-0.1320	0.1204																
ZN	0.0454	-0.0847	0.1073	-0.0749	0.0337															
AVG_RMP	-0.0015	-0.0064	0.0004	-0.0138	0.0005	-0.0468														
SPR1020	-0.0177	0.0367	-0.0480	0.0432	-0.0252	-0.0427	-0.0282													
SPR2030	0.0134	-0.0221	0.0215	-0.0337	0.0014	-0.0392	-0.0352	-0.0354												
CLAY	0.0484	-0.0996	0.1337	-0.1254	0.0668	0.0009	-0.0365	0.0238	0.0826											
SILT	-0.0102	0.0243	-0.0320	0.0407	-															

Significant No Significant

Agronomic approach:

Using the spatial correlation matrix (Figure 3), sand layer was selected for generation of management zones, considering that:

1. Withdrew layers: SPR010, due to non-significance of the spatial dependence;
2. Withdrew layers: SPRAVG030, SPR1020, SPR2030, and silt, due to their lack of correlation with soybean yield;
3. After ordering the remaining layers (clay and sand) in ascending order by degree of correlation with yield, redundant layers were eliminated.

YIELD	0.0038								
AVG_SPR	-0.0015	-0.0468							
SPR010	-0.0106	-0.0291	-0.0091						
SPR1020	-0.0177	-0.0427	-0.0251	-0.0282					
SPR2030	0.0134	-0.0392	-0.0311	-0.0352	-0.0354				
CLAY	0.0484	0.0009	-0.0212	-0.0365	0.0238	0.0826			
SILT	-0.0102	-0.0027	0.0057	0.0146	-0.0061	0.0066	-0.0293		
SAND	-0.0718	0.0021	0.0298	0.0444	-0.0338	-0.1567	0.0330	0.2326	
	YIELD	SPRAVG030	SPR010	SPR1020	SPR2030	CLAY	SILT	SAND	

■ Significant ■ No Significant

FIGURE 3. Spatial correlation matrix to agronomic approach.

Four thematic maps were generated for each approach, for divisions in 2, 3, 4 and 5 management zones, respectively (Figures 4 and 5) using the Fuzzy C-Means algorithm with parameters $m = 1.3$ and stopping criterion or error = 0.0001.

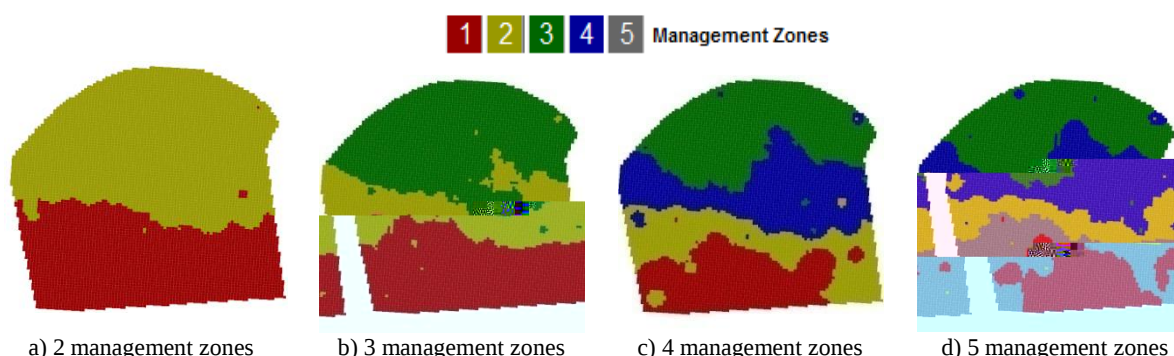


FIGURE 4. Division of the area into management zones using Fuzzy logic and Mg layer, selected by means of cross spatial correlation matrix to statistic approach.

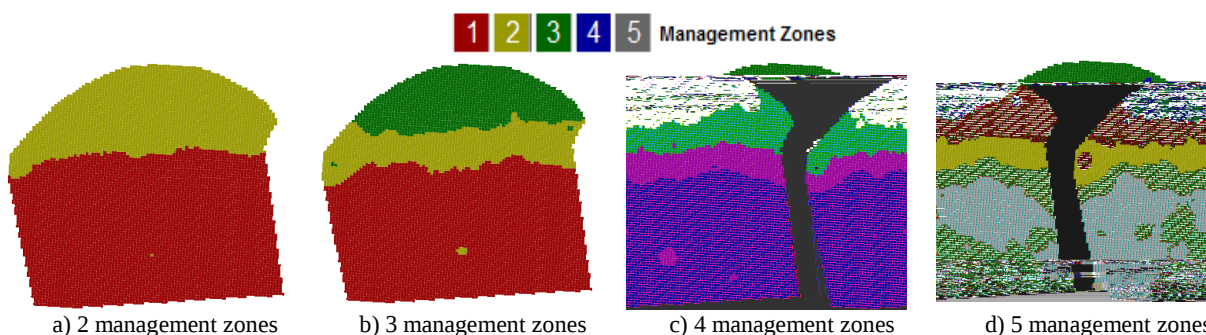


FIGURE 5. Division of the area into management zones using Fuzzy logic and sand layer, selected by means of cross spatial correlation matrix to agronomic approach.

For all performed divisions, relative efficiency (RE) was calculated (Tables 3 and 4), which showed some reduction of the total variance and that the division into management zone was satisfactory ($RE > 1$) only in statistic approach. Despite this fact, when comparing yield data using

analysis of variance, only the divisions in 2 and 3 sub-regions were considered different on average, indicating that each class has different productive potential. Thus, divisions in 2 and 3 zones in statistic approach were considered significant and maintained to evaluate whether they can serve as source of recommendation and analysis of other attributes.

The agronomic approach did not show good results for the studied divisions as $RE < 1$, while ANOVA showed that the data sets had equal averages for almost all cases.

TABLE 3. Descriptive statistics and relative efficiency of yield data ($t\ ha^{-1}$) separated by management zone generated by the Fuzzy C-Means technique for statistic approach.

Divisions	% area	N	Minimum	Mean	Maximum	SD	CV	Variance	Total Var.	RE
2 zones	41.2 58.9	21	3.93	4.74a	6.29	0.508	10.70	0.258	0.372	1.12

TABLE 5. Descriptive statistics of the data separated into two management zones.

Attributes	% area	N	Minimum	Mean	Maximum	SD	CV	Variance	Total Var.	RE
Ca (cmol _c dm ⁻³)	41.2	21	5.94	6.65a	8.02	0.54	8.2	0.30	0.370	1.31
	58.9	36	4.71	5.95b	7.28	0.64	10.9	0.42		
C (g dm ⁻³)	41.2	21	14.10	17.46a	20.04	1.55	8.9	2.41	3.089	1.12
	58.9	36	13.36	16.21b	20.78	1.88	11.6	3.56		
Cu (mg dm ⁻³)	41.2	21	7.20	8.37a	9.80	0.82	9.8	0.67	1.647	1.39
	58.9	36	8.30	9.95b	16.50	1.52	15.3	2.33		
Fe (mg dm ⁻³)	41.2	21	14.00	23.95a	33.00	5.36	22.4	28.75	36.317	1.03
	58.9	36	17.00	26.14a	43.00	6.45	24.7	41.61		
P (mg dm ⁻³)	41.2	21	8.10	19.85a	57.30	11.25	56.7	126.52	111.272	0.97
	58.9	36	6.70	20.85a	46.20	10.03	48.1	100.61		
H+Al (cmol _c dm ⁻³)	41.2	21	2.95	3.27a	3.97	0.34	10.2	0.11	0.179	1.48
	58.9	36	3.18	3.87b	4.96	0.48	12.3	0.23		

TABLE 6. Descriptive statistics of the data separated into three management zones.

Attributes	% area	N	Minimum	Mean	Maximum	SD	CV	Variance	Total Var.	RE
Ca (cmol _c dm ⁻³)	41.7	26	4.71	5.89a	7.28	0.71	12.1	0.51	0.384	1.26
	24.3	17	5.43	6.37b	8.02	0.62	9.7	0.38		
	34.0	14	5.94	6.60c	7.24	0.48	7.3	0.23		
C (g dm ⁻³)	41.7	26	13.36	16.04a	20.78	1.87	11.7	3.51	2.948	1.17
	24.3	17	14.10	16.78b	20.04	1.87	11.5	3.51		
	34.0	14	15.21	17.70b	19.29	1.37	77.2	1.87		
Cu (mg dm ⁻³)	41.7	26	8.30	9.99a	16.50	1.64	16.4	2.69	1.762	1.30
	24.3	17	7.30	9.28b	12.60	1.27	13.7	1.62		
	34.0	14	7.20	8.32b	9.80	0.85	10.3	0.73		
Fe (mg dm ⁻³)	41.7	26	17.00	25.69a	39.00	5.97	23.2	35.66	34.877	1.07
	24.3	17	14.00	26.53b	43.00	7.19	27.1	51.76		
	34.0	14	18.00	23.21ab	32.00	4.68	20.2	21.87		
P (mg dm ⁻³)	41.7	26	6.70	21.20a	46.20	10.75	50.7	115.55	103.865	1.04
	24.3	17	8.00	20.09a	57.30	12.33	61.4	152.09		
	34.0	14	12.00	19.64a	36.60	7.43	37.8	55.13		
H+Al (cmol _c dm ⁻³)	41.7	26	3.18	3.91a	4.96	0.49	12.5	0.24	0.168	1.58
	24.3	17	2.95	3.66b	4.61	0.41	11.1	0.17		
	34.0	14	2.95	3.16b	3.96	0.28	9.0	0.08		
Mg (cmol _c dm ⁻³)	41.7	26	1.56	2.36a	2.67	0.24	10.2	0.06	0.053	4.56
	24.3	17	2.60	2.81b	2.98	0.12	4.2	0.04		
	34.0	14	3.02	3.45c	3.99	0.27	7.9	0.08		
Mn (mg dm ⁻³)	41.7	26	83.00	103.92a	142.00	14.68	14.1	215.51	252.303	1.65
	24.3	17	88.00	122.53b	151.00	15.87	13.0	251.89		
	34.0	14	106.00	135.93c	167.00					

CONCLUSIONS

- The used methodology allowed the generation of management zones that can serve as source of recommendation and soil analysis;
- The subdivision into two management zones was considered the best by allowing zones with a greater number of different attributes among classes;
- The program “Software for Definition of Management Zones-SDUM” enabled a quick and easy creation of management zones, despite the complexity of the applied methodology;
- Despite the relative efficiency showing reduced variance for all attributes in divisions in the three sub-regions, ANOVA showed no consistent results.
- The agronomic approach did not show good results for the division of management units, so, it was not possible to identify different productive potential sites of the studied area.

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