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Use of the farmer's experience variable in the generation of management zones

Utilização da variável experiência do produtor na geração de zonas de manejo

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Abstract

In the spatial variability management of fields, the approach based on management zones (MZs) divides the area into sub-regions, which have spatially homogeneous topography and soil conditions. Such MZs should lead to the same potential yields. Farmers understand which areas of a field have high and low yields, and use of this knowledge may allow the identification of MZs in a field based on production history. The objective of the present study was to evaluate the application of farmer's experience to determine MZs. The study was conducted in three agricultural fields located in the west of the Paraná State in Brazil, and the MZs were generated considering three cases: a) without the use of the farmer's experience variable; b) with the variable of farmer's experience and the stable soil properties selected at the variable selection stage; and c) only with the farmer's experience variable. The generated MZs were evaluated using the Variance Reduction (VR) index, Fuzziness Performance Index (FPI), Modified Partition Entropy (MPE), Smooth Index (SI), and Analysis of Variance (ANOVA). The study showed that the use of farmer's experience to set MZs could be an efficient and simple tool, that it could reduce costs for the processes of setting MZs, compared to the traditional method of using stable soil variables and relief.

Key words: Precision agriculture. Clustering. Farmer feeling. Management units.

Resumo

No gerenciamento da variabilidade espacial das lavouras a abordagem baseada em zonas de manejo (ZMs) divide o talhão em sub-regiões, que apresentam topografia e condições do solo espacialmente homogêneas, de tal forma que tais ZMs devem conduzir aos mesmos resultados em potencial de rendimento das culturas. Os produtores têm experiência de quais áreas de um talhão apresentam altas e baixas produtividades e fazer uso dessa base de conhecimento pode permitir a identificação de ZMs em um campo com base no histórico de produção. O objetivo desse trabalho foi avaliar a eficiência de utilização da experiência do produtor na definição de ZMs. A pesquisa foi realizada em três áreas agrícolas localizadas na região Oeste do estado do Paraná/ Brasil e as ZMs foram geradas considerando

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três casos: a). Sem a utilização da variável experiência do produtor; b). Com a variável experiência do produtor e atributos estáveis do solo selecionados na etapa de seleção de variáveis; e c) Somente com a variável experiência do produtor. As ZMs geradas foram avaliadas pelos índices Redução da Variância (VR), Fuzziness Performance Index (FPI), Modified Partition Entropy (MPE), Smooth Index (SI) e Analysis of Variance (ANOVA). O estudo mostrou que a utilização da experiência do produtor para definir MZs pode ser uma ferramenta eficiente e simples, além de diminuir os custos no processo de definição de MZs, quando comparado ao método tradicional de utilização de variáveis estáveis do solo e do relevo.
Palavras-chave: Agricultura de precisão. Agrupamento. Sentimento do produtor. Unidades de manejo.

Introduction

The growing concern with the efficiency of agricultural inputs and the need to increase the yield capacity of soils increase the need for understanding the spatial variability of agricultural fields. In spatial variability management of fields, the approach based on management zones (MZs) divides the plot into sub-regions, which have topography and soil conditions spatially homogeneous (FLEMING et al., 2004; MORAL et al., 2011; XIN-ZHONG et al., 2009). Such MZs should lead to the same results, such as potential crop yields, allowing a single nutrient input rate in each sub-region (DIACONO et al., 2012; KITCHEN et al., 2005; MILNE et al., 2012; SCHEPERS et al., 2004).

As described by Yao et al. (2014), MZs have many other applications besides representing areas of the same productive potential, optimizing soil sampling grid, and reducing the number of tests required for development of nutrient application maps and fertilizers (LI et al., 2007). Such a methodology also allows conventional agricultural equipment to be used, since the application is constant within each zone and varies only between areas.

In the process of generating MZs, clustering methods have been widely used (FRAISSE et al., 2001; LI et al., 2007; REYNIERS et al., 2006; SCHENATTO et al., 2016; TAYLOR et al., 2003). The algorithm Fuzzy C-Means (BAZZI et al., 2013; LI et al., 2007; MORARI et al., 2009; MILNE et al., 2012; XIN-ZHONG et al., 2009) is a clustering method based on the fuzzy logic, defined by Zadeh (1965), which matches uncertainties associated with class and association boundaries (DOBERMANN et al., 2003).

Scientists believe that the farmer’s experience is important in the development of agriculture, as we know it today (CROOKSTON, 1996). According to Fleming et al. (2004), without the decision-making experience of farmers, much of modern agriculture would be unknown. Farmers know which areas of fields have large and low yields, and it is logical that the nutritional requirements are different between these areas. Making use of this knowledge base may allow the identification of different management areas in a field, based on the production history (FLEMING et al., 2000).

Several tools are used to obtain data to generate MZs (MORARI et al., 2009), and one of them is the visual delimitation based on the farmer´s field knowledge. However, according to Fleming et al. (2004), the potential contribution of the farmer’s experience has not been fully utilized. Hörbe et al. (2013) delineated MZs based on farmer’s experience and classified an agricultural area into high, medium, and low corn yield areas, reaching the optimal number of three MZs, and analysis of variance indicated heterogeneity of soil fertility between the MZs. Nkoka et al. (2014) established irrigation systems in Mozambique based on the specific context of each area and each system displayed a unique pattern of management, based on the history a farmer has about the field. Fleming et al. (2004) compared prescription maps developed using farmer’s experience with those developed using soil fertility analysis in two fields of corn in Colorado. The results were similar when the two methods were compared. Khosla et al. (2002) also generated MZs using soil color obtained through aerial imagery, topography, and farmer's experience of the yield history of the field and concluded that the treatment based on MZs allowed better management of field variability than conventional treatments. To this end, the aim of this study was to evaluate the efficiency of the utilization of the farmer's experience in management zone definition.

Materials and Methods

The research was conducted in three commercial agricultural areas: The first area (called field A) has about 15.5 ha (Figure 1a) and is located in Céu Azul - PR, with an approximate central geographical location of 25º06'32'' S and 53º49'55'' W and an average elevation of 620 m. The second area (field B) has 23.8 ha (Figure 1b) and is located in Serranópolis do Iguaçu - PR, with approximate geographical coordinates of 25º40'48'' S and 54º00'53'' W and average elevation of 355 m. The third area (field C) has approximately 9.9 ha (Figure 1c) and is also located in Serranópolis do Iguaçu - PR, with approximate geographical coordinates of 25º24'28'' S and 54º00'17'' W and average elevation of 355 m.

The soil of the studied area was classified as Rhodic Hapludox (Latossolo Vermelho distrófico típico) (EMBRAPA, 2006) and has been cultivated under no-tillage system with a crop sequence of soybean, wheat, corn, and oats in field A and succession of soybeans and corn in fields B and C, respectively. Irregular sampling grids were defined taking into account an imaginary axis between the contours of each field. In order to satisfy the constraints of geostatistical analysis (JOURNEL; HUIJBREGTS, 1978) as the minimum number of 30 pairs to calculate semivariances the semivariogram, a dense sampling grid was used with 2.58 ha^{-1} points in area A, 3.07 ha^{-1} points in area B, and 4.24 ha^{-1} points in area C.

Figure 1. The three experimental areas: field A- Céu Azul, Paraná, Brazil; field B- Serranópolis do Iguaçu, Paraná, Brazil; field C- Cascavel, Paraná, Brazil.

a) Field A b) Field B c) Field C

For defining classes of MZs, only those variables considered stable (excluding soil chemical properties) were used, to meet the recommendation of Doerge (2000). An electronic total station called Topcon GPT-7505 was used to determine the elevation. The soil penetration resistance (SPR) was determined with a Falker PGL 1020 penetrometer and then averaged for each depth of 0-0.1 m, 0.1-0.2 m, and 0.2-0.3 m for each of the four years under study. Soil samples were also collected from a depth of 0-0.2 m and sent to the laboratory for analysis of chemical and textural attributes of the soil. The soybean yield data for area A was determined with a yield monitor attached to a Case IV harvester. For areas B and C, the yields of soybean and corn were determined by harvesting samples from an area of 1 m^2 at each of the sampling points. For all the cases, yield's moisture content was correct to 13%. To meet the requirement of temporal yield stability, influenced by the weather and the rains, four-year agricultural yield data (2012, 2013, 2014, and 2015) were normalized to generate a single variable for the yield attribute in each area. The collection of farmer's experience was collected through a visit to each property, where the farmer divided the area into three yield classes (high, medium, and low) based on previous years' experience in the field cultivation. Thereafter, the farmer was asked to estimate the average yield for each of the three classes, thereby creating the numeric variable of farmer's experience.

In order to evaluate the spatial correlation between the attributes analyzed, the Moran's bivariate spatial autocorrelation statistic (CZAPLEWSKI; REICH, 1993) was used. This enabled examination of the attributes that influenced the yield positively or negatively. After generating the spatial correlation matrix, the variables to be used in the generation of MZs were selected using the variable selection method proposed by Bazzi et al. (2013): (a) elimination of variables with no significant spatial autocorrelation at 95% significance; (b) removal of the variables that were not correlated with yield; (c) decreasing ordination of the remaining variables, considering the degree of correlation with yield; and (d) elimination of variables which are correlated with each other, with preference to the withdrawal of those variables with lower correlation with yield.

In geostatistical analysis of the selected variables (attributes), the spherical, exponential, and Gaussian models were adjusted to the experimental semivariogram, and the best model was determined by statistical cross-validation (SUN et al., 2009; ARSLAN, 2012). The data were then interpolated by ordinary Kriging in order to create a 5 × 5 m grid, with more attributes' details which, as shown by Schenatto et al. (2016), is the best interpolation method to generate the sampling grid before the MZs generation process.

As the variables in the clustering process may be presented in different measurement units, it is recommended to normalize the data before generating the MZs, since the clustering algorithms are sensitive to the scale of the input variable values. To normalize the data, the range method (Equation 1) (MIELKE; BERRY, 2007) was used. The method is based on the data set range with values between 0 and 1 and is considered to be the best relative to other methods.

$$P_{iN} = \frac{(P_i - Median)}{Range} \qquad (1)$$

Where P_{iN} - Pixel i Normalized; P_i - pixel i to be normalized.

With the selected variables in the correlation matrix and the variable farmer's experience, the MZs were generated in each area using Fuzzy C-Means clustering method, considering three cases: a) without the use of variable farmer's experience; b) with the variable farmer's experience and stable soil properties selected in the variable selection stage; and c) only with the variable farmer's experience, considering two, three, and four sub-regions.

It is important to differentiate the nomenclatures (terms) used in this text. According to Pedroso et al. (2010), management zone (MZ) is a spatially contiguous field to which a particular treatment can be applied. A management class may consist of more than one MZ, that is, the entire field in which the same treatment can be applied.

The generated MZs were evaluated quantitatively using the following indexes:

1) Variance Reduction (VR) (DOBERMANN et al., 2003; XIANG et al., 2007), Equation 2: This index was used for the normalized average yield variable, with the expectation that the sum of the

variances for each MZ will be smaller than the total variance.

$$VR = \left(1 - \frac{\sum_{i=1}^{c} W_i * V_{mz_i}}{V_{field}} \right) * 100 \quad (2)$$

where c - number of MZs; W_i - proportion of the area in each MZ. V_{mz_i} - variance of the data from each MZ; V_{field} - variance of the sample of data for the entire area.

2) Fuzziness Performance Index (FPI), Equation 3: This index allows the determination of the separation degree (i.e., confusion) between the fuzzy c-clusters of a dataset X. When the FPI values are close to zero, distinct classes are observed, with only a small degree of sharing among members (data), whereas values close to 1 indicate no distinct classes, with a high degree of sharing among members of classes (FRIDGEN et al., 2004).

$$FPI = 1 - \frac{c}{(c-1)} \left[1 - \sum_{j=1}^{n} \sum_{i=1}^{c} (u_{ij})^2 / n \right] \quad (3)$$

Where c - number of clusters; n - number of observations; u_{ij} - element of the fuzzy membership matrix.

3) Modified Partition Entropy (MPE), Equation 4: This index estimates the amount of disorganization created by a specific number of clusters. MPE values close to 1 indicate that disorganization predominates, whereas values approaching 0 indicate better organization (BOYDELL; MCBRATNEY, 2002).

$$MPE = \frac{-\sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij} \log(u_{ij}) / n}{\log c} \quad (4)$$

Where: c - number of clusters; n - number of observations; u_{ij} - ij elements of the fuzzy membership matrix.

4) Smooth Index (SI), Equation 5: This index calculates the frequency of shifts in classes of the thematic map in horizontal, vertical, and diagonal directions. It characterizes the smoothness of the contour curves by pixels. If a hypothetical map possess a uniform area, resulting in the smoothness index of 100% because of the lack of class changes. Likewise, if a map was generated with random values, the smoothness index would be near zero.

$$SI = 100 - \left(\left(\frac{\sum_{i=1}^{k} NM_{Hi}}{4P_H} + \frac{\sum_{j=1}^{k} NM_{Vj}}{4P_V} + \frac{\sum_{l=1}^{k} NM_{Ddl}}{4P_{Dd}} + \frac{\sum_{m=1}^{k} NM_{Dem}}{4P_{De}} \right) * 100 \right) \quad (5)$$

Where: NM_{Hi} - number of changes in the i line (horizontal); NM_{Vj} - number of changes in the j column (vertical); NM_{Dd_l} - number of changes in the l diagonal (right diagonal - De); NM_{De_m} - number of changes in the m diagonal (left diagonal - De); k- maximum number of pixels in the line, column, or diagonal; P_H - possibility of changing pixels horizontally; P_V - possibility of changing pixels vertically; P_{Dd} - possibility of changes in the right diagonal - Dd; P_{De} - possibility of changes in the left diagonal - De.

5) Analysis of Variance (ANOVA): the yield values were compared between MZs using the normalized average yields, and performing the Tukey's range test to identify whether the generated sub-regions showed significant differences in normalized average yields (assuming that there was no spatial dependence within each MZ).

Results and Discussion

According to the variable selection criteria using the Moran's bivariate spatial autocorrelation statistic, the selected variables for the field A were elevation and SPR 0-0.1 m, while in fields B and C only elevation was selected (Table 1). The elevation attribute was selected to define the MZs for the three areas based on the results found by several authors, such as Bazzi et al. (2015), Fraisse et al. 2001, Jaynes et al. (2005), Peralta and Costa (2013), Schenatto et al. (2016), and Schepers et al. (2004), which suggest that when the area is not flat, the variable elevation frequently has a spatial association with crop yield.

Table 1. The variable (attribute) selection and the elimination scheme for MZs definition.

Attributes	Field A	Field B	Field C
SPR 0.- 0.1 m (MPa)	X	X	X
SPR 0.1 - 0.2 m (MPa)	X	X	X
SPR 0.2 - 0.3 m (MPa)	X	X	X
Elevation (m)	X	X	X
Slope (°)	X	X	X
Sand (%)	X	X	X
Silt (%)	X	X	X
Clay (%)	X	X	X
OM (%)	X	X	X

[ ] – Eliminated for not presenting spatial autocorrelation; [ ] - Eliminated for not presenting spatial correlation with the yield; [ ] - Eliminated for being redundant; [ ] - Selected for MZ generation. Significance level of the tests: 0.05.

The stable soil variables selected at areas A, B, and C through the spatial correlation and the variable farmer's experience were normalized by the range method and then interpolated by ordinary Kriging (Figures 2, 3, and 4) and, therefore, imported into SDUM (Software for Definition of MZs) for the definition of the MZs. Thematic maps of soil variables and yield were divided into two, three, and four classes, whereas the map of the variable farmer's experience, which by request was divided based on yield into three classes, with no sense of presenting the thematic map in two and four classes.

For the three experimental areas, MZs were defined into two, three, and four classes (Figures 2, 3, and 4), using three variable combinations: a) only stable soil variables, in other words without the variable farmer's experience (WITHOUT), b) with the variable farmer's experience and stable soil variables (WITH), and c) only the variable farmer's experience (ONLY).

It was verified that the use of the farmer's experience variable with stable soil attributes (WITH) allowed presentation of softer and well-defined MZs, facilitating the operation of the areas. Small variations in the levels of the analyzed variables were possible to verify on the thematic maps (Figure 2, 3, and 4) and were softened in the MZs after the clustering process.

Using ANOVA (Table 2), it was possible to test whether the normalized average yields were statistically different among the classes. Significant differences were found when the division was carried out in two, three, and four classes for fields A and B, whereas for field C it was not possible to find classes statistically distinct in yield. It was possible to confirmed ANOVA results using the boxplot graphs of yield data was generated after splitting into two, three, and four classes (Figures 5, 6, and 7). In field C, it was not possible to identify MZs with distinct yields using ANOVA (Tukey's range test), possibly because of the homogeneity of the yield data (Figure 7) for this area.

Figure 2. Thematic maps of soil attributes (elevation (m) and SPR 0-0.1 m) used in the generation of MZs, variable farmer's experience, and normalized average yield of four crop or agricultural years (2012, 2013, 2014, and 2015) for field A and the generated MZs without the variable farmer's experience (WITHOUT), with the farmer's experience (WITH), and only with the use of this variable (ONLY).

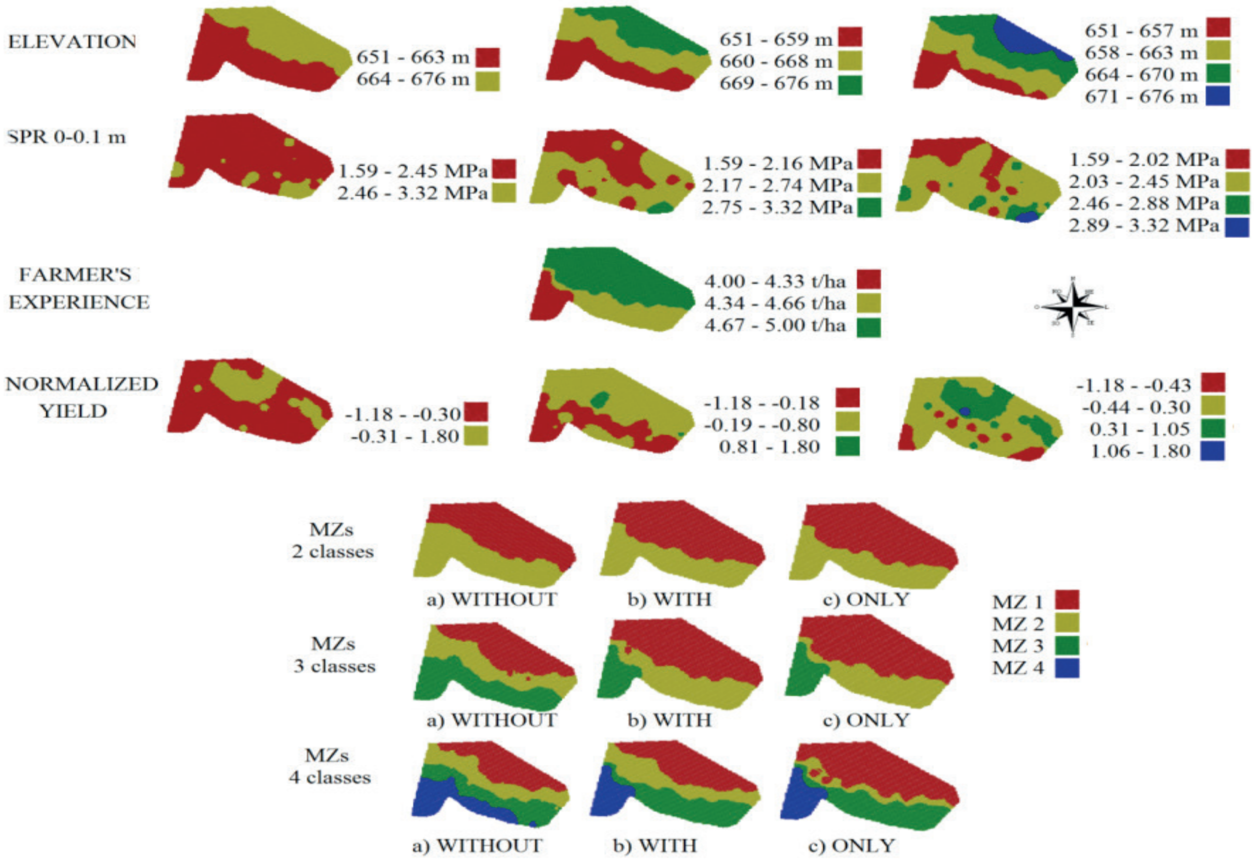


Figure 3. Thematic maps of soil attributes (elevation) used in the generation of MZs, the variable farmer's experience, and normalized average yield of four crop or agricultural years (2012, 2013, 2014, and 2015) for the field B and the generated MZs without the variable farmer's experience (WITHOUT), with the farmer's experience (WITH), and with only the use of this variable (ONLY).

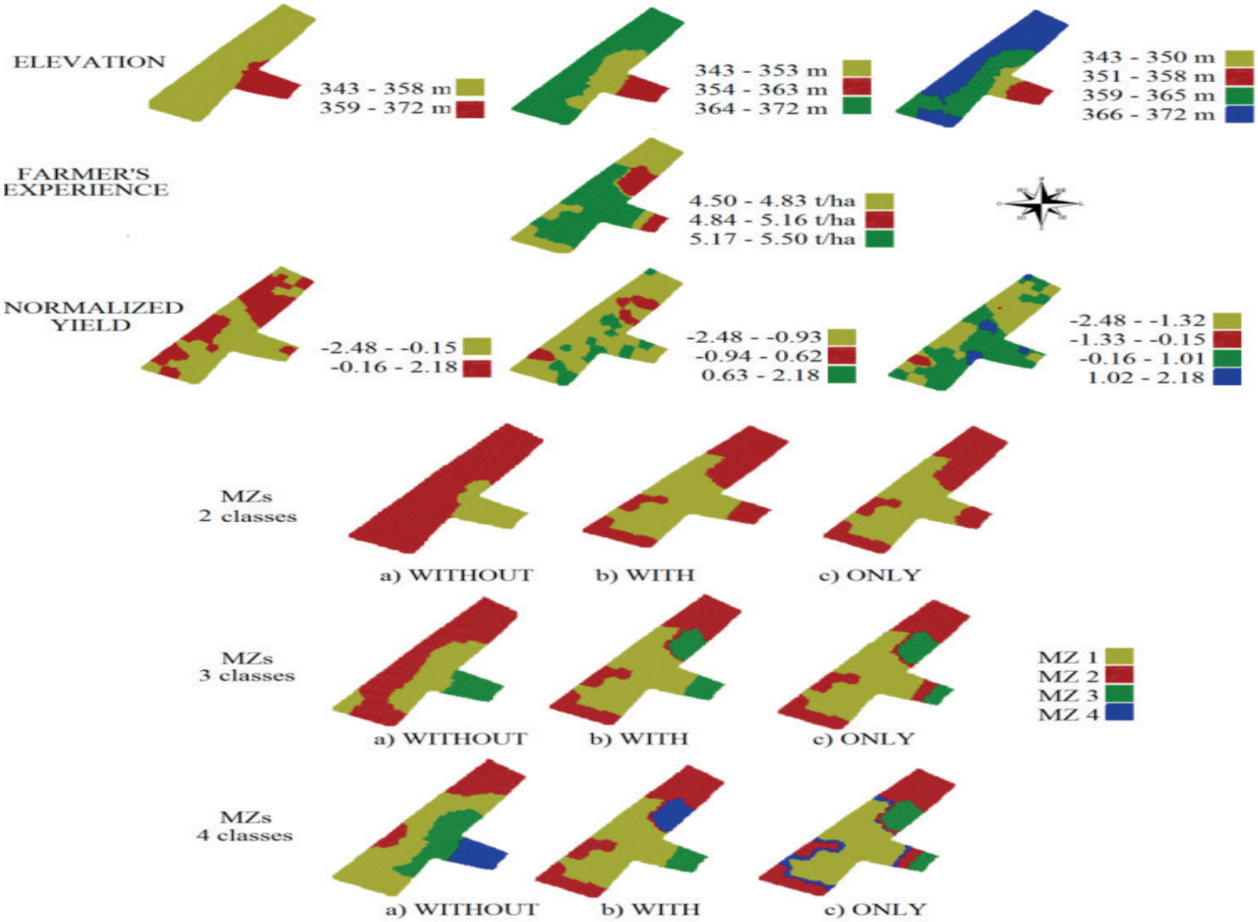
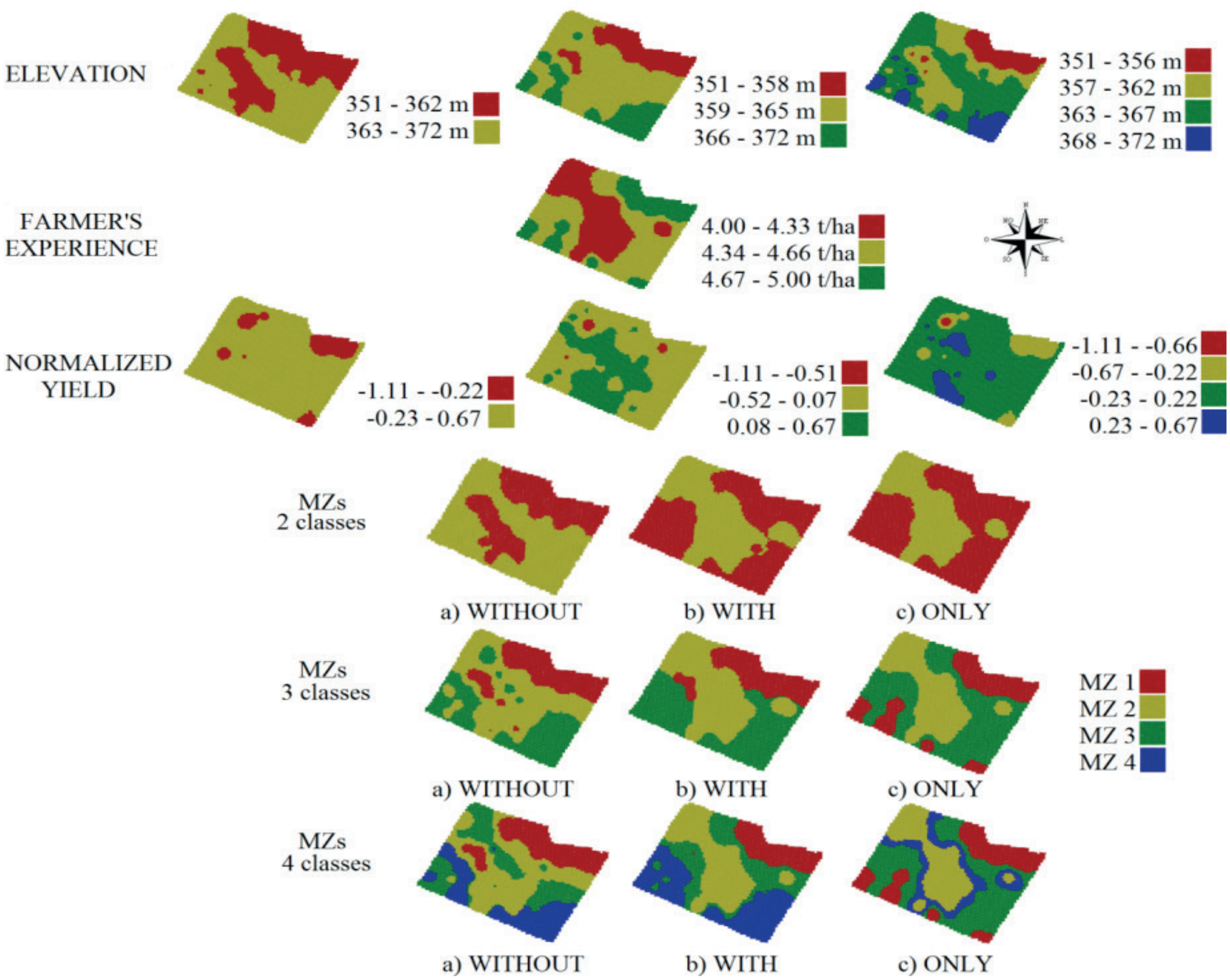


Figure 4. Thematic maps of soil attributes (elevation) used to generate MZs, variable farmer's experience, and normalized average yield of four crop or agricultural years (2012, 2013, 2014, and 2015) for the field C and the generated MZs without the variable farmer's experience (WITHOUT), with the farmer's experience (WITH), and with only the use of this variable (ONLY).



The values of VR, FPI, MPE, and SI provided by each approach evaluated with two, three, and four classes are shown in Table 2 and Figure 8. For field A, it was found that there was a higher VR when the area was divided into two classes and when only the stable soil variables were used (elevation and SRP 0-0.1 m) for the generation of the classes (VR = 42.5%). However, when the area was divided into four classes with only the variable farmer's experience, a VR = 42% was obtained. For field B, better results for VR were found when the division was made into three classes with only the variable farmer's experience (VR = 44%). In area C, the best VR was obtained using only the farmer's experience with four classes of MZs (VR = 92%).

The lowest values of FPI (larger degree of separation between the clusters), in all areas, were obtained when the division was carried out in three classes and with only the farmer's experience variable. The same division also had the lowest MPE (better organization of clusters), although other divisions also resulted in the same performance.

Table 2. Evaluation Indexes calculated considering the generation of MZs without adding the variable farmer's experience (only with stable attributes selected in the correlation matrix), with the variable farmer's experience and soil stable attributes selected in the correlation matrix, and only with the variable farmer's experience.

Field	C	Attributes	Tukey*				VR%	FPI	MPE	SI%	ZMs	ZM-C
			1	2	3	4						
A	2	Without farmer's experience	a	b			42.5	0.10	0.02	98.5	2	0
		With farmer's experience	a	b			25.4	0.07	0.02	98.5	2	0
		Only farmer's experience	a	b			25.4	0.05	0.01	98.5	2	0
	3	Without farmer's experience	a	a	b		23.7	0.19	0.04	96.7	4	1
		With farmer's experience	a	a	b		30.1	0.11	0.02	97.8	3	0
		Only farmer's experience	a	b	b		23.7	0.03	0.01	97.9	3	0
	4	Without farmer's experience	a	a	b	b	34.2	0.29	0.05	95.4	6	2
		With farmer's experience	a	ac	b	bc	23.7	0.18	0.04	96.5	4	0
		Only farmer's experience	a	a	b	b	41.5	0.06	0.01	95.6	7	3
B	2	Without farmer's experience	a	b			3.9	0.06	0.01	99.3	2	0
		With farmer's experience	a	b			8.3	0.09	0.02	97.9	5	3
		Only farmer's experience	a	b			8.3	0.04	0.01	97.9	5	3
	3	Without farmer's experience	a	b	b		11.5	0.66	0.12	97.9	4	1
		With farmer's experience	a	b	a		8.3	0.10	0.02	97.12	6	3
		Only farmer's experience	a	b	c		44.4	0.03	0.01	96.9	8	5
	4	Without farmer's experience	a	a	b	b	6.5	0.74	0.15	97.5	5	1
		With farmer's experience	a	bc	ac	d	19.4	0.09	0.02	97.1	6	2
		Only farmer's experience	a	bd	ad	c	19.4	0.03	0.01	95	7	3
C	2	Without farmer's experience	a	a			1	0.13	0.03	95.8	3	1
		With farmer's experience	a	a			8.7	0.23	0.04	95.7	5	3
		Only farmer's experience	a	a			5.3	0.09	0.02	96.3	3	1
	3	Without farmer's experience	a	a	a		11.5	0.20	0.04	92.7	14	11
		With farmer's experience	a	a	a		3.1	0.18	0.04	95.4	6	3
		Only farmer's experience	a	a	a		0	0.07	0.02	93.6	9	6
	4	Without farmer's experience	a	a	a	a	17.4	0.23	0.05	90.7	14	10
		With farmer's experience	a	a	a	a	4.8	0.22	0.05	92.4	11	7
		Only farmer's experience	a	ab	ac	-	91.9	0.10	0.02	89.8	12	8

* Tukey's range test with 95% of significance. C - Number of Classes; ZMs – Number of Zones; ZM - C: Number of Zones – Number of Classes.

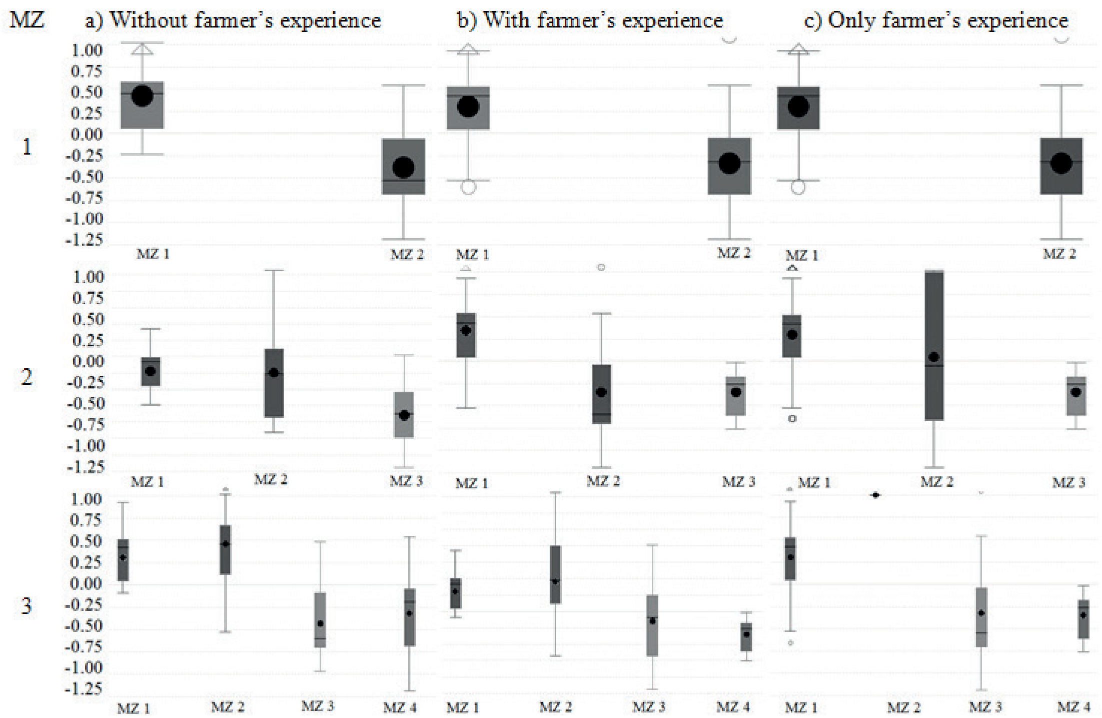


Figure 5. Boxplot graphics of normalized average yield data divided into two, three, and four classes WITHOUT the farmer's experience, WITH the farmer's experience, and ONLY with the farmer's experience for field A.

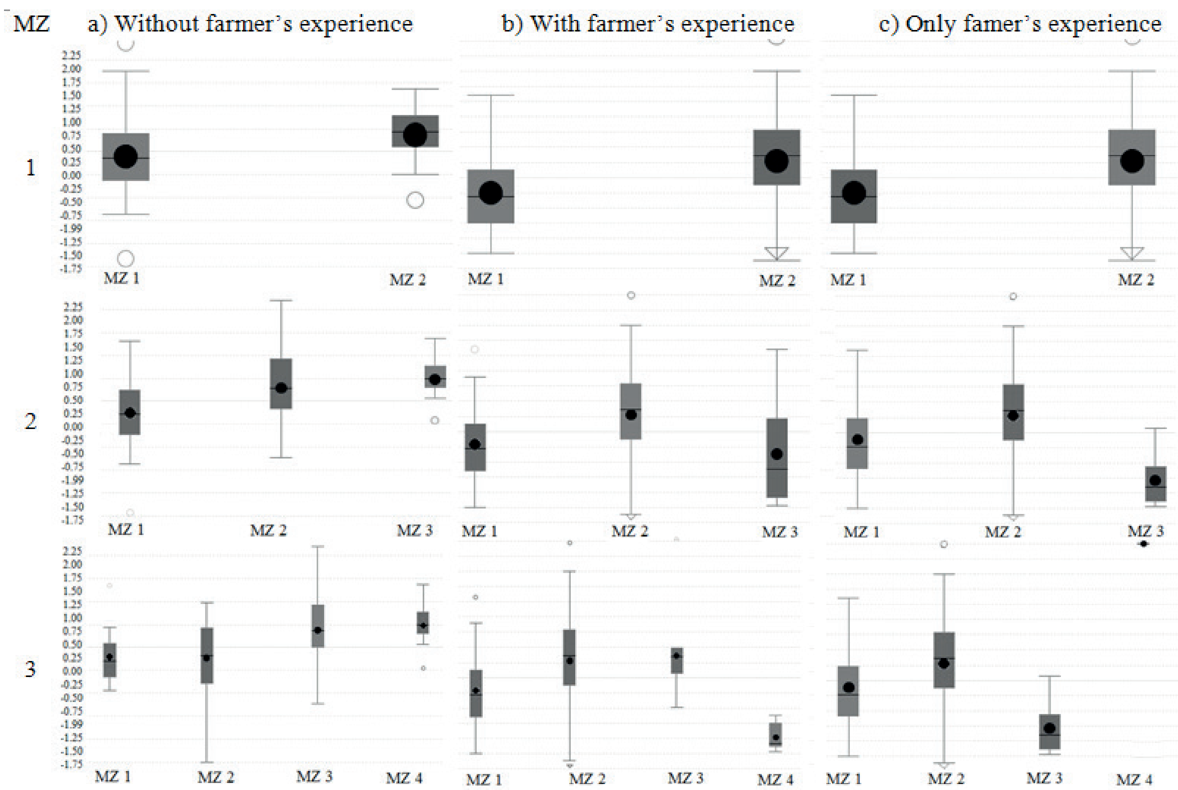


Figure 6. Boxplot graphs of normalized average yield data divided into two, three, and four classes WITHOUT farmer's experience, WITH farmer's experience, and with ONLY farmer's experience in field B.

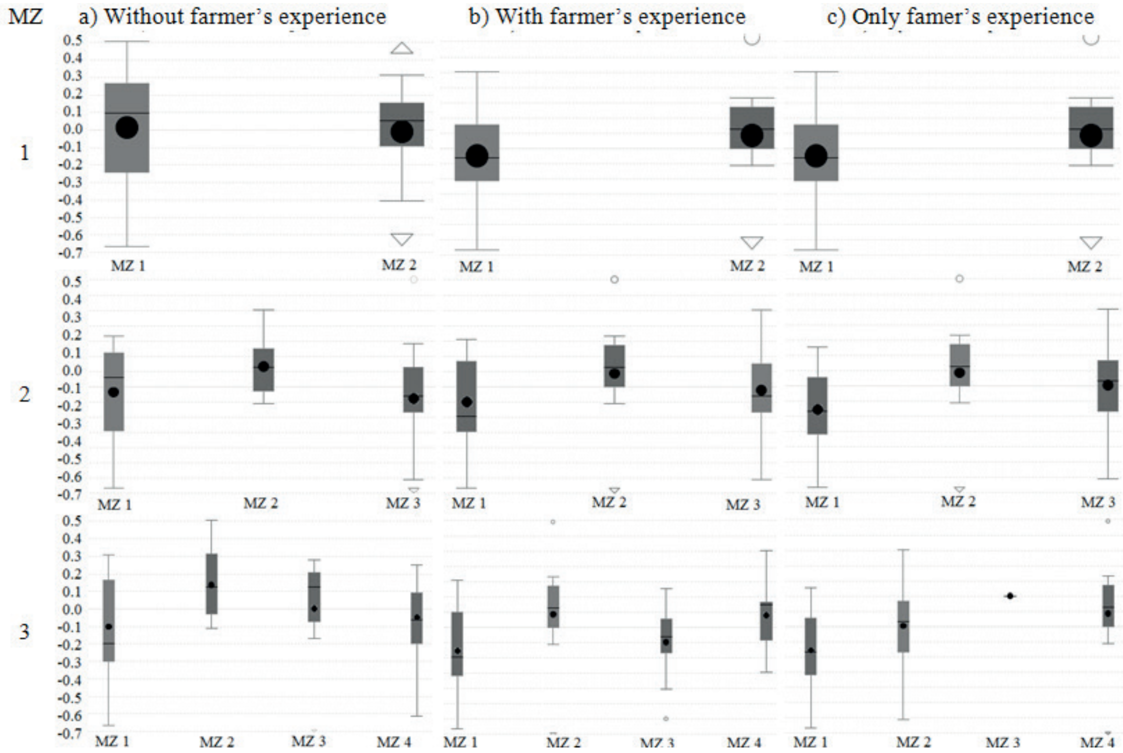


Figure 7. Boxplot graphs of normalized average yield data divided into two, three, and four classes WITHOUT farmer's experience, WITH farmer's experience, and ONLY with farmer's experience in field C.

Regarding the smoothness of the boundary curves that define the MZs as evaluated by softness index (SI), the best performance with the division into two classes, in all areas, was obtained. When the areas were divided into two classes, the SI obtained for field A was the same for the three combinations of the tested variables. In field B, the SI was more satisfactory when only stable soil attributes were used, while for field C the best SI was obtained when only the farmer's experience variable was used. With three classes, the best SI results were obtained in field A when only the farmer's experience variable was used, in field B without the variable farmer's experience, and in field C with the variable farmer's experience and the stable soil variables. With four classes, the best SI results for the three studied areas were found when the variable farmer's experience and stable soil attributes were used. However, the SI values varied by less than 5% for all the cases, suggesting that there were no significant differences in the softness of the maps when comparing different combinations of variables and number of classes.

Another useful evaluation in choosing the number of variables to be used is that the number of created zones must be equal or slightly higher than the number of classes. This means that the number of zones minus the number of classes (MZ-C) should be ideally zero. The best results were found with two classes, because it showed a lower value of this variable for the three areas under study. The worst results, or the classification that generated a higher value of MZ-C, were as follows: Field A- MZs generated using four classes and only the variable farmer's experience; Field B- with three classes and only the variable farmer's experience; Field C- only with stable soil attributes with three classes.

All the three combinations of variables (stable soil attributes and farmer's experience) allowed defining expressive MZs. The evaluation indexes used (Table 2 and Figure 8) showed more satisfactory results when only the farmer's experience variable was used with three management classes for the three areas. However, most of the evaluated indexes showed similar values for the three combinations of the variables used. These results indicate the importance of the variable farmer's experience in defining MZs, which can be an economical and simplified approach for MZs generation for soil sampling optimization and variation of certain management and planting operations. This is in line with the results obtained by Fleming et al. (2004), Khosla et al. (2002), and Hörbe et al. (2013) who also found satisfactory results using empirical knowledge of the farmer to define MZs. When the farmer suggests a specific number of classes (in this study the division into three classes was performed using the variable farmer's experience by the owner), the division into more classes (four or five classes) has no practical application and, as demonstrated by the performance indexes, they do not show satisfactory results.

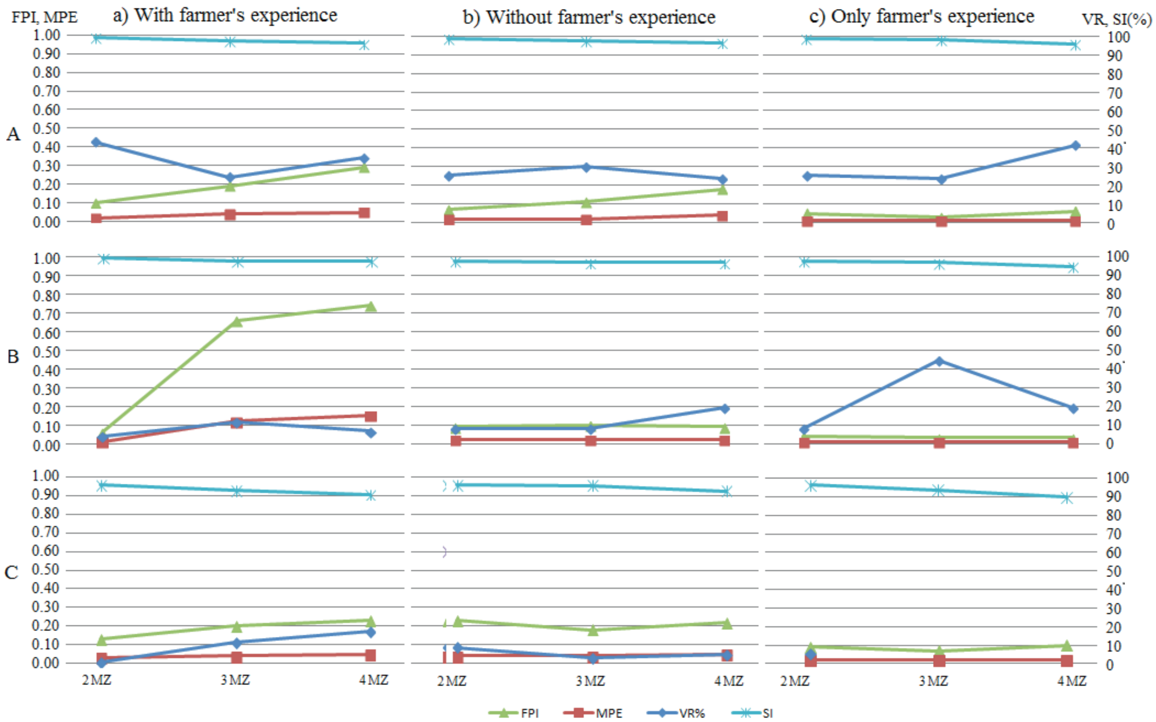


Figure 8. Graphs for FPI, MPE, VR%, and SI for the three approaches evaluated, considering two, three, and four classes.

Another important factor is to check whether the MZs showed significant differences compared to other attributes. Using Tukey's range test (ANOVA, Table 3) analysis of MZs generated with textural soil attributes (clay, silt, sand), chemical (pH, Al, Ca, C, Cu, Fe, P, H + Al, Mg, Mn, K, Zn), organic matter (OM), physical attributes (soil penetration resistance, density, macroporosity, microporosity, total porosity), and elevation was performed. The order of their presentation is variable according to their relevance in the Tukey's range test.

It was found that the attributes that showed greater differences were elevation, yield, SPR 0-0.1 m, sand, C, Cu, OM, and SPR 0.1-0.2 m. Among these, elevation and the SPR 0-0.1 m were the attributes used to generate the MZs. It is noteworthy that the macronutrients P and K also presented significant differences. The cases where the MZs were generated without the variable farmer's experience and with this variable showed the best significant differences in the evaluated soil attributes, and the division into two classes showed the most significant differences in the values of soil attributes.

Table 3. Tukey's range test for the soil attributes in fields A, B, and C in relation to the MZs generated with two, three, and four classes WITHOUT farmer's experience, WITH farmer's experience, and ONLY with farmer's experience.

Field	A									B									C								
Nº Classes	2			3			4			2			3			4			2			3			4		
Variable	W	WO	O	W	WO	O	W	WO	O	W	WO	O	W	WO	O	W	WO	O	W	WO	O	W	WO	O	W	WO	O
Elevation	**	**	**	**	*	*	*	*	*	**	**		**	**	*	**	**	*	**	**	**	**	**	*	**	*	*
Yield	**	**	**	*	*	*	*	*	*	**	**	**	*	*	**	*	*	*									*
SRP 0.0-0.1	**	**	**	*	*	*	*	*	*	**	**		*	*	*	*	*	*									
Sand	**	**	**	**	*	*	*	*	*				*		*	*	*	*							*	*	
C										**	**		*	*	*	*	*	*		**	**	*	*	*	*	*	*
Cu	**	**	**	*	*	*	*	*	*	**			*	*		*		*							*	*	
O.M.										**	**		*	*	*	*	*	*		**	**	*	*	*	*	*	*
SRP 0.1-0.2					*	*		*	*		**	**	*	*	*	*	*	*	**			*			*	*	
H+Al	**			*	*											*				**	**	*	*	*	*	*	*
Micro							*				**	**	*	*	*	*	*	*					*	*	*	*	*
SRP 0.2-0.3					*	*		*	*	**			**	*	*	*	*	*						*			*
P				*			*	*	*											**	**	*	*	*	*	*	*
Clay				*	*	*	*	*	*										**			*	*	*	*	*	*
K							*			**			**	*		*	*									*	*
Mn				*	*	*	*	*	*						*	*		*				*			*		
Density							*				**	**		*	*		*	*									
pH	**			*												*			**			*					
Zn										**			*	*		*	*					*			*		
PT							*			**			*	*		*	*	*									
Fe										**					*	*		*								*	*
Al																			**			*			*		
Macro							*			**																*	
Silt				*	*																	*			*		
Ca													*			*	*										
Slope							*									*											
Mg																											

W – Without the variable farmer's experience; WO – With variable farmer's experience; O – Only the variable farmer's experience; ** - significant difference between the averages of all classes at 95% level of significance; * - Significant difference between at least two classes at 95% level of significance. The order of presentation is variable according to their relevance in the Tukey's range test.

It should be highlighted that the good results obtained with the variable farmer's experience in the studied areas may have been positively influenced due the fact that the interviewed farmers have greater knowledge of their areas. The representativeness of this variable can be reduced in areas with little cultivation experience by the farmers and also with the increase in the area under consideration, because in larger areas farmers possibly cannot perform such management practices. Thus, it is a solution for small-scale farmers and a low cost alternative.

Conclusions

The study showed that the use of the farmer's experience to set management zones can be an efficient and simple tool, besides cost reduction in the MZs setting process, compared to the traditional method of using stable soil variables and topography. According to the evaluated indexes, the division that presented better results was the approach using only the variable farmer's experience with three management classes, but the Tukey's range test showed higher significant differences in soil attributes when the MZs were generated with the use of stable soil variables and topography.

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