__Original Research Article__

Confused pixels interference in maps of agricultural management zones

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ABSTRACT

Management zones can be delimited using fuzzy logic, a technique that assigns values of degrees of pertinence to each pixel of a map. When the value tends to 1, these degrees indicate that there is certainty that the pixel belongs to a certain class of the management zone. However, in the boundary region between classes, degrees of pertinence do not tend to 1, indicating that there is confusion about which class such pixels belong. Depending on the area occupied by confused pixels, the use of management zones as a precision agriculture technique can be compromised. Thus, the behavior of the area occupied by pixels with different degrees of pertinence was evaluated as a function of the amount of information used to generate the management zones. Those zones were generated based on altitude, soil apparent electrical conductivity in soil depths of 0.20 m and 0.40 m, soil water content and clay content. When adding information to generate the management zones, there was an increase in the area occupied by pixels with degrees of pertinence lower than 0.5. However, the insertion of more than one layer of information to delineate the management zones improved the concordance between the management zones and the maps of the soil attributes. We suggest that some samples should be distributed in the border regions between the management zones, when these are delimited from the use of two or more variables.

Keywords: Precision agriculture; fuzzy logic; degrees of pertinence.

1. INTRODUCTION

Soil properties are susceptible to temporal and spatial variation due to intensive agricultural activities. As a result, it is of utmost importance a continuous follow-up of the soil physical and chemical properties throughout the area [1]. Within this context,precision agriculture proposes a re-organization of the traditional agricultural management system by considering the spatial variability inside the area, towards a low-input, high-efficiency, and sustainable agriculture [2, 3].

In order to obtain crop productivity data, expressed by maps, it is necessary to perform data collection. The more data collected, the more consistent is the information generated and the diagnosis regarding the variability in the crop [3]. However, depending on the area extension and the desired sample density, the sampling cost may be a limiting factor. Therefore, the generation of management zones appears as one of the solutions to this impasse [4].

In order to delimit management zones, several variables can be used to generate maps. Some of these variables are: soil apparent electrical conductivity [5, 6, 7, 8], productivity maps [9, 10], soil granulometry [11], soil water content [12] and images obtained by aerial platforms [13]. As a typical geographic information system, the base information for mapping the zones is associated with Cartesian coordinates, which allow the mapping of the area. Classification algorithms analyze these information and divide the data into distinct zones. Fuzzy logic is commonly used for this purpose.

Unlike the conventional logic and the classical set theory, the fuzzy logic assigns values of degree of pertinence to each classified pixel. These values can range from zero to one and mean, respectively, that an element does not belong to a particular set and that an element belongs completely to the classified set. Values between zero and one represent partial degrees of pertinence.

In the agricultural sector, there are several studies that use fuzzy logic to map crop productivity. The authors [14] use the fuzzy logic to map the fertility of a humic Yellow Red Oxisol cultivated with arabica coffee variety, based on the sum of bases, cation exchange capacity and base saturation, considering the spatial variability. The authors [15] applied a GIS-based integration model, using fuzzy logic as a function of three variables: soil electrical capacity, nitrogen adequacy index and elevation, resulting in a nitrogen requirement map. The authors [16] analyze the fertility of an experimental area, based on soil chemical attributes and its relation with conilon coffee productivity, using geostatistics and the fuzzy classification system.

It is likely that in the border region between the management zones, the classified pixels present partial degrees of pertinence, which may indicate the existence of confusion about which class these pixels belong to. Depending on the range of the area occupied by the pixels, with confused classification, the use of management zones as a precision agriculture technique may be compromised. Thus, the present study evaluated the behavior of the area occupied by pixels with different degrees of pertinence, as a function of the information used to generate the management zones.

2. MATERIAL AND METHODS

2.1. Experimental Site

Soil samples were collected from an area with 20.2 ha of coffee cultivation (Coffea arabica L.), where there is predominance of Yellow Red Latosol. The experimental site presents mountainous relief, with average altitude of 915 m, and is located at the coordinates 20° 42' 33" S and 42° 34' 17" W.

2.2. Georeferencing of soil sampling sites

The sampling points in the field were allocated following a systematized distribution, with a grid size of approximately 25 x 25 m, totalizing 275 points. These were georeferenced using the Topographic DGPS (L1), Trimble brand and Pro XT model. The differential correction was made using the Brazilian Institute of Geography and Statistics (IBGE) database. The coordinate system used was the UTM, with Datum South America 1969 and zone 23S.

2.3. Determination of soil attributes

The soil apparent electrical conductivity (ECa) was determined using a portable sensor manufactured by Landviser©, model LandMapper© ERM-02 whose measurement occurs by the principle of electrical resistivity. The ECa measurement occurred in the soil depth from 0 to 0.20 m and from 0 to 0.40 m. Granulometric composition analyses were carried out based on the methodology of the author [17, 18]. Soil water content was determined using a real-time sensor manufactured by Spectrum Technologies, FielScout TDR 300 model, in the same spots where the ECa were measured and soil samples, for determination granulometric composition analyses, were taken. In a radius of 1 meter around each of the 275 georeferenced points, soil samples were collected. Each sample was composed of two simple subsamples in soil depth from 0 to 0.20 m. For this, a dutch-type auger was used. The soil samples were analyzed in the laboratory, in order to obtain the contents of pH, phosphorus (P), potassium (K), calcium (Ca^{2+}) and magnesium (Mg^2).

The available phosphorus and potassium contents were determined by the Mehlich-1 extractor [19]. The exchangeable contents of calcium and magnesium were determined by the KCl extractor (1 mol L^{-1}). The pH content in water was determined using a ratio of 1:2.5 (parts of suspended soil : parts of water) by using a potentiometer with combined electrode.

2.4. Analysis for outliers detection in the database

The database was submitted to a previous analysis, in order to detect possible outliers. The sample, which had an absolute value higher than the average added three times the standard deviation and lower than the average subtracted three times the standard deviation [20], or if the neighboring samples had very different values, this would be considered as an outlier and, consequently, excluded from the database for further analysis.

2.5. Determination of spatial variability of the soil attributes

The collected data were submitted to geostatistical analysis for spatial variability characterization. The geostatistical analysis procedure was performed using the Optimize Model feature of the Geostatistical Wizard tool, available in ArcGIS v. 10.3.

The spatial models chosen in the semivariogram adjustment were those with the lowest root mean square error (RMS) in the cross-validation. With the spatial models fitted, ordinary kriging was used to interpolate the data. Then, maps of the spatial variability of altitude, soil water content, soil apparent electrical conductivity and soil clay content were generated.

2.6. Delimitation of management zones

The management zones were established by the computer program KRIG-ME [21], based on the maps generated by the interpolated data of altitude, soil water content, clay content and soil apparent electrical conductivity in soil depths from 0 to 0.20 m and 0 to 0.40 m. The area was divided into three management zones and the pixels size of the maps were 5 x 5 m. As a result, nine maps were generated containing three management zones each. Table 1 shows the variables used to define the management zones and their respective representations.

Table 1. Variables used to define the management zones and their respective representations.

Management Zones	Variables	Representation
1	Soil apparent electrical conductivity in soil depth of 0.20 m	ZM20
2	Soil apparent electrical conductivity in soil depth of 0.40 m	ZM40
3	Soil water content	ZMU
4	Soil apparent electrical conductivity in soil depth of 0.20 m and altitude	ZM20A
5	Soil apparent electrical conductivity in soil depth of 0.20 m and soil water content	ZM20U

6	Soil apparent electrical conductivity in soil depth of 0.20 m and clay content	ZM20Arg
7	Soil apparent electrical conductivity in soil depth of 0.20 m, clay content and altitude	ZM40ArgAlt
8	Soil apparent electrical conductivity in soil depth of 0.20 m, altitude and soil water content	ZM40AltU
9	Soil apparent electrical conductivity in soil depth of 0.20 m, soil water content and clay content	ZM40UArg

2.6.1. Analysis of the degrees of pertinence

The degrees of pertinence of each pixel were obtained by the computer program KRIG-ME [21], as one of the results of map classification in three management zones. As each map was divided into three management zones (ZM1, ZM2 and ZM3), a map pixel should present three degrees of pertinence, G1, G2 and G3, referring to its possibility of belonging to ZM1, ZM2 and ZM3, respectively. The sum of the three degrees of pertinence of a pixel must be equal to one. Thus, if any of the degrees of pertinence has a value greater than 0.5, it means that the pixel to be classified in one of the management zones has an absolute majority (> 50%) in relation to the chance of pertinence to the corresponding zone. In this way, the pixels that presented all degrees of pertinence lower than 0.5 were considered as confused pixels.

After the design of the management zones 1, 2 and 3, the pixels considered confused were separated from the others. With the combination of the variables altitudes, soil water content, clay content and soil apparent electrical conductivity, from soil depths of 0 to 0.20 m and 0 to 0.40 m to delimit the management zones, the result of this stage were nine maps containing, each of them, three management zones and one zone composed by the confused pixels.

2.7. Comparison between the results for each level of information used to generate the management zones

The variability of the attributes pH, phosphorus (P), potassium (K), calcium (Ca^{2+}) and magnesium (Mg^{2}) was classified in three management zones using the KRIG-ME software program [22]. Thus, five additional maps were generated, consisting of three management zones each. These maps of the areas of management of the attributes pH, phosphorus (P), potassium (K), calcium (Ca^{2+}) and magnesium (Mg^{2}) were used as reference for comparison between the maps containing the three management zones and the maps containing the zone of confused pixels which, in turn, were based on the variables altitude, soil water content, clay content and soil apparent electrical conductivity in soil depths of 0 to 0.20 m and 0 to 0.40 m.

This comparison allowed to estimate the Kappa concordance coefficient (equation 1) based on the data from the error matrix [22].

$$\hat{K} = \frac{n\sum_{i=1}^{c} x_{ii} - \sum_{i=1}^{c}(x_{i\oplus} x_{\oplus i})}{n^2 - \sum_{i=1}^{c}(x_{i\oplus} x_{\oplus i})} \quad (1)$$

Where:
$\hat{K}$ = Kappa coefficient estimation;
x_{ii} = value in line i and column i (diagonal) of the error matrix;
$x_{i\oplus}$ = total in line i;

$x_{\oplus i}$ = total in column i;
n = total number of samples; and
c = total number of zones.

The difference between two independent Kappa coefficients was tested at a 5% significance level. The calculated Z value (equation 2) that exceeded the tabulated Z value, corresponding to the determined level of significance, reflected the lack of statistical equality between the two Kappa coefficients, differentiating them significantly from each other. If the Kappa coefficients are statistically different, it is concluded that the confused pixels interfere in the result provided by the management zones map. Otherwise, the opposite is true.

$$Z = \frac{\hat{K}_1 - \hat{K}_2}{\sqrt{\hat{\sigma}(\hat{K}_1) + \hat{\sigma}(\hat{K}_2)}} \quad (2)$$

Where:
Z = Z standardized and normally distributed statistics;
$\hat{K}_1$ e $\hat{K}_2$ = Kappa coefficients to be compared;
$\hat{\sigma}$ = Kappa coefficient variance.

3. RESULTS AND DISCUSSION

3.1. Spatial variability

Figures 1 and 2 show the results of the spatial variability characterization of the attributes used in the present work. It can be observed in Figure 1 that there is a similarity in the spatial patterns between the attributes ECa20, ECa40 and soil water content. This can be justified by the fact that soil water content has an influence on soil apparent electrical conductivity [23, 24, 25]. Also, it can be analyzed by the comparison between the maps of soil apparent electrical conductivity and the calcium and magnesium attributes, that there are similarities between their spatial distribution patterns, which can be an indication that the ECa is a good parameter for defining management classes for these attributes.

In the maps of altitude and clay content variables it is possible to verify the most continuous spatial patterns among all the generated maps. This feature makes those information relevant to the delimitation of the management zones, because the more continuous the delimited zones, the easier it will be to manage the application of inputs at a variable rate.

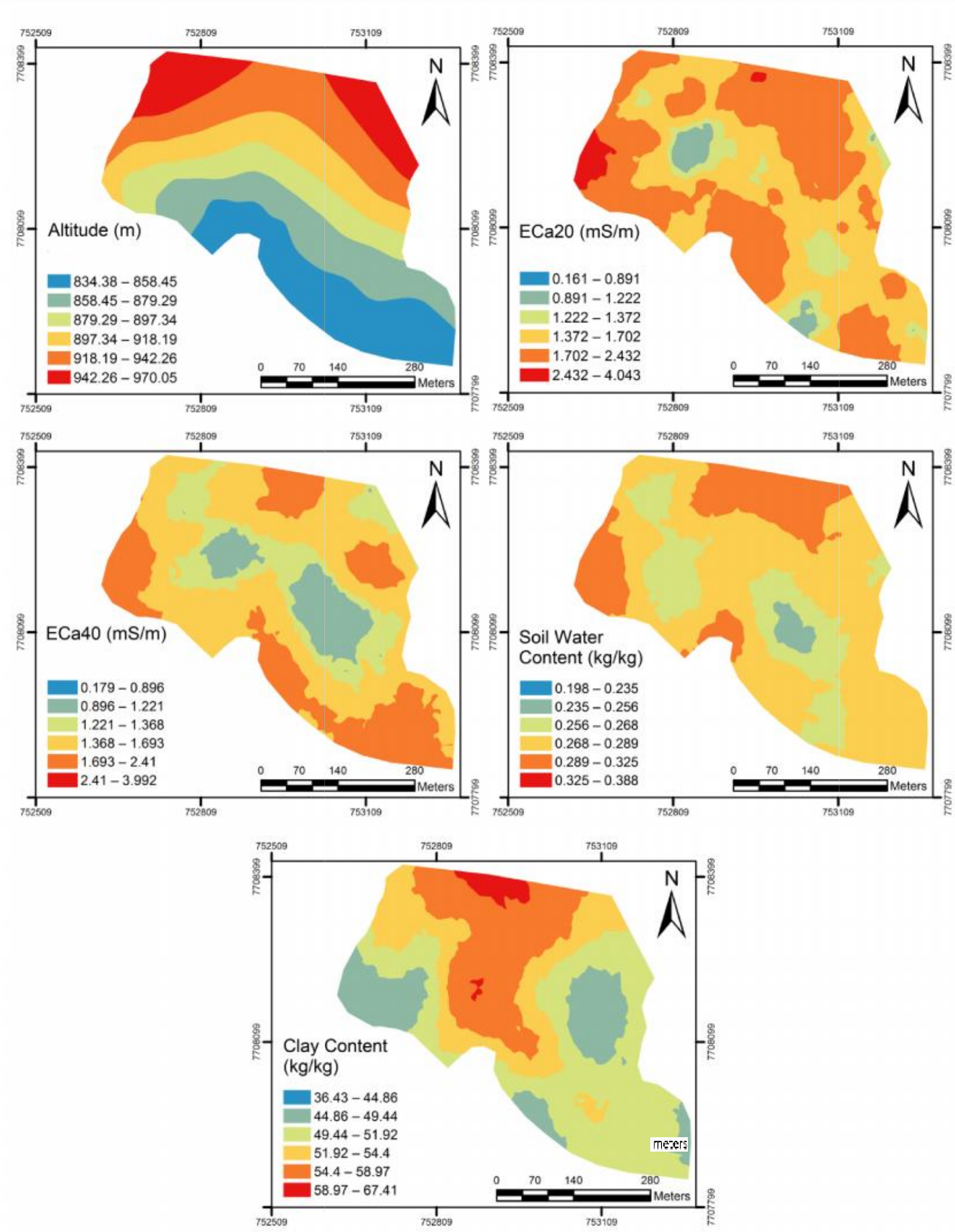

Fig. 1. Maps of spatial variability of the attributes used in the management zones delimitation.

It can be observed in Figure 2 that the use of more than one layer of information in the definition of management zones can be interesting, if this information contains characteristics of interest, such as spatial continuity and similarity with the spatial pattern of the attributes of interest, for soil fertility correction. The authors [26] and [21] indicate that the use of two information for delimitation of management zones provides better results.

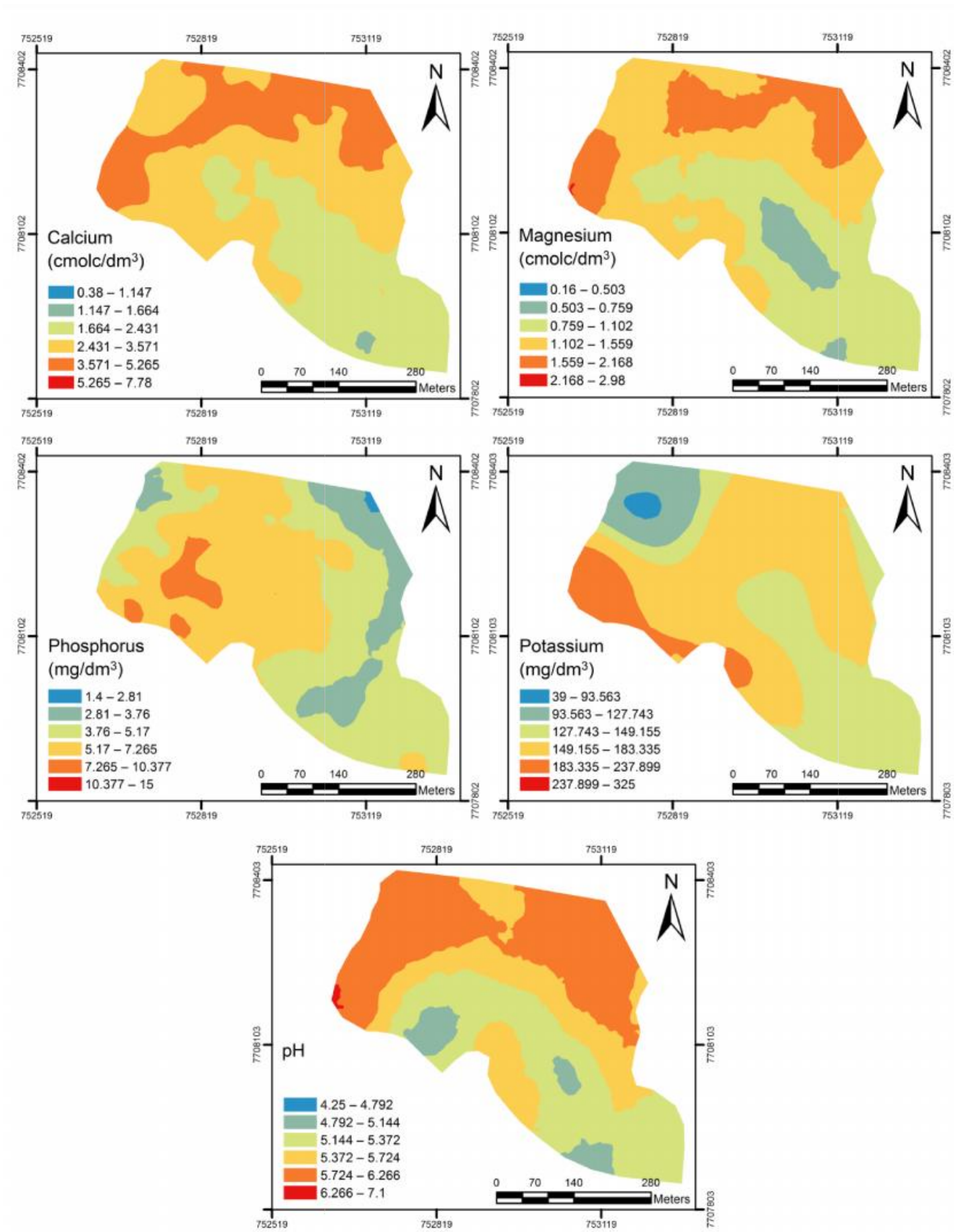

Fig. 2. Maps of spatial variability of the soil atributes.

3.2. Comparison of sampling strategies

As the area was classified in three management zones, if the degrees of pertinence (G1, G2 and G3) of a given pixel are equal to 0.33, it indicates that this pixel reached the highest possible level of confusion. Among the matrices of pertinence generated after the design of the management zones, only those generated on the basis of two and three variables presented pixels with degrees of pertinence mathematically close to 0.33, as represented in Table 2.

Table 2. Highest degrees of pertinence and quantity of pixels per management zone.

Management zone	Representation	Highest degree of pertinence	Number of pixels
1	ZM20	0.47	9
2	ZM40	0.47	6
3	ZMU	0.46	5
4	ZM20A	0.35	5
5	ZM20U	0.39	1
6	ZM20Arg	0.34	4
7	ZM40ArgAlt	0.34	36
8	ZM40AltU	0.34	2
9	ZM40UArg	0.34	3

As the number of information used to define the management zones increased, the area occupied by confused pixels grew, with degrees of pertinence less than 0.5, as shown in Figure 3. The confused pixels may belong to zones different from those that they were initially classified. Thus, the larger the area occupied by these pixels, the greater the possibility of a wrong decision regarding the treatment that this area should receive.

Fig. 3. Area occupied by pixels with degrees of pertinence lower than 0.5 (C%).

An area with uncertain classification may receive a management beyond or below what is necessary. It may occur that the area requires simpler management (lower cost), but instead it receives a treatment that will result in waste of the input, or even the area receives a management that is less than necessary, resulting in ineffective treatment and, consequently, in a decrease in productivity. In both cases, financial losses occur. Thus, the management zones generated with more than two variables may be more sensitive to these problems, since the area occupied by confused pixels may correspond to 20% of the total area (Figure 3).

In general, the insertion of more than one layer of information to delimit the management zones, although it increased the area occupied by confused pixels, it also improved the concordance of the management zones with the maps of the soil attributes (Table 3). Comparing the concordances of the management zones maps without the distinction of the confused pixels with the concordances of the management zones maps without the confused pixels, it is noticed that in most cases there was no significant difference between them. This result is specifically observed in cases where one or two variables were used to delimit the management zones. In other words, the confused pixels did not interfere in the concordance between the management zones and the maps of the soil attributes. The exception occurred when the management zones were delimited using three variables.

Table 3. Kappa coefficient of concordance between management zones and soil attributes maps.

Variables	Management Zone	Kappa				
		pH	Phosphorus	Potassium	Calcium	Magnesium
1	ZM20	0.20^{A**}	0.08^{A}	0.20^{A}	0.26^{A}	0.25^{A}
	ZM20C*	0.20^{A}	0.08^{A}	0.20^{A}	0.25^{A}	0.25^{A}
	ZM40	0.09^{B}	0.11^{B}	0.13^{B}	0.10^{B}	0.13^{B}
	ZM40C*	0.09^{B}	0.11^{B}	0.13^{B}	0.09^{B}	0.13^{B}
	ZMU	0.19^{A}	0.12^{B}	0.08^{C}	0.24^{A}	0.28^{C}
	ZMUC*	0.19^{A}	0.12^{B}	0.07^{C}	0.19^{C}	0.28^{C}
2	ZM20A	0.28^{C}	0.12^{B}	0.27^{D}	0.35^{D}	0.42^{D}
	ZM20AC*	0.19^{A}	0.12^{B}	0.07^{C}	0.24^{A}	0.28^{C}
	ZM20U	0.21^{D}	0.08^{A}	0.19^{A}	0.30^{E}	0.33^{E}
	ZM20UC*	0.20^{A}	0.09^{A}	0.19^{A}	0.29^{E}	0.31^{E}
	ZM20Arg	0.28^{C}	0.20^{C}	0.26^{D}	0.20^{C}	0.22^{F}
	ZM20ArgC*	0.24^{E}	0.19^{C}	0.24^{E}	0.18^{C}	0.21^{F}
3	ZM20AltArg	0.47^{F}	0.09^{A}	0.19^{A}	0.39^{F}	0.37^{G}
	ZM20AltArgC*	0.39^{G}	0.19^{C}	0.17^{F}	0.35^{D}	0.37^{G}
	ZM20AltUmi	0.41^{G}	0.14^{D}	0.14^{B}	0.37^{D}	0.34^{E}
	ZM20AltUmiC*	0.36^{H}	0.13^{B}	0.12^{B}	0.33^{D}	0.31^{E}
	ZM20UArgUmi	0.20^{A}	0.17^{E}	0.14^{B}	0.29^{E}	0.29^{C}
	ZM20UArgUmiC*	0.16^{I}	0.13^{B}	0.12^{B}	0.25^{A}	0.25^{A}

* Management zones with area represented by pixels classified as confused; * Different letters in the columns indicate statistical difference at a 5% level of significance.

In order to practice precision agriculture, these results show that fuzzy logic can be used to delimit management zones. However, when more than one information is used to delimit the zones, and at the moment of the variables sampling after this delimitation, we suggest that some samples should be distributed in the boundary regions between the zones. Thus, it is possible to better analyze which zone a given area belongs to, using information from the attributes to be surveyed in the area.

4. CONCLUSION

Fuzzy logic has proven to be an efficient technique to delimit management zones. Even though there are confused pixels in the classification, the final result is not negatively influenced by the uncertainty of the technique.

The use of more than one information for the delimitation of management zones increased the concordance between the defined management zones and the maps of soil attributes.

We suggest that some samples should be distributed in the border regions between the management zones, when these are delimited from the use of two or more variables.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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