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DELINEATION OF MANAGEMENT ZONES IN A GRAIN PRODUCTION AREA

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Abstract
The delineation of management zones (MZs) is an important strategy for implementing precision agriculture. However, it is a complex process that requires further study. The objective of this study is to delineate MZs and validate them with respect to soil characteristics as well as corn and soybean yield in a 97-ha land cultivated under a no-till farming system. Samples were collected for physio-chemical analysis of soils and apparent electrical conductivity (EC). Moreover, data on the altitude and yield of soybean and corn were obtained. The data were initially analyzed descriptively and using Pearson correlation. Data interpolation and the elaboration of spatial variability maps for each characteristic were then performed. Furthermore, MZ thematic maps were developed. The ideal number of MZs for each combination or strategy studied was determined by the lowest value of the fuzziness performance index and normalized classification entropy. For MZ validation, Fuzzy K-means algorithm and Kappa index were used. The delineation of MZ was possible with the use of the soil characteristics with a higher temporal stability, such as the combined use of EC, soil organic matter, and clay, enabling the validation of differences in corn and soybean yield using Fuzzy algorithm and Kappa index. Data collected in different sample density did not interfere in the definition and validation of the MZ. No correlation was found between the soil EC and other chemical characteristics and yield. Furthermore, the correspondence of soil chemical properties for each MZ was not be feasible in areas with built-up soil fertility.

Keywords: Differentiated management units. Precision agriculture. Spatial variability.

1. Introduction

Brazil is known for its high grain production, with constant and directed increments in the use of digital tools for the management of inputs. Although there is a continuous insertion of technologies in agribusinesses, the inputs will always be a finite resource, making rationalization essential (Vallentin et al. 2020). In essence, precision agriculture (PA) plays a vital role by studying existing variations in crops to improve the use of inputs (Silva et al. 2022).

Using information based on average data from the field does not allow the spatial analysis of factors limiting yields. Yields vary between fields due to the spatial behavior of soil and plant attributes (Wang 2021).

The establishment of management zones (MZ) is a strategy used for this purpose, which differentiates heterogeneous locations in crops due to a greater homogeneity in restrictive factors in production (Molin and Castro 2008). Its definition encompasses productive factors, emphasizing attributes that are stable over time, such as topography, texture, and electrical conductivity of soil, and those related to yield (Zanella et al. 2019). Management zones can be defined using natural breakdown and Fuzzy conglomerate techniques (Gili et al. 2017), multivariate analysis by clusters (Gavioli et al. 2019), Fuzzy logic (Alves et al. 2013; Ramos et al. 2017) or models for determining rectangular zones (Cid-Garcia et al. 2013). A worthwhile point is the ideal number of zones, seeking minimum variation for each one, where the *fuzziness performance index* (FPI) and *normalized classification entropy* (NCE) serve as aid (Bottega et al. 2017).

The component attributes of the MZ can be obtained from predefined sampling grids (Resende and Coelho 2017) or by using sensors embedded in platforms, with gains in speed and cost (Bottega et al. 2017). It highlights the soil's apparent electrical conductivity (EC) sensor's relationship with soil attributes texture, moisture, organic matter, cation exchange capacity, and base saturation (Carmo et al. 2016). Excess soil salts restrict plant growth and compromise water uptake due to the reduced osmotic potential (Rabello 2009).

Data collected in lower sample densities, such as those obtained using meshes, are better used when interpolated. In this sense, machine learning (ML) has proven to be a valuable tool in precision agriculture, given its assistance in the interpolation of data and the generation of MZs (Karkra et al. 2020).

In the field, it is common to collect information regarding low sampling densities from meshes and high sampling densities using sensors and images. The definition of the MZs is only feasible when treated correctly, and it ranges from the removal of data with noise to the correct use of interpolation.

This study has as hypothesis that the common use of data collected from different sampling densities can contribute to defining management zones and validating data yield. Thus, the objective of the work was to define management zones and their soil validation attributes, while considering the yield of corn and soybean in a rainfed area cultivated under a no-till farming system.

2. Material and Methods

The present work was conducted in the municipality of Uberlândia, State of Minas Gerais, Brazil (19°32'S, 47°99'W). The region's climate is classified as tropical, type Aw according to Köppen, with a rainy season in summer (average of 1. 342 mm) and a dry season in winter.

The plot used for this study was 97 ha, with an average altitude of 950 m, and the soil is classified as dystrophic Red-Yellow Latosol (Typic Hapludox) (Embrapa 2018). Since 2005, it has been cultivated with grains using the no-till system, with soybean as the first crop (summer) and corn as the second crop (winter).

Data collection

Before soybean planting (summer), soil collection was performed in the 2017–2018 crop year. The sampling was georeferenced and removed 20 composite samples, considering an irregular grid of 5 ha with a depth of 0–0.2 m. Although it does not represent the most significant proportion of root masses, this depth was chosen because it coincided with the soil preparation layer. In turn, areas with PA adoption receive primary attention in soil sampling in this layer, which helps in the practical application of the results by producers. The physical attributes of sand, silt, and clay were analyzed using the pipette method (Camargo et al. 2009), and the pH chemical attributes, soil organic matter (SOM), phosphorus-resin (P_{resin}), potassium (K), calcium (Ca), magnesium (Mg), sulfur (S), aluminum (Al), H+Al, boron (B), copper (Cu), iron (Fe), manganese (Mn) and zinc (Zn), were used in calculating the base saturation (BS%) and cation exchange capacity (CEC) (Teixeira et al. 2017).

The soil apparent electrical conductivity (EC) was obtained using the Veris 3100 sensor (Veris Technologies®) at a depth of 0–0.3 m. The data were georeferenced and collected at a speed of 3.3 m s^{-1}, with records taken every 2.4 s. The passage of the sensor in the area was performed immediately after the soybean harvest, with the presence of the crop straw on the soil, which neither interfered in the displacement nor information recording.

The yield data for soybean, cultivar Brasmax Única 686168 RSF Ipro (harvest in January 2018) and corn, and hybrid DKB 225 Pro (harvest in August 2019), were obtained using a self-propelled harvester equipped with GNSS antenna, as well as grain flow and moisture sensors, with records every 2 s, on the John Deere® Green Star-3 2630 monitor. The altitude of the field was obtained using the GNSS sensor for the same locations of yield recordings.

The EC and yield data were filtered to eliminate noise. For the EC, values with absent GNSS signals were removed. This could occur by the passage of sensors in places with a high straw presence, causing a loss in sensor-soil communication and the data point record. Data were also removed when inconsistencies concerning the median value of the data in the area were verified. For yield, data discrepancies at the level of the platform width, mass flow, and grain moisture were removed (Menegatti et al. 2004), reducing the original mass of data by 16%. After filtering, the data were adjusted considering a grain humidity equal to 13%, which is favorable for storage.

The data were analyzed using descriptive statistics and Pearson's linear correlation at $p<0.05$ and $p<0.10$. For the soil attributes, the analyses considered the sampling grid points. For the altitude, EC, and yield obtained using sensors, the average of the data in a radius equal to 10 m was used, starting from the center of the sampling grid for each point.

Delineation and validation of management zones

The MZ can be created by using different data sources. For this study, several strategies were designed to define MZs, based on the attributes altitude (A), apparent soil electrical conductivity (EC), soil organic matter (SOM), and clay (Table 1). These attributes were used to present high spatial and temporal stability (Bottega et al. 2017) for the practical obtention by producers. The plants serve as a sensor of the soil attributes and may present spatial and temporal responses directed by the interaction of these attributes. The difference in altitude can reflect the movement of sediments in the relief (Inacio et al. 2007). The SOM is the primary source of soil loads in tropical climate regions (Fontes et al. 2001) and is related to the clay content, with emphasis on the cementing action in the soil (Ferreira et al. 2018). The EC is linked to the presence of salts in the soil and is related to the soil attributes texture, humidity, organic matter, cation exchange capacity, and base saturation (Alves et al. 2013). The attributes used can be linked to others related to the chemical and physical matrix of the soil. Their individual or collective use can provide an opportunity to define the MZ, mainly because they present high temporal stability.

Table 1. List of the combination of characteristics used in MZ delineation.

Strategies for management zones	Characteristics used
1. MZ-A	Altitude (A)
2. MZ-EC	Apparent electrical conductivity (EC)
3. MZ-SOM/Clay	Soil organic matter (SOM) + Clay
4. MZ-A/EC	Altitude (A) + EC (EC)
5. MZ-A/SOM/Clay	Altitude (A) + SOM + Clay
6. MZ-EC/SOM/Clay	EC (EC) + SOM (SOM) + Clay
7. MZ-A/EC/SOM/Clay	Altitude (A) + EC (EC) + SOM (SOM) + Clay

The spatial analysis and definition of management zones (MZ) were carried out in the Qgis 3.16 environment (Qgis Development Team 2020), with the aid of the Smart Map Plugin (https://plugins.qgis.org/plugins/Smart_Map). The Smart Map was created to assist the producer in defining the management zones.

The definition of the MZ was as follow: selection of attributes, data interpolation, the definition of the ideal number of zones, and mapping of the MZ. The interpolation of data from the attributes components of the MZ was performed by *machine learning* from the algorithm *Support Vector Machine* (SVM).

The ideal number of MZ for each strategy was directed by the lowest values of *fuzziness performance index* (FPI) and *normalized classification entropy* (NCE) (Song et al. 2009). The management zones' maps were generated using multivariate cluster analysis, following Smart Map's standard recommendations, with the number of interactions of 100, a Fuzzy coefficient of 1.25, and the number of zones directed by the FPI and NCE indexes.

The Fuzzy K-means algorithm and the Kappa index validated the management zones (Valente et al. 2012). This validation took into account the agreement analysis between the respective management zones and the soil attributes and yield using cross-tabulation between maps generated for the same number of classes (Alves et al. 2013). This work seeks to verify the validity of MZs definition, especially when using data yield.

3. Results

Characterization of the plot

Nine of the 24 evaluated attributes were classified with a low coefficient of variation (CV<12%) (Warrick and Nielsen 1980). Among these are the attributes used to define the MZs, which indicates high homogeneity (Frogbrook et al. 2002) and spatial stability of the attributes (Table 2). Low CV% were observed in corn and soybean yields, expressing low heterogeneity in the data. This type of data can present homogeneous patches of larger size in the area to a certain extent.

Table 2. Descriptive analysis of yield, altitude, and soil characteristics data.

Characteristics	Minimum	Maximum	Mean	Median	CV (%)*	Asymmetry	Kurtosis
Soybean (kg ha^{-1})	3586.0	4243.0	3889.7	3889.4	4.1	0.1	0.4
Corn (kg ha^{-1})	8251.3	10178.1	9258.6	9315.9	5.5	-0.6	-0.1
Altitude (m)	944.7	960.4	952.7	952.6	0.5	0.0	-0.8
EC (mS m^{-1})	5.6	8.2	6.6	6.5	9.1	0.9	1.6
Clay (g kg^{-1})	586.0	728.0	664.5	657.0	5.6	-0.1	-0.4
Silt (g kg^{-1})	80.0	309.0	166.9	156.0	34.1	0.8	0.8
Sand (g kg^{-1})	105.0	216.0	168.5	179.0	18.4	-0.9	0.0
pH ($CaCl_2$)	5.2	5.7	5.4	5.5	2.5	0.0	-0.6
SOM (g kg^{-1})	14.5	23.3	20.7	21.2	9.4	-1.8	4.6
P resin (mg dm^{-3})	14.0	39.0	24.2	23.5	23.7	0.8	1.4
Potassium (mmolc dm^{-3})	0.7	4.5	1.4	1.2	57.5	3.0	11.3
Calcium (mmolc dm^{-3})	23.0	45.0	30.0	29.0	16.7	1.6	3.4
Magnesium (mmolc dm^{-3})	7.0	28.0	13.6	12.0	40.0	1.5	2.0
Sulfur (mg dm^{-3})	6.0	15.0	9.2	9.0	27.5	0.7	0.1
Aluminum (mmolc dm^{-3})	0.0	0.3	0.0	0.0	447.2	4.5	20.0
H+Al (mmolc dm^{-3})	33.1	46.3	39.9	39.8	10.4	-0.1	-1.3
SB (mmolc dm^{-3})	31.4	74.7	44.9	42.3	22.4	1.5	2.9
CEC (mmolc dm^{-3})	76.0	110.0	84.9	80.0	11.2	1.5	1.3
BS (%)	40.3	67.9	52.5	51.8	12.1	0.4	0.6
Boron (mg dm^{-3})	0.2	1.1	0.6	0.6	33.3	0.4	0.7
Copper (mg dm^{-3})	0.6	2.8	0.8	0.6	62.7	3.6	14.1
Iron (mg dm^{-3})	15.0	31.0	24.9	26.0	16.6	-0.6	0.1
Manganese (mg dm^{-3})	1.1	2.2	1.7	1.7	20.5	-0.1	-1.2
Zinc (mg dm^{-3})	0.5	2.8	1.2	1.0	44.1	1.8	3.8

*CV = coefficient of variation; Soybean, corn = yield; EC = apparent soil electrical conductivity (0-0.3 m); SOM = soil organic matter; P resin = phosphorus-resin; SB = sum of bases; CEC = cation exchange capacity; BS = base saturation.

The clay content ranged from 586 to 728 g kg^{-1}, moving the soil classification from clayey to very clayey. The soil organic matter (SOM) was classified as low, with values ranging from 14.5 to 23.3 g kg^{-1}. For the base saturation (BS), the range of 40.3% to 67.9% indicated that part of the area presented ideal contents for cultivating soybean (BS> 50%) and corn (BS> 60%) (Raij 2011). The proximity of the mean and median suggests a homogeneous data behavior, with no outliers in these central tendency values. The asymmetry and kurtosis values, close to zero for most attributes, contributed to this observation.

Grain yield was higher than the national average, that is 51% for soybean and 67% for corn (Conab 2021). The soil fertility condition of the constructed soil was verified in its agronomic classification (Raij 2011), with levels ranging from ideal to very high for 15 of the 17 soil chemical attributes, especially the bases. According to the classification, the low levels of manganese may have limited the productive ceiling of soybean because of its function in nitrogen metabolism (Basso et al. 2011). Thirty-five percent of Potassium values were low, thereby impacting the balance between the bases and maize yield (r = 0.49), in line with Parente et al. (2016). The inverse correlation of sand with altitude (r = -0.53) and the direct correlation between sand and soybean yield (r = 0.66) shows a possible displacement of sediments in the soil formation process and its impact on final production (Kämpf and Curi 2012). The correlation with the altitude data shows its importance as an attribute for defining MZs (Table 1) (Yari et al. 2017).

The absence of significant correlation was verified among higher temporal EC stability, SOM, and clay attributes. The data do not explain the relationship between soil salts and the water matrix (Rabello 2009). For SOM and clay, this may be due to the reduced amplitude in SOM contents (Table 2). In turn, the correlation of pH alongside corn yield (r = 0.49) and BS (r = 0.57) considers soil acidity attributes as causal agents of a possible variability in the area, which is also seen in the high CV% values for potassium (58%) and magnesium (40%), close to levels considered as high (CV >60 %).

Delineation of management zones

The maps of the spatial variability of altitude, EC, SOM, and clay used for the MZ delineation (Table 1) show a low correlation between these characteristics (Figure 1).

Punctually, the upper region of the plot shows the lowest values for altitude, EC, and clay and the highest for SOM (Figure 1). For SOM and clay, there is an inverse spatial relationship, which can be explained by the conflicting behavior between the altitude and SOM, giving room for greater accumulation of moisture at lower elevations of the plot, reflecting higher corn yields. The close relationship of EC with the water matrix and soil salts (Corassa et al. 2016) was not verified from the data. The maps make it possible to visualize an inverse relationship between EC and corn yield (Figure 1). However, the validation of management zones should preferably be carried out based on cluster analyses that include yield data since it is proof of what happens in the field (Ramos et al. 2017).

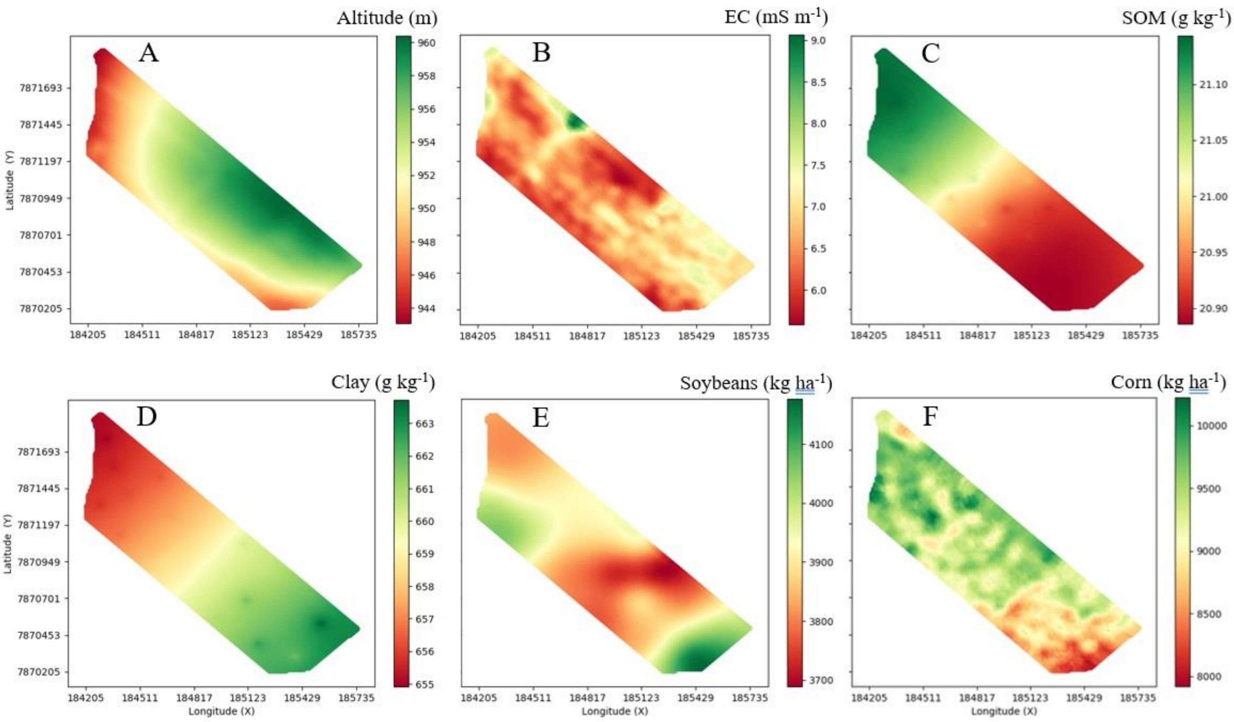

Figure 1. ML-interpolated spatial variability maps for A – altitude, B – soil apparent electrical conductivity at 0-0.3 m, C – soil organic matter, D – clay, E – soybean yield, and F – corn yield.

In the process of defining the MZs, a grouping analysis was performed based on the Fuzzy K-means logic and subsequent use of the FPI and NCE indexes, directing the creation of up to four management zones (Figure 2, Table 3). The process of defining MZs may present zones with irregular contours. Practically, adjusting MZs contours to rectangular formats to facilitate inputs application is recommended (Cid-Garcia et al. 2013).

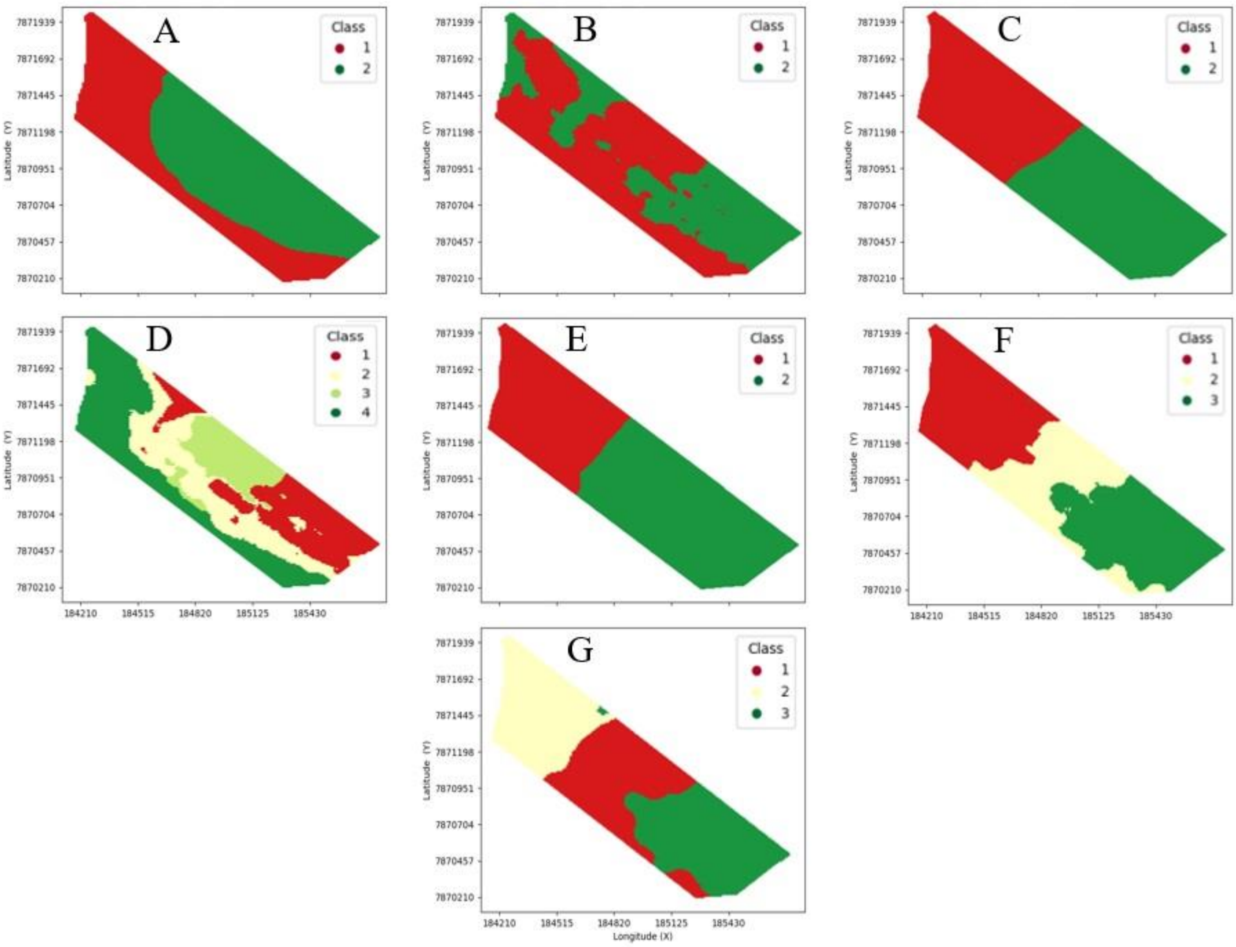

Figure 2. MZ defined by mapping the spatial variability of A – altitude (MZ-A), B – EC (MZ-EC), C – SOM and clay (MZ-SOM/Clay), D – altitude, and EC (MZ-Alt/EC), E – altitude, SOM, and clay (MZ-Alt/SOM/Clay), F – EC, SOM, and clay (MZ-EC/SOM/Clay) and G – altitude, EC, SOM, and clay (MZ-Alt/EC/SOM/Clay), using Fuzzy K-means algorithm.

In the defined MZ strategies with the individual use of the attributes' altitude, EC, and SOM/Clay (Figures 2A, 2B, and 2C), a similar pattern of spatial behavior to that the interpolated maps were observed (Figure 1). Regarding strategies with the common use of attributes (Table 1), it can be observed that by incorporating the EC attribute in the strategy defined using SOM/Clay (Figures 3C, 3F), one more MZ was generated, thus increasing from two to three. The impact of this change can be measured in the data validation process. In contrast, the inclusion of the altitude attribute in the strategy defined using SOM/Clay (Figures 2C and 2E) did not show relevance in providing additional information, thus maintaining the spatial format like that found in the absence of the altitude attribute. Here, the inclusion of this attribute did not show any influence on improving the strategy with the joint use of EC, SOM, and clay (Figures 2F, 2G).

The producer should seek MZs that adjust to his field's productive reality and management. A good definition of MZ is relevant for decision making in the field, aiming to optimize the use of inputs in seeding, fertilization, spraying, or irrigation activities (Yari et al. 2017).

Table 3. Comparison of physio-chemical characteristics of soil, and the yield of soybean and corn in MZs defined using Fuzzy K-means algorithm.

Strategies	Zones	Altitude	EC*	SOM	Clay	Soybean	Corn
MZ-Alt	1	949[a]	6.4	20.8	661	3947	9275
	2	956[b]	6.7	20.6	669	3838	9242
MZ-EC	1	952	6.3[a]	20.9	661	3869	9401[a**]
	2	955	7.0[b]	20.4	672	3925	8994[b]
MZ-SOM/Clay	1	950[a]	6.4	21.6[a]	651[a**]	3923	9487[a]
	2	955[b]	6.7	19.8[b]	680[b]	3860	9030[b]
MZ-Alt/EC	1	947[a]	6.2[a]	21.6[a]	662	3934	9572[a]
	2	954[b]	6.7[b]	21.2[a]	653	3893	9145[b]
	3	958[c]	6.2[a]	19.9[b]	691	3836	9395[ab]
	4	957b[c]	7.2[b]	20.6[ab]	661	3794	9292[ab]
MZ-Alt/SOM/Clay	1	949[a]	6.4	21.8[a]	651	3945	9508[a**]
	2	955[b]	6.7	20.0[b]	674	3857	9093[b]
MZ-EC/SOM/Clay	1	949[a]	6.4[a]	21.8[a]	651	3945[a]	9508[a]
	2	955[b]	6.3[a]	19.9[b]	675	3822[b]	9362[a]
	3	955[b]	7.0[b]	20.0[b]	673	3893[ab]	8823[b]
MZ-Alt/EC/SOM/Clay	1	949[a]	6.4[a]	21.9[a]	652[a]	3949[a]	9538[a]
	2	955[b]	6.4[a]	20.2[b]	661[ab]	3823[b]	9255[ab]
	3	955[b]	7.0[b]	19.9[b]	687[b]	3908[ab]	8938[b]

*EC: soil apparent electrical conductivity, 0-0.3 m; SOM: soil organic matter; MZ-A: MZ from altitude; MZ-EC: MZ from EC; MZ-SOM/Clay: MZ from SOM and clay; MZ-Alt/EC: MZ from altitude and EC; MZ-Alt/SOM/clay: MZ from altitude, SOM, and clay; MZ-EC/SOM/Clay: MZ from EC, SOM, and clay; MZ-Alt/EC/SOM/Clay: MZ from altitude, EC, SOM, and clay. [a, b] Distinct letters in columns indicate different values among zones for each management strategy by t-test ($p < 0.05$); ** ($p < 0.10$).

4. Discussion

Validation of management zones

After defining the number of MZ for each strategy (Table 1, Figure 2), the component attributes of each strategy and the yield of the crops were statistically evaluated. There was a statistical difference for the component attributes of each strategy (Table 3), which validated their use in the composition of the strategies. Corn yield was differentiated in MZ using the proposed strategies, except for MZ-A, which was partly due to the low correspondence between the spatial behavior of yield and that of the strategy (Figure 1F, 2A). For soybean yield, differentiation in MZ was possible using the strategies with EC, SOM, and clay (MZ-EC/SOM/Clay) and when the altitude was added to it.

This first analysis proposal validates the definition of various MZ concerning the strategies formulated, especially for crop yield. However, it does not assign a value or weight that permits the classification of the strategies. For corn yield, it would be possible to direct the use of most of the proposed strategies (Table 3).

With the aim of improving MZ's validation result, a second analysis was performed using the Kappa index. The index was used due to its strong analytical robustness as compared to the random classification offered by the Fuzzy K-means algorithm (Valente et al. 2012).

In this second proposal, the agreement between crop yield and the respective MZ of each strategy was evaluated, considering about four zones (Table 4), because this is the maximum number of MZ found in the Fuzzy analysis (Figure 2).

The average of Kappa values, for the agreement between values of both yield and proposed MZ, allowed the identification of the highest analysis value (0.36) when considering the definition of two management zones (Table 4). For this number of MZ, the strategies MZ-EC/SOM/Clay or MZ-A/EC/SOM/Clay obtained the highest Kappa value (0.49) (Table 4). For Alves et al. (2013), management zones defined from altitude, EC, and SOM allow validating the difference of texture and soil chemical attributes. Yari et al. (2017) identified the altitude and EC for validation of MZ of soil physical-water parameters. The isolated use of altitude (MZ-A) received the lowest Kappa value, corroborating what was observed in the Fuzzy analysis.

From this second validation analysis, it is possible to direct the use of two management zones to analyze yield (Table 4). When Kappa values were determined for each yield and two MZ, corn obtained excellent values (0.82) for the strategy using EC, SOM, and clay. For soybean yield, the best Kappa was considered reasonable (0.30) and obtained using altitude, SOM, and clay.

Table 4. Mean Kappa coefficients determined for corn and soybean yields regarding MZs classified into two, three, and four zones.

Strategies	Mean Kappa value for corn and soybean yields		
	2 zones	3 zones	4 zones
1. MZ-A*	0.15	0.21	0.20
2. MZ-EC	0.22	0.12	0.15
3. MZ-SOM/Clay	0.49	0.44	0.48
4. MZ-A/EC	0.25	0.24	0.26
5. MZ-A/SOM/Clay	0.43	0.36	0.44
6. MZ-EC/SOM/Clay	0.49	0.38	0.37
7. MZ-A/EC/SOM/Clay	0.49	0.35	0.36
Mean value of the strategies	0.36	0.30	0.32

*MZ-A: MZ from altitude; MZ-EC: MZ from EC; MZ-SOM/Clay: MZ from SOM and clay; MZ-Alt/EC: MZ from altitude and EC; MZ-Alt/SOM/Clay: MZ from altitude, SOM, and clay; MZ-EC/SOM/Clay: MZ from EC, SOM, and clay; MZ-Alt/EC/SOM/Clay: MZ from altitude, EC, SOM, and clay.

As a final step, the validation analysis considered the correspondence between yield data and both highlight strategies (MZ-A/SOM/Clay; MZ-EC/SOM/Clay), and two MZ as indicated by the Kappa index (Figure 3, Table 5). From the maps, you can observe a similar arrangement of the MZs, but with inversion concerning the size of each of them.

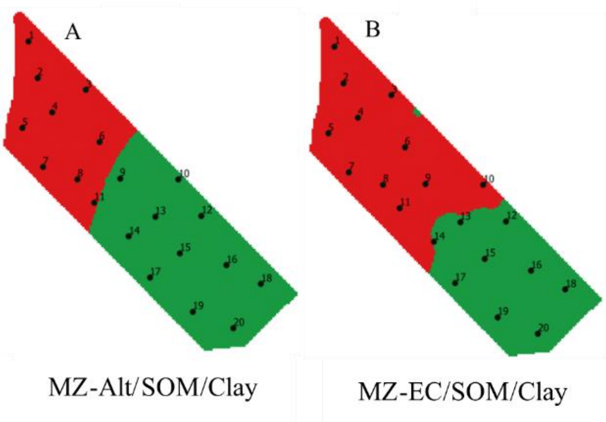

Figure 3. MZs with two zones defined for the strategies A – altitude, SOM, and clay (MZ-Alt/SOM/Clay) and B – EC, SOM, and clay (MZ-EC/SOM/Clay).

This correspondence analysis for both strategies showed only the statistical significance of corn data (Table 5). The use of EC, SOM, and clay (MZ-EC/SOM/Clay) showed the amplitude of MZ (507 $kg.ha^{-1}$), 90 $kg.ha^{-1}$ higher, regarding the use of altitude, SOM, and clay ($p<0.10$).

Table 5. Comparison of physio-chemical properties mean of soil, as well as soybean and corn yields between MZs, considering two zones.

Strategies	Zones	Altitude	EC*	SOM	Clay	Soybean	Corn
MZ-Alt/SOM/Clay	1	950[a]	6.5	21.7[a]	644[a]	3929	9488[a**]
	2	955[b]	6.6	19.8[b]	683[b]	3862	9071[b]
MZ-EC/SOM/Clay	1	951	6.4[a**]	21.5[a]	658	3930	9487[a]
	2	955	6.8[b]	19.7[b]	674	3845	8980[b]

*EC: Apparent soil electrical conductivity, 0-0.3 m; SOM: soil organic matter; MZ-Alt/SOM/Clay: MZ from altitude, SOM, and clay; MZ-EC/SOM/Clay: MZ from EC, SOM, and clay. [a,b]Distinct letters in the columns indicate different values among zones for each management strategy by t-test ($p < 0.05$); ** ($p < 0.10$).

Fields with above-optimal levels of attributes referred to as soil fertility status may not contribute to the definition of homogeneous management zones.

Considering the validation analyses, the other soil attributes surveyed in the study (Table 2) showed no statistical difference in relation to the proposed zones. This could be due to the built-up soil fertility, wherein 15 of the 17 evaluated attributes were verified to be above the acceptable levels (Raij 2011).

5. Conclusions

The use of soil attributes for greater temporal stability permits the subdivision of the plot in homogeneous management zones (MZ), where the smaller number of zones contribute to simplifying the management of inputs by farmers.

The data shows that strategies using altitude or EC associated with SOM and clay contribute to the best definition of MZ for corn yield.

The use of data collected from different sampling densities using meshes or sensors does not interfere in the definition and validation of the MZs. The use of Fuzzy logic algorithms and the Kappa index should be complementary in MZs validation process.

Electrical conductivity data may not represent the existing relationship between the availability of salts in the soil and yield, keeping reservations for the use of data found in the literature.

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