COMPARISON OF ALGORITHMS FOR DELINEATING MANAGEMENT ZONES

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ABSTRACT

Precision agriculture is aimed at field management considering its spatio-temporal variability. Its widespread use has been made possible with the development of tools for data collection and georeferencing of productivity, soil properties and others. The large amounts of data generated require the use of information technology resources for processing, allowing better definition of management zones. The correct selection of parameters is a complex task due to the large number of interrelated parameters, resulting in a nonlinear problem which, associated to the inherent problems in data collection make it appropriate to use statistics and computational intelligence techniques in their approach. Our aim was to compare some algorithms for delineating management zones. Fuzzy c-means, expectation maximization, X-means and self-organizing map were used. Georeferenced point measurements of physical and chemical properties were obtained from a 134.2 ha field. The properties used were pH, Ca, Mg, K, SB, CEC, P, C, OM, V, clay, silt and sand. The data were interpolated to a 10m x 10m grid. The software platforms used for delineating the management zone were Weka, Management Zone Analyst and Matlab, which together provide different algorithms. They were applied to a set of soil attributes and the result obtained shows differences between the techniques used. Some algorithms, such as expectation maximization, provided an excessive number of management zones when the number was not defined by the user. In addition, the algorithms delineated different number of management zones, depending on the soil properties used and on the parameters or the structure of the method. Initial results

show differences between maps generated by linear and nonlinear methods. Moreover, some of them require the user to choose parameters or/and structures, imposing a complex procedure to the end user. Final analyses will determine more differences between used methods.

KEYWORDS: spatial variability, precision agriculture, clustering, management zone

INTRODUCTION

The main objective of precision agriculture is enable field management, considering spatio-temporal variability. The proper delineating zones, through the study of the relationship between yield, soil properties and relief, avoids chemical exhaustion and degradation of their physical attributes, seeking the maximum sustainable productivity and profitability (MOLIN et al., 2006; MOLIN, 2004; TSCHIEDEL and FERREIRA, 2002).

To achieve these aims, georeferenced data are frequently used and analyzed to verify the most appropriate interventions for a specific area. With the advent of new computer technologies and geoprocessing, this work has become more agile and precise, with these tools being used at all stages of the crop.

Thus, the farmer can make the soil zoning by quantifying and visualizing various aspects from soil properties and attributes up to the yield obtained in the field. Due to this progress, there are currently several mechanisms for data acquisition in precision agriculture; such mechanisms allow the acquisition of a large amount of data that may contain important information to the process of decision making related to actions performed in the field, allowing productivity and profitability increase.

Although there is a diversity of tools, the correct management zone delineation is a complex task owing to the large number of interrelated parameters, resulting in a nonlinear problem. The nonlinearity of the problem combined with the occurrence of errors and inconsistencies in the spatio-temporal yield maps, as well as the soil maps indicates the use of Artificial Intelligence techniques. Several Artificial Intelligence techniques have been used for knowledge discovery (VRIESMANN et al., 2004; HUANG et al., 2010; DIMITRIADIS & GOUMOPOULOS, 2008; GUASTAFERRO et al. 2010; FU et al. 2010; MORAL et al., 2011; PEDROSO et al. 2010; RODRIGUES et al., 2011), each of which is suitable for different types of data gathered. In this context, the objective of this work is a comparison of clustering algorithms in the delineating of management zones using soil attributes.

MATERIALS AND METHODS

The study was conducted using data from a 134.2 ha field, containing 62 georeferenced soil samples, obtaining soil nutrients, pH, Ca, Mg, K, sum of bases - SB, cation exchange capacity - CEC, P, C, Organic Matter - MO and saturation of bases - V. From these 62 samples, 13 were chosen for the physical soil attributes, sand, silt and clay. The statistical description of these data is presented in Table 1.

The wheat yield maps were filtered, removing the outside field points, null or missing yield points, removal of partial-width platform, removing null or missing moisture points, null distance points and outliers yield (MENEGATTI and MOLIN, 2004).

The maps of soil attributes were interpolated using ordinary kriging and the yield map was interpolated using Inverse Distance Weight. The models were defined by average prediction errors and root-mean-square standardized error obtained using cross-validation. The characteristics of semivariograms calculated for variables are shown in Table 2. From the interpolation maps, sample were generated with cells from 10 meters x 10 meters, resulting in 13,284 cells.

In the next step, the data were converted into the format used by WEKA software (Hall et al., 2009), were normalized to the interval [0,1] to prevent the numerical difference between the attributes from influencing the results and they were used in all the methods evaluated.

The simulations were performed with the following sets: only chemical attributes, only physical attributes, set of all physical and chemical properties of soil and only yield.

In this work, the EM algorithm (expectation maximization) and X-means available in the WEKA software (Hall et al., 2009) are used, Fuzzy c-means algorithm implemented in management zone analysis software (MZA) (FRIDGEN et al., 2004) and self-organizing map (THEODORIDIS et al., 2009) with toolbox available in MATLAB.

The simulations were performed using the parameters suggested by the developers of the software used, except for the X-means algorithm, in which we change the maximum number of groups to 6, being the same interval for the Fuzzy c-means algorithm.

Table 1. Statistical description of soil properties and yield.

Soil attributes	***n***	***Mean***	***Median***	***Std. Desv.***	***Min.***	***Max.***
pH	62	5.19	5.20	0.36	4.30	5.90
Ca ($mmol_c/dm^3$)	62	33.65	34.60	8.64	10.60	57.30
Mg ($mmol_c/dm^3$)	62	17.74	18.15	4.74	5.20	30.50
K ($mmol_c/dm^3$)	62	4.18	3.90	1.82	1	8.40
SB ($mmol_c/dm^3$)	62	55.57	56.85	14.2	18.50	91.50
CEC ($mmol_c/dm^3$)	62	106.33	105.55	12.05	78.29	134.29
P (mg/dm^3)	62	42.92	36.50	25.92	9	119
C (g/dm^3)	62	23.11	23.24	3.40	15.39	33.74
OM (mg/dm^3)	62	39.85	40.06	5.87	26.53	58.17
V (%)	62	52.36	54.80	11.51	14.30	72.22
Sand (%)	13	47.91	50.20	9.86	31.60	68.95
Silt (%)	13	18.96	18.45	1.71	16.35	23.10
Clay (%)	13	33.13	31.55	10.42	10.60	50.80
Yield (t/ha)	74455	2.20	2.21	0.41	1.07	3.317

Table 2. Parameters of the experimental semivariogram for soil attributes.

Soil attributes	**Model**	**C_0**	**C**	***Nugget* (%)**	**Spatial Class**	**Range**
pH	Circular	0.019	0.125	13.38	S	491.64
Ca ($mmol_c/dm^3$)	Rational Quadratic	49.780	35.168	58.60	M	1271.47
Mg ($mmol_c/dm^3$)	Rational Quadratic	14.602	10.920	57.21	M	1224.95
K ($mmol_c/dm^3$)	Rational Quadratic	1.344	2.252	37.39	M	808.40
SB ($mmol_c/dm^3$)	Rational Quadratic	137.544	88.036	60.97	M	1349.54
CEC ($mmol_c/dm^3$)	Rational Quadratic	68.804	99.776	40.81	M	943.87
P (mg/dm^3)	Exponential	608.547	19.531	96.89	W	272.41
C (g/dm^3)	Gaussian	7.376	7.212	50.56	M	988.34
OM (mg/dm^3)	Gaussian	21.922	21.437	50.56	M	988.34
V (%)	TetraSpherical	38.311	106.902	26.38	M	525.51
Areia (%)	Gaussian	35.547	117.432	23.24	S	1169.70
Silte (%)	Rational Quadratic	1.476	2.075	41.57	M	1750.15
Argila (%)	Gaussian	43.567	131.574	24.88	S	1237.34

The delineation of management zones using self-organizing maps, was performed using the Matlab to generate the U-matrix and then delineating management zones applying the K-means algorithm on the U-matrix, resulting in management zones, according to the method used in (RECKNAGEL et al., 2006). To generate maps of management zones, the sample points were considered to belong to the group of neuron that are activated when presented to artificial neural network, thus creating groups of points from the groups obtained with the U-matrix.

The map obtained from using each of the methods, was examined visually to verify if they had a manageable number of management zones, as well as the existence of well-defined boundaries between them.

The number of points in each of the zones and the average values for each attribute allows a quantitative analysis of the generated maps.

RESULTS

The maps generated using the EM algorithm with the parameters suggested by the WEKA software, when not indicating the number of groups, resulted in an excessive number of groups (management zones) with small area which makes them impracticable for precision agriculture applications, as can be seen in Table 3. In addition, simulations required a runtime many times superior to that of other methods, regardless of the set of attributes used.

Table 3. Number of groups created by the EM algorithm.

Attributes	Group Number
Physical	82
Chemical	58
Physical + Chemical	77
Yield	10

The statistical results of the groups defined with the X-means algorithm, Fuzzy c-means and self-organizing maps using the physical and chemical properties are presented in Tables 4, 5 and 6, where the center of each group for each the variables of soil can be seen. The numbers in parentheses indicate the number of points in each group.

Figures 1 to 3 illustrate the division of the field using the X-means algorithm, fuzzy c-means and self-organizing maps, respectively.

Analyzing Table 4, the central values of the groups for each attributes can be seen to vary to a greater or lesser extent, indicating attributes with greater or lesser influence in the setting groups. Attributes that have similar mean values in all groups has little influence on management zone delineation.

Figure 1 shows that the four groups defined by the X-means algorithm resulted in 5 management zones with well-defined borders, but with a small management zone which, in practice, can be attached to a neighbor management zone.

Table 5 presents the statistical analysis of groups generated by the Fuzzy c-means algorithm using the physical and chemical soil properties. The number of groups was defined by NCE and FPI when minimum values for both were found, dividing the field into three groups.

Table 4. Statistical description of the groups generated by the X-means algorithm with physical and chemical soil properties.

Var	C1 (5753)	C2 (4325)	C3 (1144)	C4 (2062)
	mean	Mean	mean	mean
Clay	39.93	31.07	24.73	25.57
Silt	17.57	18.99	18.87	18.33
Sand	41.03	48.23	54.49	55.01
pH	4.96	4.87	4.29	4.23
Ca	36.56	32.57	29.20	27.10
Mg	19.15	16.90	15.03	13.87
K	3.77	3.64	4.93	3.11
SB	60.38	54.10	49.62	45.62
CEC	109.15	97.33	108.05	112.49
P	51.17	32.02	29.51	44.57
C	24.14	19.94	22.23	23.97
OM	41.99	34.78	38.72	41.68
V	55.48	55.16	46.93	38.45

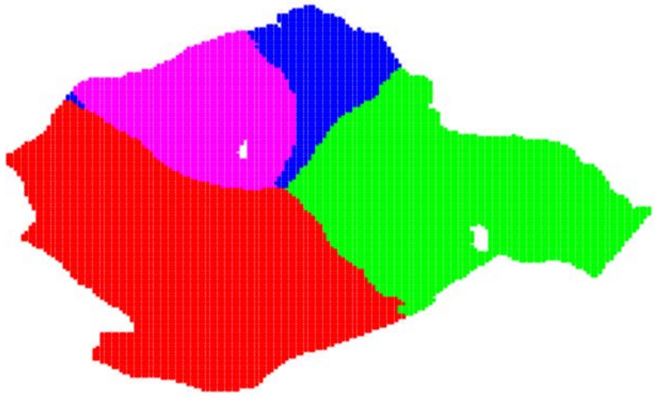

Figure 1. Management zones delineated by the X-means algorithm with physical and chemical attributes.

Figure 2 shows that the three groups defined by the Fuzzy C-means algorithm, resulted in three management zones with well-defined borders and the southwestern and southeastern zones are very similar to those obtained by the X-means algorithm.

Table 6 presents the statistical analysis of groups generated by the self-organizing map using the physical and chemical soil properties. We observed that the number of groups generated by the method was at least three times greater than the number defined by the X-means algorithm, resulting in small groups.

Figure 3 shows the 13 groups defined by the self-organizing map, resulting in 13 well-defined border management zones, but due to the high number and small size, the management zones may become impracticable to use in precision agriculture.

Table 5. Statistical description of the groups generated by the Fuzzy c-means algorithm with physical and chemical soil properties

Var	**C1 (5703)**	**C2 (2888)**	**C3 (4693)**
	mean	**mean**	**mean**
Clay	40.012	25.27	30.68
Silt	17.57	18.47	18.97
Sand	40.95	54.92	48.64
pH	4.96	4.2	4.86
Ca	36.58	27.54	32.45
Mg	19.17	14.11	16.83
K	3.78	3.68	3.70
SB	60.42	46.57	53.93
CEC	109.16	111.82	97.80
P	51.19	40.74	31.73
C	24.14	23.58	20.06
OM	42.01	41.03	34.99
V	55.50	40.34	54.91

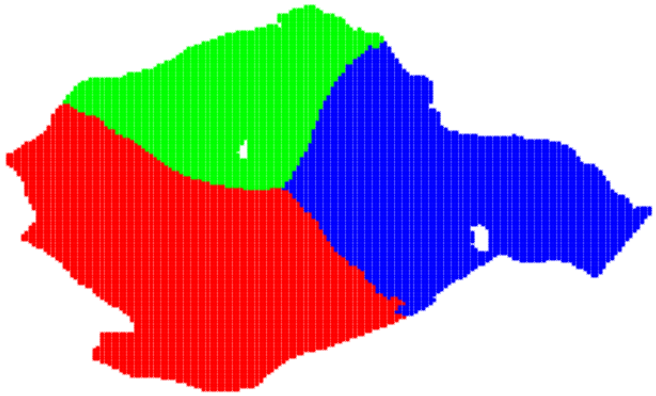

Figure 2. Management zones delineated by the Fuzzy c-means algorithm with physical and chemical attributes.

The statistical results of the groups defined with the X-means algorithm, Fuzzy c-means and self-organizing map using only the physical attributes are presented in Tables 7 and 8.

Figures 4 and 5 show the division of the field by X-means algorithm, fuzzy c-means and self-organizing map.

Analyzing Table 7, the values of the central groups for each of the attributes can be clearly seen to indicate the division into two areas with a higher percentage of clay and the other with a higher percentage of sand.

Figure 4 shows that the two groups defined by the X-means algorithm resulted in two large well-defined borders management zones, facilitating the practice of precision agriculture.

Table 8 shows the statistical analysis of groups generated by the self-organizing map using only the physical attributes of the soil. It is worth noting that this method produced a high number of groups, being four times greater than the number defined by the X-means algorithm and Fuzzy C-means, resulting in small and unsuitable management zones for precision agriculture.

Figure 3. Management zones delineated by the self-organizing map with physical and chemical attributes.

Table 6. Statistical description of the groups generated by the self-organizing maps with physical and chemical soil properties.

Var	C1 (995)	C2 (405)	C3 (1149)	C4 (2114)	C5 (748)	C6 (839)	C7 (1415)	C8 (796)	C9 (888)	C10 (654)	C11 (706)	C12 (1747)	C13 (828)
	mean	**mean**	**mean**	**mean**	**mean**	**mean**	**mean**	**mean**	**mean**	**mean**	**mean**	**mean**	**mean**
Clay	40,39	26,32	33,38	29,32	35,45	28,40	24,39	24,37	31,49	35,90	42,14	46,36	33,18
Silt	17,31	18,36	17,00	18,84	18,09	17,74	18,57	19,00	20,42	17,80	18,00	17,77	18,36
Sand	40,78	53,98	48,12	49,1	45,13	52,69	55,93	54,51	46,15	45,06	38,24	34,36	47,08
pH	5,00	4,32	5,00	4,92	5,0	4,79	4,01	4,3	4,3	5,00	4,71	5,00	4,54
Ca	37,50	29,26	34,77	30,91	34,96	31,16	25,43	29,36	35,88	36,3	33,44	39,13	32,35
Mg	19,67	15,1	18,22	15,93	18,31	16,12	12,95	15,10	18,84	19,21	17,24	20,52	16,79
K	3,33	3,33	4,84	3,64	2,68	3,39	3,06	5,44	5,42	2,31	3,17	4,32	2,40
SB	61,83	48,70	58,40	51,65	56,47	51,58	43,25	50,15	60,42	58,92	55,31	64,63	52,95
CEC	106,53	100,1	106,23	93,51	107,25	110,39	113,59	110,58	102,58	106,88	111,21	112,62	97,02
P	50,38	38,26	49,55	26,70	44,7	48,70	42,42	27,01	30,11	46,62	52,71	54,98	40,11
C	24,48	21,75	24,14	19,53	21,59	24,26	23,88	22,31	19,75	23,67	23,06	24,89	20,42
OM	42,58	37,96	42,09	34,13	37,64	42,11	41,53	38,86	34,37	41,18	40,10	43,29	35,53
V	57,05	48,83	55,44	53,49	55,22	47,6	34,69	46,50	61,48	56,94	46,59	58,11	52,91

Table 7. Statistical description of the groups generated by the X-means and Fuzzy c-means algorithm with physical soil properties.

Var	C1 (4831)	C2 (8453)
	mean	**mean**
Clay	41.78	28.78
Silt	17.69	18.59
Sand	39.05	51.07

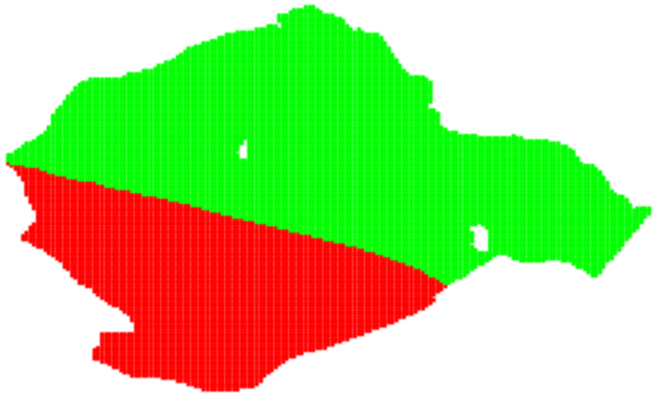

Figure 4. Management zones delineated by the X-means and Fuzzy c-means algorithm with physical attributes.

Figure 5 shows the 8 groups defined by the self-organizing map, resulting in 8 small well-defined border management zones, but due to the large number of zones, it may make management zones impractical for use in precision agriculture.

Table 8. Statistical description of the groups generated by the self-organizing maps with physical soil properties.

Var	**C1 (1528)**	**C2 (1980)**	**C3 (1391)**	**C4 (1300)**	**C5 (2346)**	**C6 (1491)**	**C7 (2189)**	**C8 (1059)**
	mean	**mean**	**mean**	**mean**	**mean**	**mean**	**mean**	**mean**
Clay	33.38	27.34	39.69	30.89	45.56	31.26	24.32	35.78
Silt	17.17	17.94	17.57	18.42	17.79	20.08	18.91	18.29
Sand	48.01	53.32	41.27	49.07	35.13	46.8	55.18	44.65

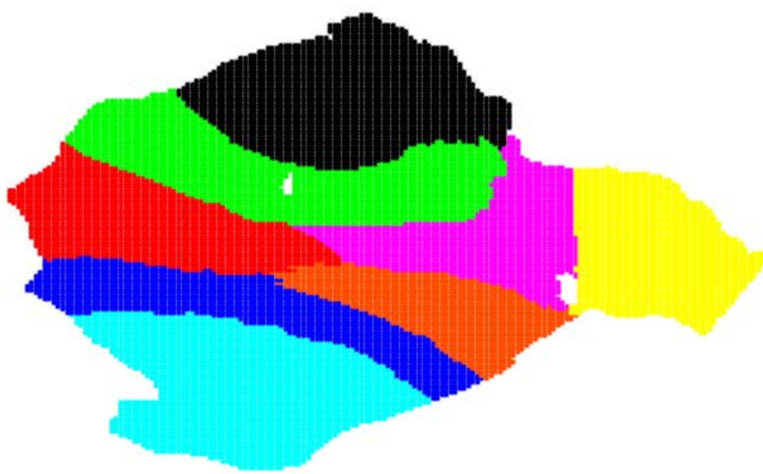

Figure 5. Management zones delineated by the self-organizing map with physical attributes.

Table 9. Statistical description of the groups generated by the X-means algorithm with chemical soil properties.

Var	C1 (5294)	C2 (4669)	C3 (2072)	C4 (1249)
	mean	mean	mean	mean
pH	5.00	4.87	4.38	4.00
Ca	36.86	32.47	30.05	25.21
Mg	19.34	16.85	15.46	12.83
K	3.86	3.68	3.95	2.98
SB	60.88	53.95	50.37	42.9
CEC	108.93	97.73	110.59	113.96
P	51.17	31.88	41.36	42.51
C	24.28	20.05	23.15	23.89
OM	42.24	34.97	40.26	41.57
V	56.41	54.93	45.08	33.78

The statistical results of the groups defined by the X-means algorithm, Fuzzy C-means and self-organizing map using only the chemical properties are presented in Tables 9, 10 and 11.

Figures 6 to 8 illustrate the division of the field by the X-means algorithm, fuzzy c-means and self-organizing map, respectively.

The analysis of Table 9 shows the central values group for each attributes, indicating that the Ca, Mg, V and SB attributes have great influence on the division of the groups.

Figure 6 shows that the four groups defined by the X-means algorithm, resulted in five management zones with well-defined borders and there is great similarity between the southwest and southeast management zones in comparison with those obtained by using the physical and chemical attributes.

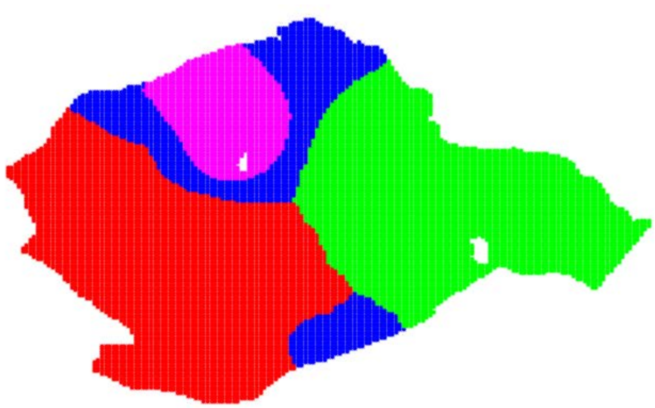

Figure 6. Management zones delineated by the X-means algorithm with chemical attributes.

Table 10. Statistical description of the groups generated by the Fuzzy c-means algorithm with chemical soil properties.

Var.	C1 (4844)	C2 (2941)	C3 (5499)
	Mean	Mean	Mean
pH	4.86	4.16	5.00
Ca	32.43	27.75	36.7
Mg	16.82	14.21	19.24
K	3.7	3.55	3.85
SB	53.88	46.85	60.62
CEC	98.09	112.21	108.98
P	31.95	41.61	51.17
C	20.12	23.49	24.26
OM	35.08	40.88	42.20
V	54.77	39.70	56.12

Table 10 presents the statistical analysis of groups generated by the Fuzzy C-means algorithm using only the soil chemical properties. The number of groups was defined using NCE and FPI index and the field was divided into three groups. As the X-means algorithm, analyzing the mean values of the attributes, it is possible to observe that the attributes Ca, Mg, V and SB, had a significant influence in the definition of the groups.

Figure 7 shows the three groups defined by the Fuzzy c-means algorithm, which resulted in 4 management zones with well-defined borders. The map was very similar to that obtained with the X-means algorithm; the only difference was the union of the two management zones to the north in a single zone management.

Table 11 presents the statistical analysis of groups generated by the self-organizing map using only the soil chemical properties. Note that, for this method, the number of groups was high, being almost double the number set by the X-means algorithm and fuzzy c-means, resulting in small and unsuitable management zones for precision agriculture.

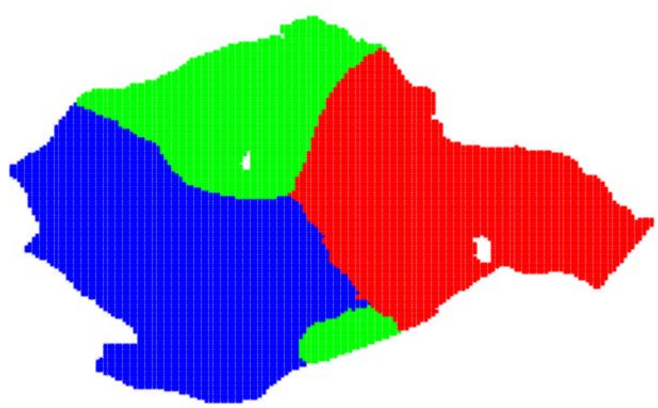

Figure 7. Management zones delineated by the Fuzzy c-means algorithm with chemical attributes.

Table 11. Statistical description of the groups generated by the self-organizing map with chemical soil properties.

Var.	C1 (922)	C2 (1327)	C3 (804)	C4 (1297)	C5 (2940)	C6 (1527)	C7 (4467)
	mean	mean	mean	mean	mean	mean	mean
pH	4.27	4.91	5.00	4.76	4.82	4.01	5.00
Ca	29.25	34.63	36.13	31.82	31.17	25.60	37.27
Mg	15.04	18.11	18.99	16.42	16.09	13.04	19.56
K	5.13	2.62	5.56	3.42	3.4	3.07	3.97
SB	49.81	56.11	60.85	52.81	51.87	43.5	61.66
CEC	108.74	107.01	102.84	110.53	94.30	113.09	108.84
P	28.3	45.28	30.55	50.66	29.74	42.27	51.51
C	22.24	21.70	19.79	23.94	19.74	23.79	24.47
OM	38.73	37.78	34.45	41.55	34.47	41.40	42.59
V	46.92	54.33	62.10	46.65	53.30	35.18	56.97

Figure 8 shows that 7 groups defined by the self-organizing map, resulted 8 small and well-defined border management zones, but due to the large number of zones, it is impractical for use in precision agriculture.

Another set of simulations was performed using only the yield map, but the results were not satisfactory, because they do not present well-defined boundaries for any of the algorithms used. Furthermore, in the case of the fuzzy c-means algorithm, there was not convergence of FPI and NCE indexes and the self-organizing map resulted in 17 groups, which is a high number, following the trend observed with other data sets. Figure 9 shows the map produced with the X-means algorithm.

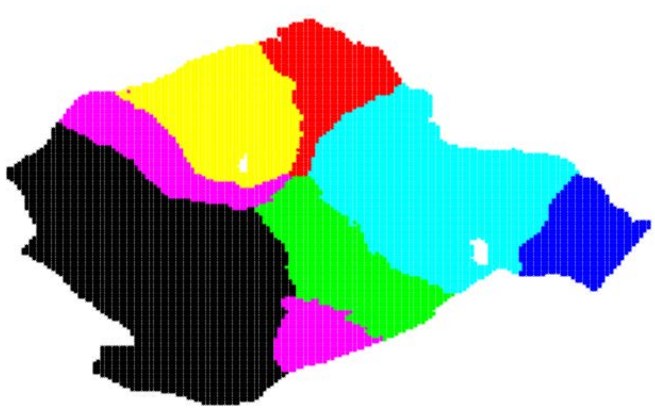

Figure 8. Management zones delineated by the self-organizing map with chemical attributes.

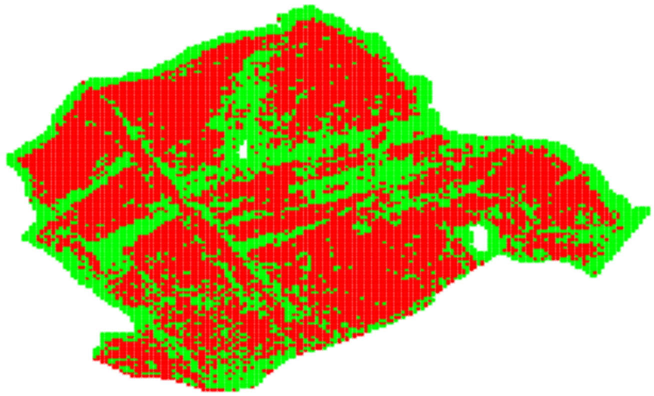

Figure 9. Management zones delineated by the X-means algorithm with yield map.

Analyzing the all the results, the fuzzy c-means algorithm showed to be the best of the methods used, providing management zone maps with well-defined borders and without excessive management zones.

The second best algorithm is the X-means, providing some small management zones which, in practice, may be incorporated into one another.

The self-organizing map provided better results than the EM algorithm, but an excessive number of management zones. Additionally, despite being fast to run, the method requires the choice of the dimensions of the map of neurons and the use of a clustering algorithm to generate management zones from the U-matrix. In this work, the K-means algorithm was used.

The EM algorithm presented the worst results, generating maps with a large number of management zones and requiring a runtime ten times higher than the other methods.

CONCLUSIONS

Based on the results, we can conclude that the maps generated by X-means algorithm and Fuzzy c-means are very similar.

The Fuzzy c-means algorithm was the best among the algorithms used.

The method using self-organizing maps generated many management zones and the process for obtaining management zones requires the use of one clustering algorithm.

Finally the EM algorithm fails to delineate management zones when used to automatically adjust their number, resulting in a high number and a long processing time.

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