Potential of Apparent Soil Electrical Conductivity to Describe Soil Spatial variability in Brazilian Sugarcane Fields

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Abstract. *The soil apparent electrical conductivity (ECa) has been highlighted in the literature as a tool with high potential to map the soil fertility of fields. However, sugarcane fields still lack results that show the applicability of this information to define the soil spatial variability and its fertility conditions. The objective of the present paper was to provide a comprehensive assessment of the relationship between ECa, evaluated by electromagnetic induction (EMI) sensor, and the spatial variability of clay content, organic matter (OM) and cation exchange capacity (CEC) in sugarcane fields. Six experimental sugarcane fields were evaluated, totaling 412 hectares mapped and 2,000 soil samples collected between 2011 and 2017. The results showed that ECa was able to map sites with higher clay content, OM and CEC, corresponding to classes of greater soil electrical conductivity. Low ECa classes presented greater spatial variability of the evaluated soil attributes, being places that should be sampled with greater accuracy, that is, with a higher sample density for a suitable soil spatial characterization. The ECa variability was directly proportional to clay content (R^2 = 0.97), OM (R^2 = 0.65) and CEC (R^2 = 0.76) variabilities, where 1.0 mS m^{-1} corresponded to 1.5 g kg^{-1}, 0.11 g dm^{-3} and 0.24 mmol dm^{-3} of clay content, OM and CEC, respectively. The EMI sensor is an excellent tool to define the spatial variability of soil fertility and could be used for a guided soil sampling to manage the sugarcane fields in an adequate sustainable way.*

Keywords. *apparent electrical conductivity, proximal sensing, precision farming, site-specific management.*

Introduction

The high-quality soil fertility mapping is one of the main procedures to ensure more sustainable production. Intrinsically related to Precision Agriculture (PA), this mapping consists in a detailed soil sampling using modern equipment and techniques (Bullock *et al.*, 2007). Map the soil spatial variability is the way where PA can make decisions and efficient agronomic practices to increase profitability of production. However, to ensure a precise mapping of this variability, a dense sampling has to be adopted; turn the activity unfeasible and unable to perform a differential management of crops. On the other hand, with the increase advent of information technology (IT) in agriculture, many soil sensing techniques (Rossel and Bouma, 2016) are available to map the spatial variability of fields.

Within the historical context of affordable technologies to acquire high-quality information to manage the crop spatial variability, the apparent electrical conductivity (ECa) of soil it has been highlighted as an effective method to evaluate quickly, with high resolution and low cost the general soil fertility conditions (Sudduth *et al.*, 2005) and soil yield potential (Corwin e Lesch, 2005; Corwin e Lesch, 2003). ECa measurement has several advantages, such as high-speed data acquisition, easy to use, portable for field applications, and is a non-invasive method (Reedy e Scanlon, 2003). As a tool first applied to geology, ECa has been highlighted as a powerful information in agriculture in the last decades, showed great correlation with soil salinity, clay content, cation exchange capacity (CEC), clay minerals, pore size and distribution, organic matter and temperature (Molin e Faulin, 2013; Ekwue e Bartholomew, 2011; Corwin e Lesch, 2005; McBratney et al., 2005; Tarr et al., 2005; Domsch e Giebel 2004; Triantafilis et al., 2000; Sudduth et al., 2001; Kitchen et al., 1999; Rhoades et al., 1999). How ECa reflects the cumulative effect of soil matrix properties (mainly soil texture, cation exchange capacity, SOM and solute content), since these soil matrix properties are correlated with the yield, the ECa can also be highly correlated to crop yield (Godwin et al. 2003; Kitchen et al. 2005). Even more, recently Serrano et al. (2017) addressed the ECa data and it's great spatial and temporal stability, turn it a valuable information for site-specific management of crops.

Heil and Schmidhalter (2017) showed a broad review of the ECa potential by an electromagnetic induction (EMI) sensor. However, within the crops assessed by Heil and Schmidhalter where the technology has been applied, neither of them were in sugarcane fields. In Brazil, ECa has been used mainly to define the soil productive potential, soil fertility mapping, moisture differences and, management zones. Moreover, the studies mostly applied sensors that measure ECa by direct contact principle, with few studies that use IEM. Within this context, the objective of the present paper was provided a wide-ranging assessment of the relationship between soil attributes and ECa at spatial and temporal level in Brazilian sugarcane fields by an EMI sensor. We intended to provide a comprehensive knowledge if ECa information, provided by an EMI sensor, can reflect the soil attributes variability and how it can help the producers to ensure an adequate site-specific management of their fields.

Material and Methods

Experimental fields

All experimental fields (Figure 1), labeled as field A (21°16'35.65"S 47°32'15.65"W), field B (21°49'11.69"S 48°35'44.21"W), field C (21°46'28.12"S 48°37'34.05"W), field D (21°38'12.18"S 48°39'05.49"W), field E (21°49'04.10"S 48°25'35.97"W) and field F (21°49'04.10"S 47°44'11.29"W), are in São Paulo state, Brazil. In average, the fields slope ranged from 3.3% to 9.4% (Figure 2). The experimental fields are in the cities of Serrana (Fields A), Nova Europa (Fields B, C and D), Bebedouro (Field E) and Descalvado (Field F).

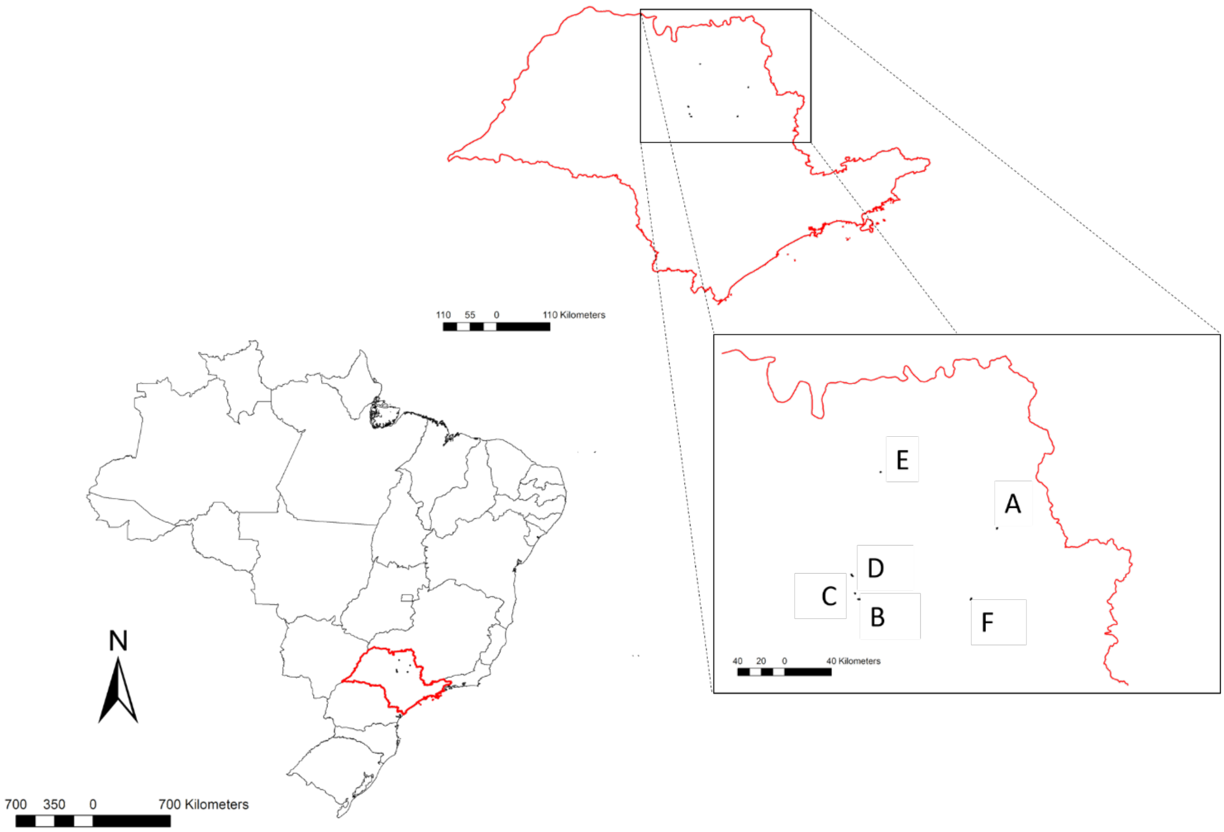

Figure 1. Geographic location of the sugarcane experimental fields in São Paulo state, Brazil.

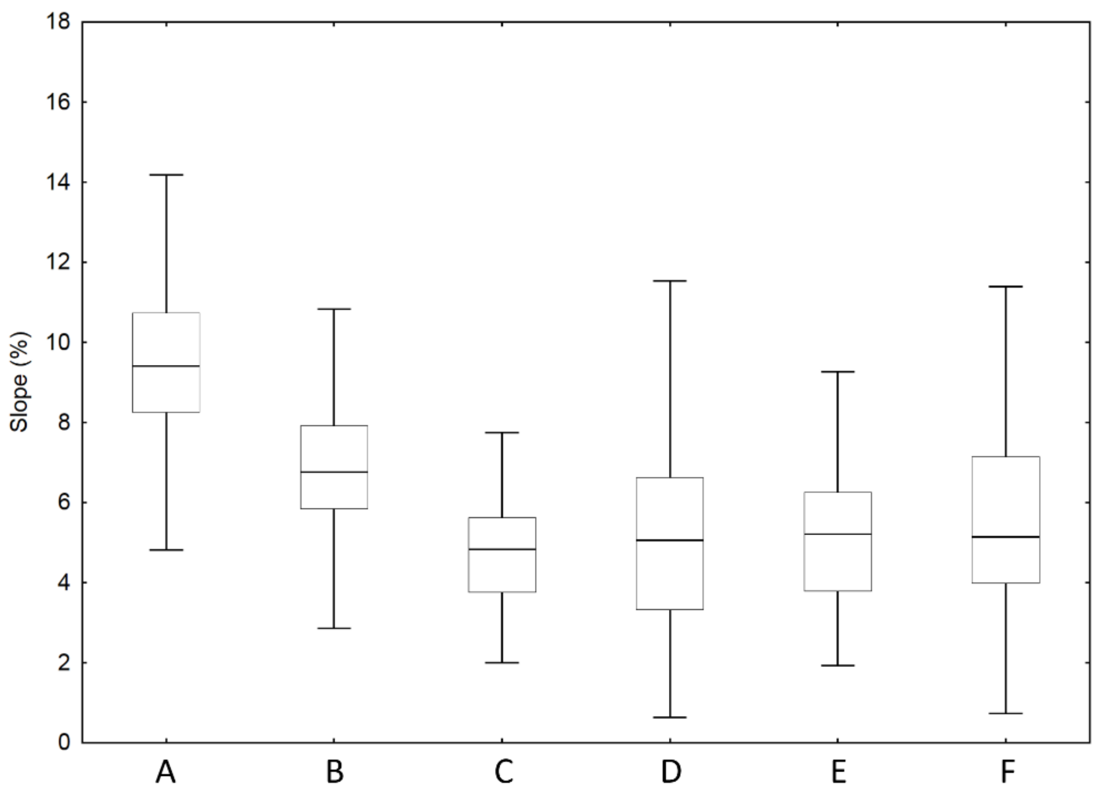

Figure 2. Slope (%) variability of the sugarcane experimental fields in São Paulo state, Brazil.

Soil dataset

The soil dataset used come from six sugarcane experimental fields (Figure 3) where PA researches are carried out by the University of Campinas (UNICAMP). All data are stored in the Agronomic Database (BDAgro), reported in Driemeier et al. (2016). Only the soil surface layer data (0.00 to 0.20 m) were evaluated. For all fields, the soil was sampled by regular grids with different densities (Table 1). The experimental fields A and D were sampled for more than 1 year. About 2000 soil samples, collected between 2011 and 2017, were evaluated. The attributes clay content, OM and CEC were assessed; soil attributes that directly impact the spatial and temporal variability of sugarcane yield.

Table 1. Soil sampling characteristics of the sugarcane experimental fields.

Field	Area [ha]	Years	Grid [m]	Samples	Dens. [samples ha^{-1}]
A	52.57	2011, 2012, 2013 and 2014	50 x 50	204	3.88
B	95.88	2014	50 x 50	303	3.16
C	34.81	2014	50 x 50	128	3.68
D	102.06	2016 and 2017*	50 x 50	424	4.15
E	37.50	2017	75 x 75	66	1.76
F	90.04	2017	100 x 100	119	1.32

* 100 x 100 m grid with 214 samples was collected.

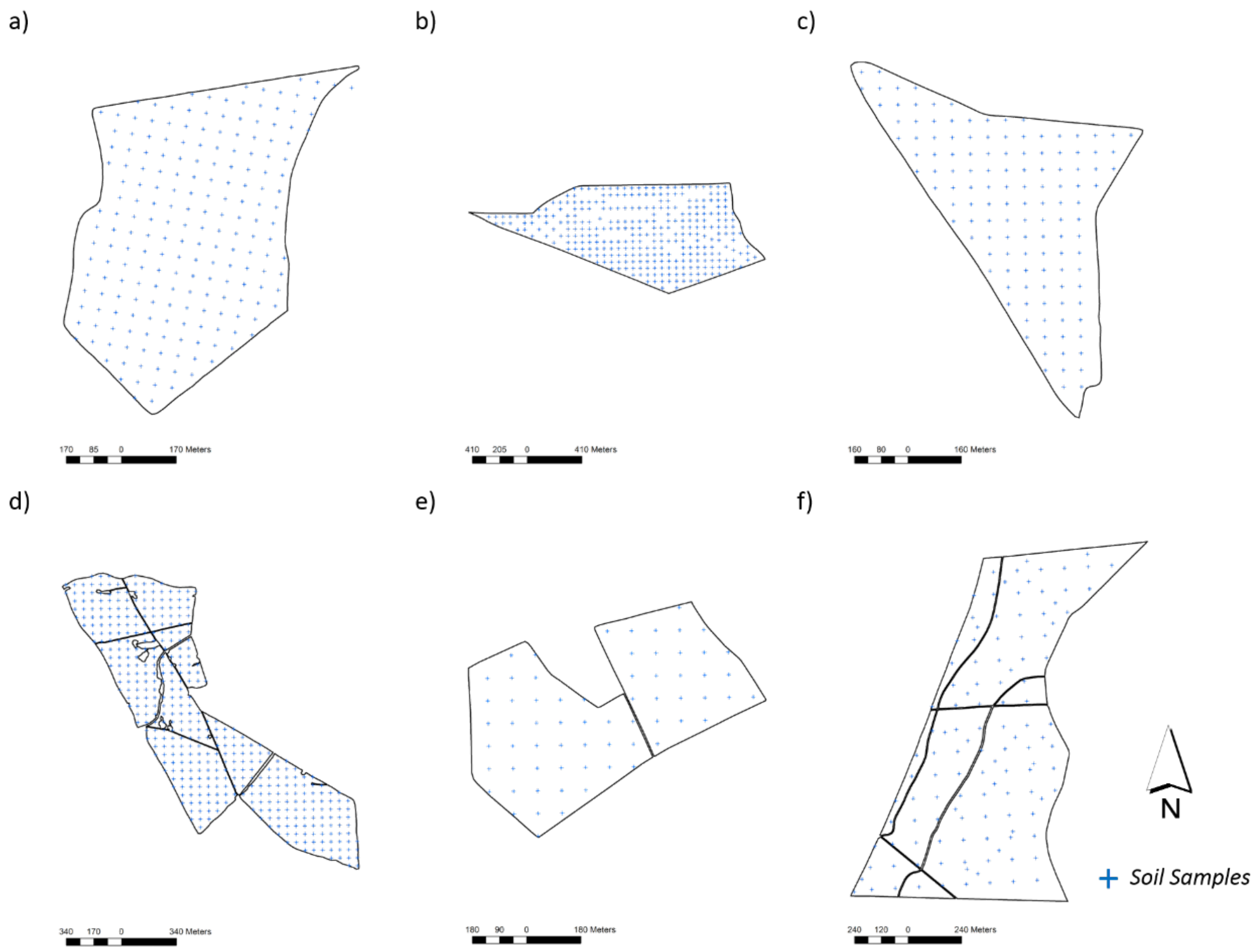

Figure 3. Soil sampling grids of experimental fields A (a), B (b), C (c), D (d), E (e) and F (f).

Apparent Electrical Conductivity (ECa) data set

The soil ECa was measured using the electromagnetic induction (EMI) sensor EM38-MK2® (Geonics, Ontario, Canada), the most widely used EMI sensor in agriculture (Doolittle and Brevick, 2014). The measures were obtained between May and July, the lowest rainfall season in all fields assessed. The investigated depth range depends on the coil configuration and the distance between coils. We used the 0.5 m coil separation readings in the horizontal dipole mode, that reaches a maximum sensitivity directly below to the instrument. Technical data, construction and tool specification of EM38-MK2® are described in Heil and Schmidhalter (2017). The ECa was measured in parallel rows with intervals of 5 to10 m pulled by a field vehicle. The data logger frequency was 1 Hz (Table 2). The ECa readings of each experimental field was performed in a period shorter than one day. No precipitation was occurred on the ECa measurement days that could change the soil humidity and, consequently, influence the ECa measurements. Finally, the ECa maps was obtained by applying ordinary kriging (OK).

Table 2. Apparent electrical conductivity (ECa) data of the sugarcane experimental fields.

Field	Valid N	Area [ha]	Dens. [readings ha^{-1}]	Mean	Median	Min.	Max.	Range	SD	CV
				[mS m^{-1}]						
A	18438	52.57	350.74	122.838	117.403	15.352	225.117	209.765	45.693	37.198
B	25657	95.88	267.59	30.851	29.844	-55.430	227.500	282.93	43.517	141.052
C	13312	34.81	382.45	5.055	4.727	-4.766	78.008	82.774	3.737	73.931
D	79304	102.06	777.04	-51.846	-70.958	-124.727	137.190	261.9173	34.394	-66.338
E	10102	37.50	269.40	-57.095	-57.695	-77.695	38.789	116.484	7.626	-13.357
F	24499	90.04	272.09	-4.228	-15.508	-109.414	242.695	352.109	68.343	-1616.474

Data analysis

To assess the relationship between ECa and soil attributes, data analysis process was performed Figure 4. First, the ECa and soil data were analyzed to remove discrepant values from field readings or laboratory errors. Any input value that deviated from the mean by more than three standard deviations was treated as an outlier. The ECa data were reduced to the soil sample grid by linear polynomial surface regression (*fittype fuction*) using Matlab software (MathWorks, Natick, Massachusetts) in a buffer zone according to the linearization method described by Driemeier et al. (2016). After the removal of discrepant values, the correlation between soil attributes and ECa was calculated by Pearson's correlation coefficient (*r*). Second, all soil attributes were normalized to the interval 0 to 1 (Equation 1), within the respective experimental field and evaluated year. This step put the data, regardless of the site and year, in the same range of variation to allow future comparisons.

$$X_p = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where X_p is the normalized attribute value, x_i is the original attribute value; x_{min} and x_{max} is, respectively, the minimum and maximum values of the attribute assessed within the respective experimental field and evaluated year.

The ECa data of each experimental field was divided into five classes by three types of classification methods. We tested the Quantil (Q), Natural Breaks (NB) and Geometrical Intervals (GI) classification methods. One hundred samples, per ECa class, were adopted for each z_j iteration of the random sampling. We performed 10 iterations. At each iteration was calculated the mean (M) and coefficient of variation (CV), by ECa class, of the soil attribute assessed. At first time, we evaluated the clay content within ECa classes divided by the three types of classification methods tested. The objective was to decide what classification method show better difference between classes. The best classification method was selected, and the steps was performed again for clay content, OM and CEC. The box-plot was used to visualize the data variability of all iterations by ECa classes, using the mean as the second quartile. Linear adjustment between ECa and soil attributes (ranges of measurement) was performed to verify the robustness of ECa data to measure the soil spatial variability of fields. Finally, to verify the spatial patterns at temporal level, we evaluated the OM and CEC content at fields A and D, where sampling was performed for more than 1 year.

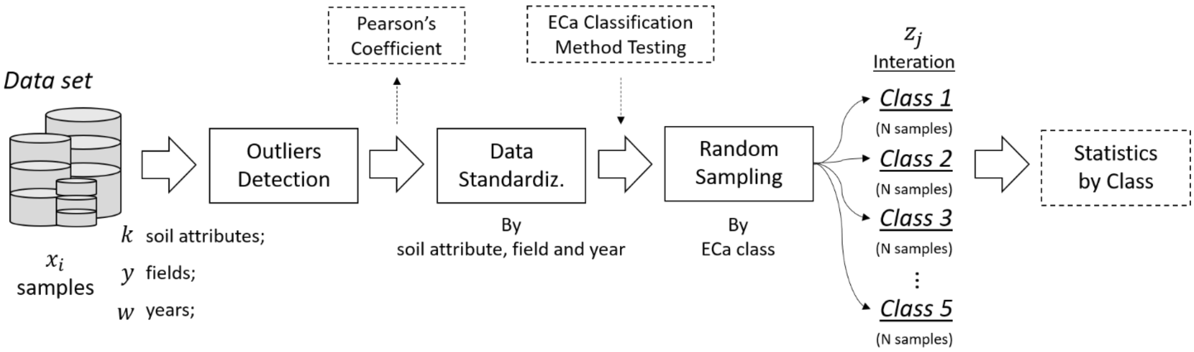

Figure 4. Data analysis process applied to dataset.

Results

The present study comprised experimental fields with wide clay content variability (Figure 5 - a). Fields assessed were from very sandy (clay <150 g kg^{-1}) until very clayey (clay> 600 g kg^{-1}). Fields B and F showed the greatest clay content variability, while fields C and E the smallest. Fields B and F showed measurement ranges equal to 648 g kg^{-1} and 520 g kg^{-1}, respectively. Fields C and E, which presented lower clay content variability, also presented lower variability of OM and CEC (Figure 5 - b and c, respectively). While field B showed the highest average levels for clay and CEC, field F had the highest OM content on average.

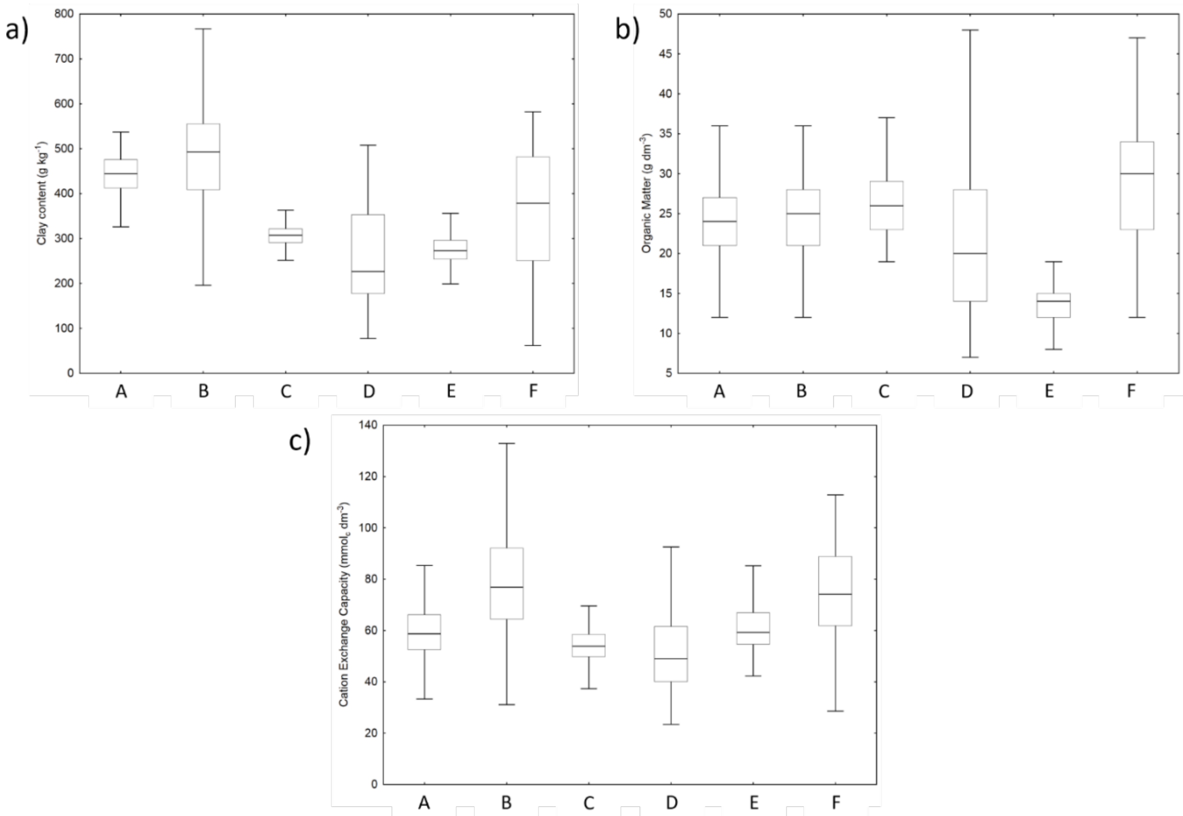

Figure 5. Clay content (a), organic matter (b) and cation exchange capacity (c) variability of experimental fields.

Like clay content variability, fields B and F showed the greatest variability in soil ECa (Figure 6). Except for field A (Figure 6 - a), the other fields presented negative values in the ECa readings, justified by the principle of measurement and equipment calibration as reported in Heil and Schmidhalter (2017). The highest ECa variability was observed in field F (Figure 6 - f), with a measurement range equal to 352 mS m^{-1}. Fields C and E showed the lowest ECa measurement ranges, following clay content, OM and CEC variability trends.

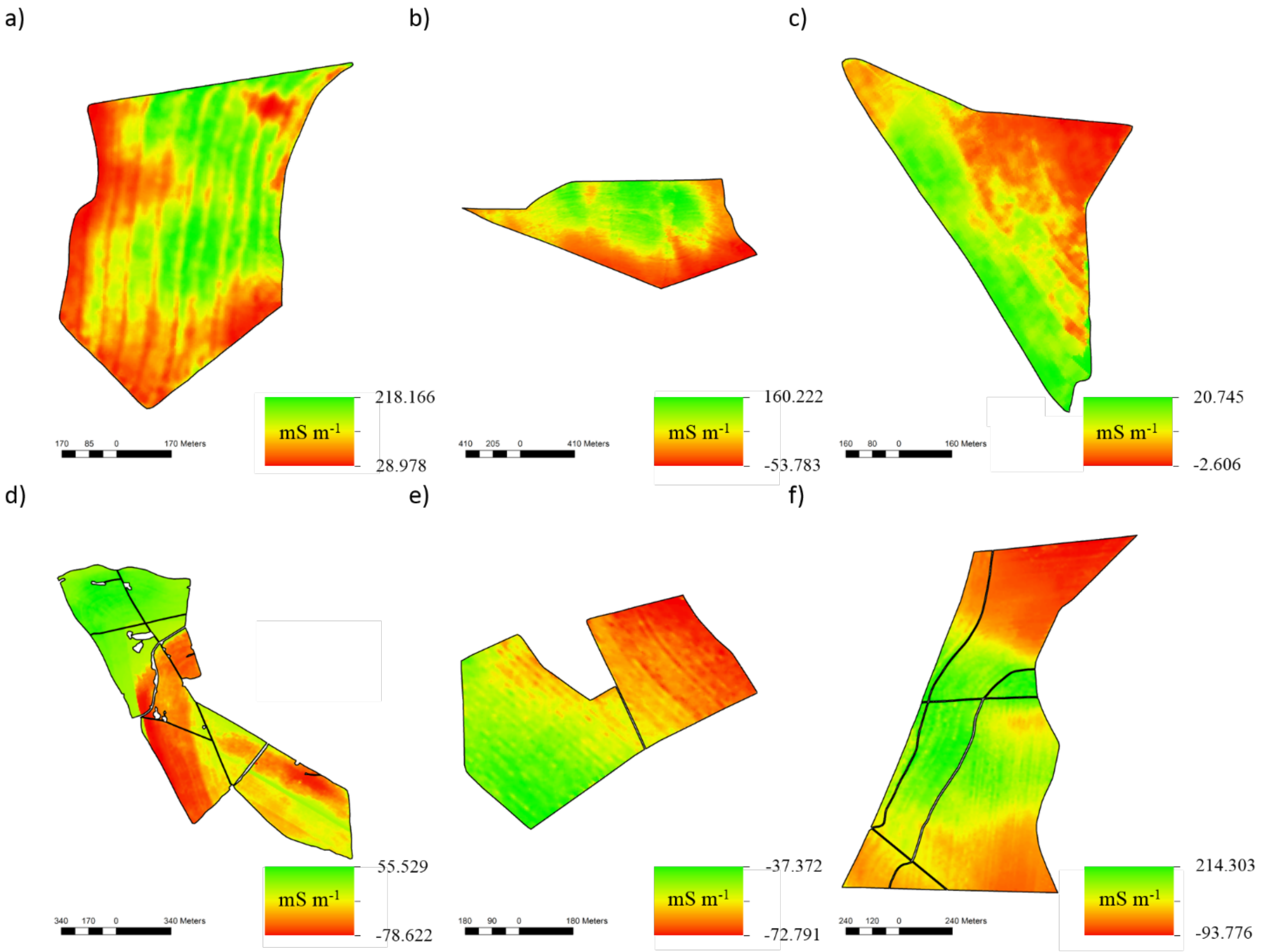

Figure 6. Spatial variability maps of apparent electrical conductivity (ECa) of experimental fields A (a), B (b), C (c), D (d), E (e) and F (f).

A direct and significant correlation was founded between ECa and clay content (Table 3) for fields A, B, D and F (r = 0.48, 0.71, 0.81 and 0.78, respectively), corresponding to the fields with high clay content variability. In the fields C and E, where low clay content variability was observed, the correlation with ECa was not significant (r = 0.08 and -0.12, respectively). Excepted for OM content at field E, OM and CEC correlated positively with ECa for all fields and years assessed, where the highest correlation of these attributes was for field D (r = 0.70 in 2017 and r = 0.59 in 2016, respectively, for OM and CEC).

Table 3. Pearson's correlation coefficient between ECa and soil attributes assessed.

Field	Year	Clay	OM	CEC
A	2011	0.48*	0.16*	0.06
	2012		0.12	0.15*
	2013		0.25*	0.04
	2014		0.09	0.07
B	2014	0.71*	0.30*	0.37*
C	2014	0.08	0.13	0.14
D	2016	0.81*	0.62*	0.59*
	2017		0.70*	0.56*
E	2017	-0.12	-0.28*	0.07
F	2017	0.78*	0.59*	0.28*

*Significant at 5%.

Quantil classification method showed the best division of clay content for ECa classes (Figure 7). All iterations produced, for NB and GI methods, overlap of classes 3 and 4. Thus, we assumed that the Q method was the most suitable for separation and classification of ECa data into classes, adopted in subsequent analyzes.

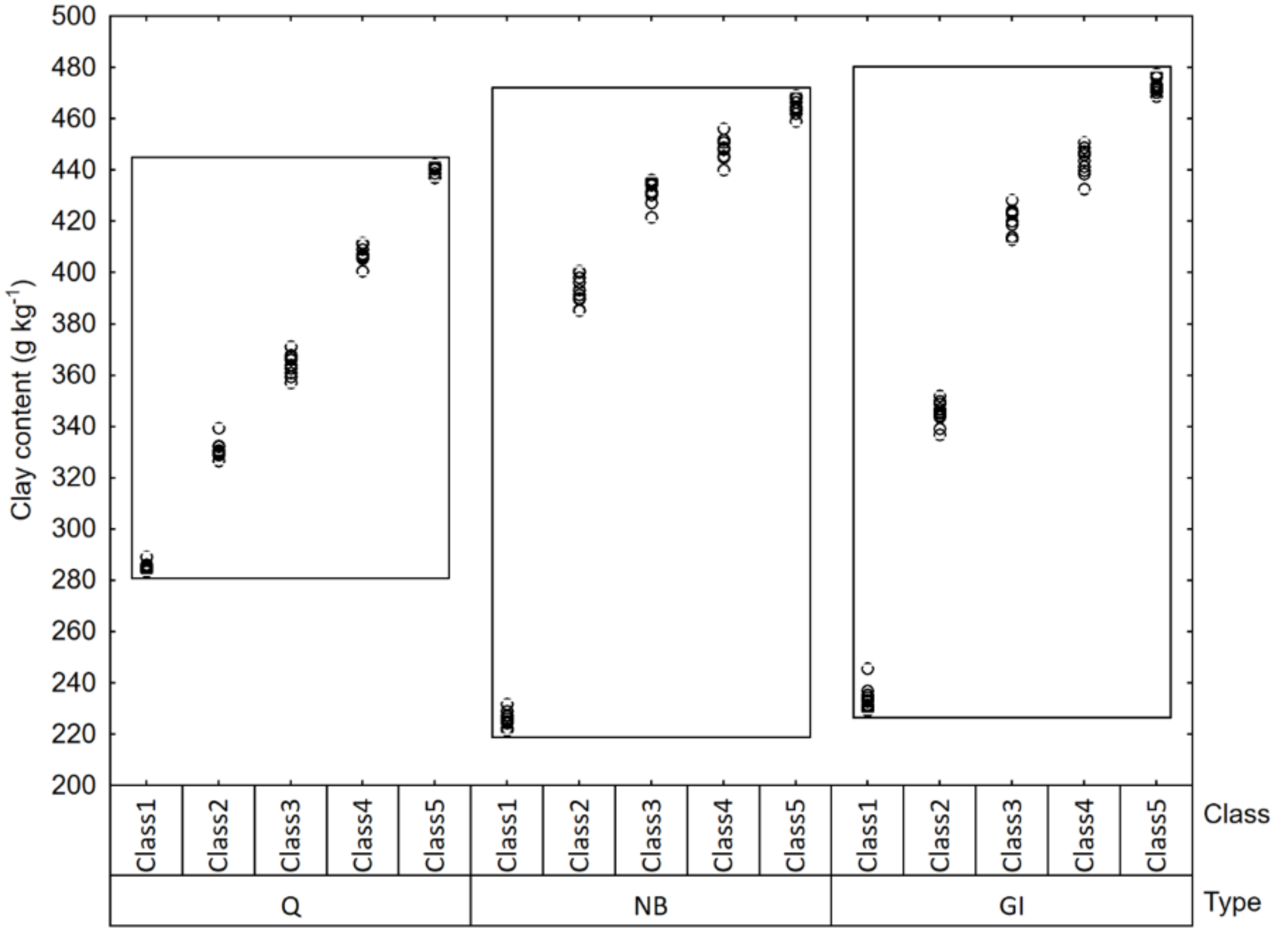

Figure 7. Clay content variability (g kg^{-1}) by five classes defined according quantil (Q), natural breaks (NB) and geometrical intervals (GI) classification methods.

How class 1 has the lowest and class 5 the highest values of ECa, clay content (Figure 8 - a), OM (Figure 8 - b) and CEC (Figure 8 - c) showed a clear trend of growth from class 1 to 5 according to box-plot performed by random sampling assessment. In this way, as expected, the classes with low ECa evidenced sandy areas with lower contents of OM and CEC. The CV from 10 iterations performed, showed that the less conductive classes also present greater variability in the contents, with a decrease trend from class 1 to 5. Clay content and CEC showed a significant decreasement starting from class 3, while OM (Figure 8 – b) showed a linear decrease.

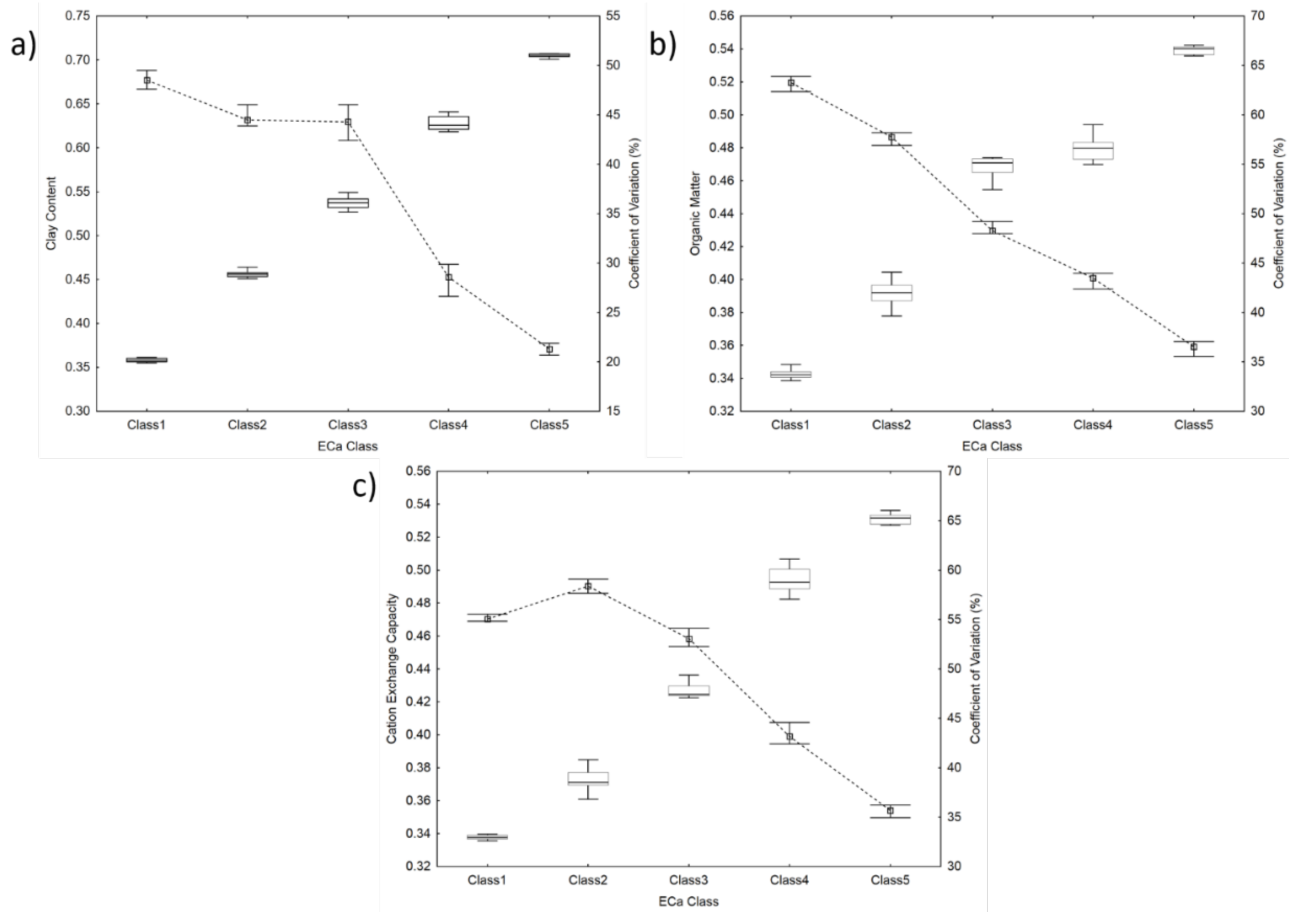

Figure 8. Standard content (y-axis left) and coefficient of variation (y-axis right – dashed line) of the iterations, per ECa class, of clay content (a), organic matter (b) and cation exchange capacity (c).

By linearly adjust of ECa measurement range with clay content, OM and CEC of all the experimental fields assessed, it is possible to visualize that, excluding field B, a variation of 1.0 mS m^{-1} meant a variation of 1.5 g kg^{-1}, 0.11 g dm^{-3} and 0.24 $mmol_c$ dm^{-3} in clay content, OM and CEC, respectively (Figure 9 – a, b and c, respectively). The results showed that ECa, measured by an EMI sensor, shows a high correlation with soil texture variability of fields assessed (R^2 = 0.97), showing great correlations with OM (R^2 = 0.65) and CEC (R^2 = 0.76).

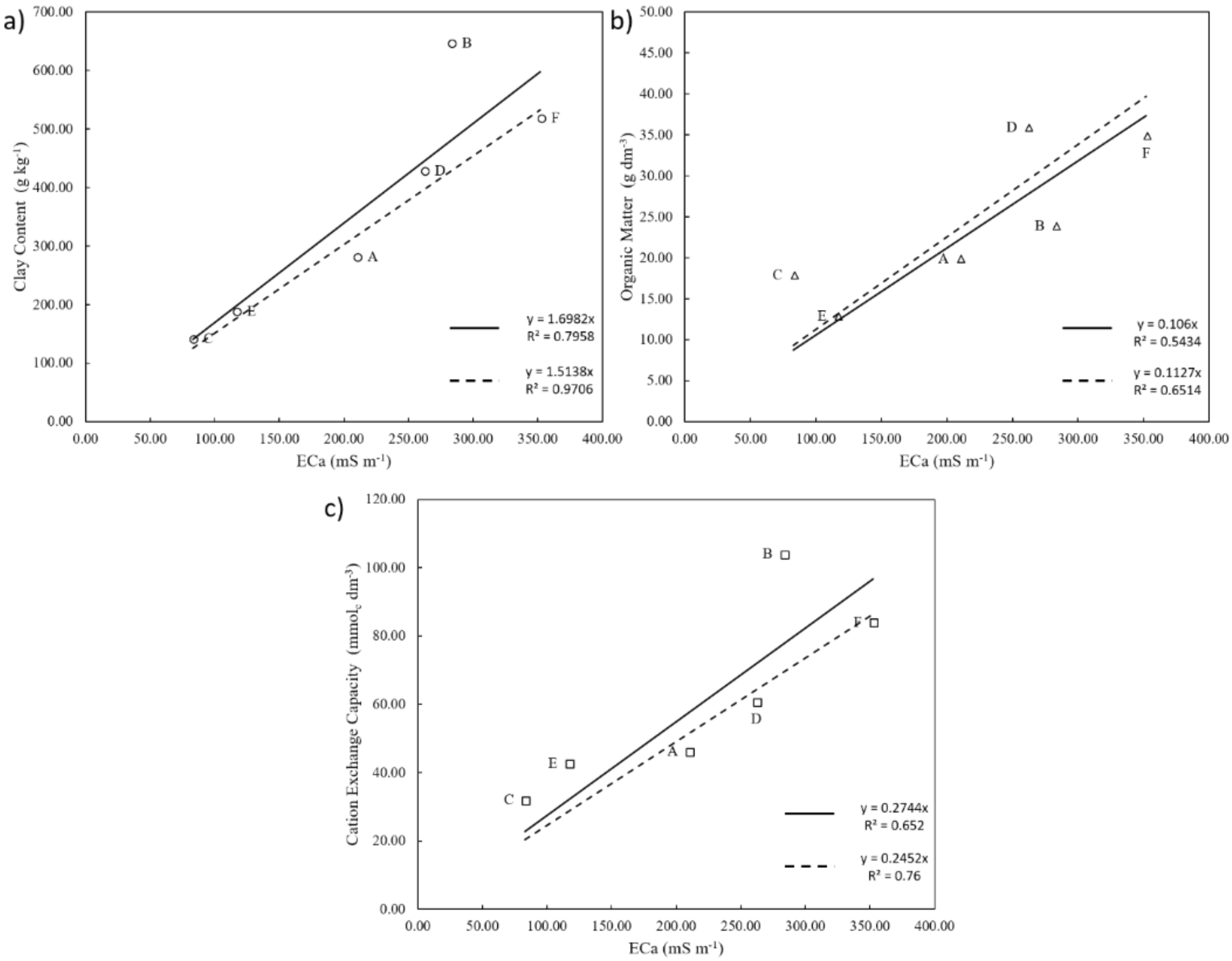

Figure 9. Linear adjustment of clay content (a), organic matter (b) and cation exchange capacity (c) with apparent electrical conductivity (ECa) variability of experimental fields assessed. Adjustment including (solid line) and excluding (dashed line) the field B.

At time level, OM and CEC showed the same growth trend from class 1 to 5, as previously observed (Figure 8), for the first two year of assessment for field A (Figure 10) and field D (Figure 11). The trend is clear evidenced in field D for both soil attributes assessed, while in field A this trend is not as clear in 2013 and 2014. In field A, from 2011 to 2013, the average level of OM showed a declining trend, as can also be clearly seen from 2016 to 2017 in field D (Figure 11 - a). Excepted in 2013 for field A, the variability of OM and CEC is lower for class 5 compared to class 1, evidencing the higher CV found in the lower ECa classes, as showed previously (Figure 8). For field D, classes 4 and 5 always showed greater contents than classes, 1, 2 and 3 for both OM and CEC. In general, the patterns founded at spatial variability level, were temporarily remained, where class 1 showed smaller average contents than class 5.

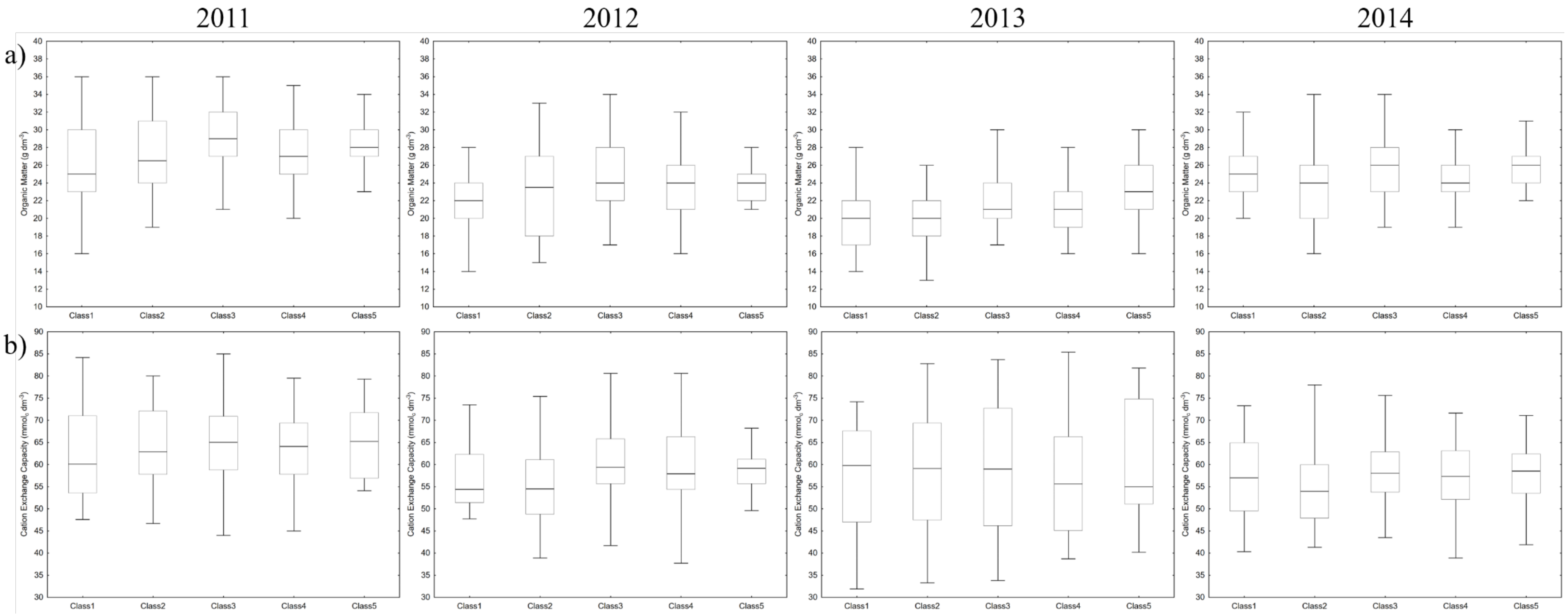

Figure 10. Organic matter (a) and cation exchange capacity (b) variability by ECa classes for the evaluated years in experimental field A.

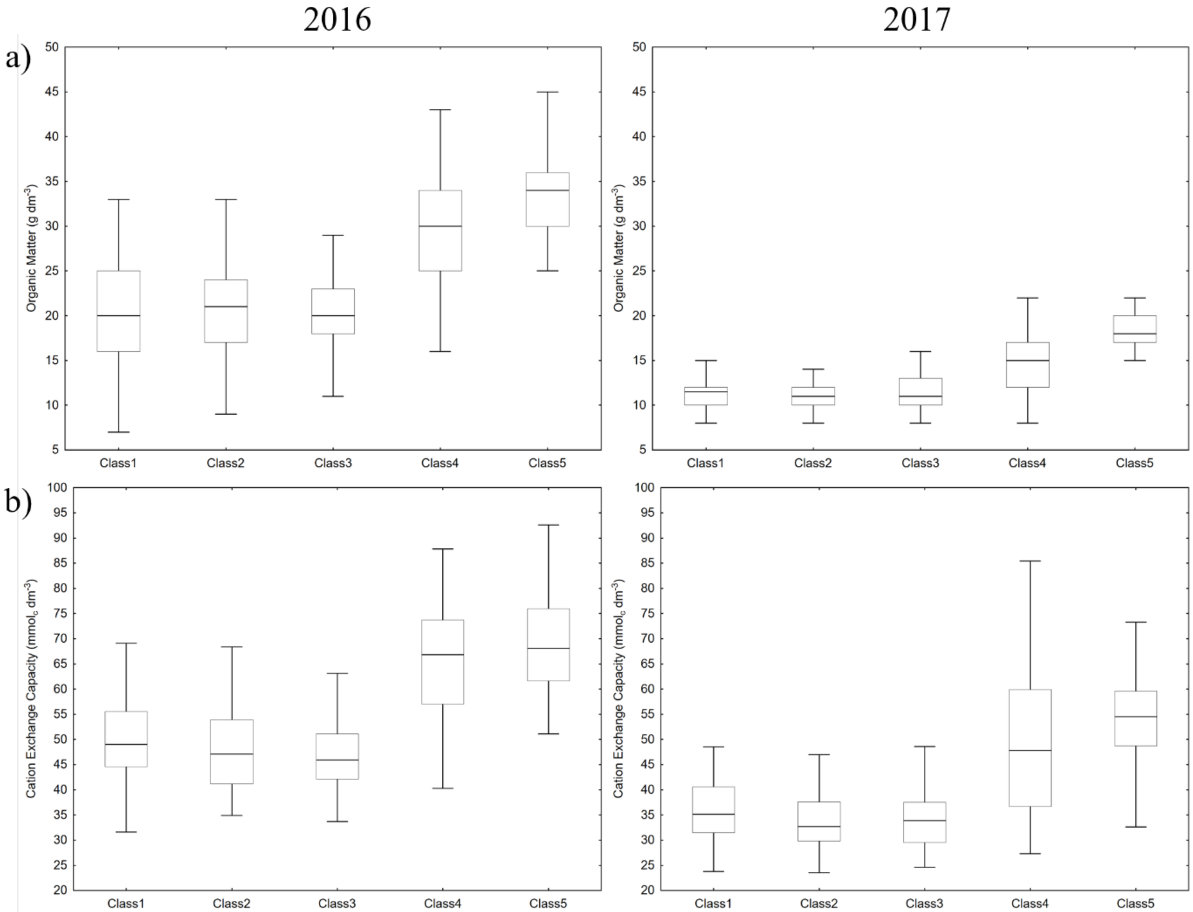

Figure 11. Organic matter (a) and cation exchange capacity (b) variability by ECa classes for the evaluated years in experimental field D.

Discussion

By clay content observed in the experimental fields, the present study covered different soil types and slope classes. Even more, different soil fertility classes were included, since soil textural class is directly related to the availability of water and nutrients (Raij, 2001), addressing the wide-range assessment proposed in sugarcane fields. Soil ECa, measured by IEM sensors, proved to be a high-quality information from fields to map the soil fertility in sugarcane fields, showing high potential to map yield potential zones. The ECa division into classes, by quantil method, showed be the most suitable to distinguish the differences between soil texture zones, where areas with high ECa showed higher clay content and, thus, higher OM and CEC, soil attributes that driven sugarcane yield (Nogueirol et al., 2014).

Related to soil spatial variability mapping, an issue that still arouses interest of the scientific community is related to an efficient (economically and physically feasible) soil spatial characterization of its variability, as reported by Peets et al. (2012). The results founded in the present study can addressed this bottleneck, as evidenced by the ECa division into classes by quantil method. The CV can be an excellent indicative to assist the sampling and soil mapping process. While ECa lower classes must be sampled more rigorously, that is, with a higher sample density, the more conductive classes can be sampled with fewer samples for an adequate soil characterization. Among the different types of sensing technologies for soil nutrient mapping, as addressed in Adamchuk et al. (2004), ECa sensors are an excellent and complementary alternative to map the spatial variability of soil fertility of fields. Furthermore, ECa can also aid the interpolation methods as an auxiliary variable to map the soil spatial variability (Sanches et al., 2018). Moreover, conductive classes can receive smaller amounts of fertilizers in comparison to the lower conductivity classes, helping to a sustainable site-specific management of sugarcane fields.

Clay content and CEC are important soil attributes which are related to both nutrient supply and water availability, with several studies indicating their prediction with EMI (De Benedetto et al., 2012; Mahmood et al., 2012; Piikki et al., 2013; Huang et al., 2014). The present study showed that, despite the low correlation between ECa and soil attributes (Table 3), the measurement range of these attributes were highly adjusted (R^2 = 0.97, 0.65 and 0.76 for clay content, OM and CEC, respectively). The extreme behavior of field B, treated as an outlier, may be related to the soil fertility of the field. One of the hypotheses is that the field, located near to the mill production unit, received fertilization through vinasse application (residue generated in the manufacture of sugar and ethanol and rich in potassium). Vinasse application can lead to soil acidification and groundwater contamination, thus influencing ECa and justifying the behavior founded.

Temporally stable (Serrano et al., 2017), ECa can be extremely valuable information for a site-specific management of sugarcane fields. Fields A and D, assessed, respectively, for 4 and 2 successive years (Table 1), showed that the ECa classes are good indicative to differentiate sites with higher and lower OM and CEC contents (Figures 10 and 11). This fact is clearly observed for the first year of evaluation for both fields, exactly when the crop was planted. In another years of cultivation, the trend does not seem to be so clear. A possible explanation can be the management used in the fields, justifying the results founded. The management of the sugarcane in Brazil, characterized by the low adoption of precision agriculture technologies (Silva et al., 2011) and high mechanization of agricultural operations (Franco et al., 2018), has been causing serious problems on fertility and, consequently, on crop yield. This fact can be observed by OM decreasement content in the fields, especially in field D, where we can see a significant decrease from 2016 to 2017. As one of the most important soil attributes to define sugarcane yield and the availability of nutrients such as phosphorus and nitrogen in the soil (Nogueirol et al., 2004), this decreasing trend in soil OM is common in Brazilian sugarcane fields, especially if soil tillage operations are used. In this way, especially in field A, the sugarcane management can be promoted a disturbance in soil fertility and quality conditions, where the ECa higher classes not showed the expected higher soil OM and CEC contents than ECa lower classes. Despite the disturbance observed, in general, patterns at spatial variability level were temporarily remained, where class 1 always showed smaller average contents than class 5. As reported by Carvalho et al. (2016), soil conservation management can help to maintain adequate soil OM levels over time and, consequently, maintain the adequate soil quality and fertility conditions. Even more, the low adoption of PA and the inadequate management of sugarcane fields justify the crop yield stagnation in the last decade, not exceeding the average yield of 80 Mg ha^{-1} (CONAB, 2017).

Finally, the ECa mapping of sugarcane fields can be an excellent alternative for a site-specific management as showed here. Despite the low Pearson's correlation founded between ECa and soil attributes, the ECa quantil classes are a good option for farmers establish zones in their fields to manage the soil fertility, allow the establishment of precision production environments (Sanches et al., 2017) and the yield potential zones.

Conclusion

The ECa classes, defined by quantil method, showed that the low electrical conductivity sites present lower OM and CEC contents. The higher ECa classes showed smaller CV for all soil attributes assessed, i.e., sites that can be characterized with smaller amounts of samples to an adequate soil mapping than lower ECa classes. The clay content variability was directly proportional to the ECa variability (R^2 = 0.97), where 1.0 mS m^{-1} of ECa corresponded to 1.5 g kg^{-1} of clay. OM (R^2 = 0.65) and CEC (R^2 = 0.76) showed great correlation with ECa variability too. The EMI sensor is an excellent tool for defining the spatial variability of soil fertility and can be used for site-specific management of sugarcane fields.

Acknowledgments

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