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Apparent Electrical Conductivity Sensors and their Relationship with Soil Properties in Sugarcane Fields

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Abstract. One important tool within the technological precision agriculture (PA) package are the apparent electrical conductivity (ECa) sensors. This kind of sensor shows the ability in mapping soil physicochemical variability quickly, with high resolution and at low cost. However, the adoption of this technology in Brazil is not usual, particularly on sugarcane fields. A major issue for farmers is the applicability of ECa, how to convert ECa data in knowledge that may assist the producer in decision-making for crop management. The objective of this study was to map the ECa by three different sensors, commercially available, to assess their relations with soil properties in order to help farmers in selecting the proper device for soil characterization. Soil ECa data was collected in a sugarcane field (100 ha) with three sensors, two based on resistivity principle (ARP® and Veris 3100®) and other based in electromagnetic induction (EM38-MK2®). Thirty-four soil samples were collected (≈1 sample each 3.0 ha) at two depths. This approach sough to determine the correlation between sensors and soil properties in strategic places of the field, aiming to determine which sensor brings more reliable information about soil fertility. Results show the ECa present significant correlations with many soil properties, where the electromagnetic induction (EMI) sensor presented the highest correlation with

clay content (r = 0.83), Organic Matter (r = 0.73), Cu (r = 0.87) and Mn (r = 0.77). The variables that represent main soil properties by principal component analysis (PCA) showed that the EMI sensor showed the greatest potential for physicochemical characterization of soil spatial variability. One reason for the difference between correlations can be explained by the sensors sensibility depth, but further investigations should be carry on seeking to explain with more details the difference among the information provided by the sensors. Through ECa using of commercial available sensors, it is possible to assess soil spatial variability, making it a powerful tool for farmers in a decision-making.

Keywords. *ECa sensors; soil fertility, reliable fertilizer maps, principal component analysis*

Introduction

Brazil is the largest sugarcane producer, harvesting 9 million hectares and milling 658.7 million tons in 2015. However, the country yield needs to improve (≈73 Mg ha^{-1} - Conab, 2015) to achieve the yield average obtained in the best production units (≈ 107 Mg ha^{-1} without irrigation). The biggest limitations of sugarcane yield in Brazil are related to water deficit, to inadequate crop management and the availability of nutrients for plants. One approach that may assist to achieve high crop yield ensuring better sustainability in the production process is the technology package of Precision Agriculture (PA). Within this context, reliable soil properties maps continue to be a goal for allow adequate and accurate soil fertility management (Peets et al., 2012). This management must be done by a precise characterization of the soil spatial variability to allow proper variable-rate fertilizers application, which is crucial for high yields and hence a more profitable and sustainable production. Within the historical context of affordable technologies to acquire quality information to manage crop spatial variability, the apparent electrical conductivity (ECa) of soil 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). Intrinsically related to moisture content, many researches shows that ECa is able to detect soil properties changes, such as salinity, clay content, cation exchange capacity, size and distribution of pores, organic matter and temperature (Kaffka et al., 2005; Kitchen et al., 2003; Corwin and Lesch, 2005). It is evident that the ECa is an effective information that is able to show physicochemical soil matrix, often neglected by the lack of applicability of this information. One of the first decisions which growers have to make is which is the most appropriate tool. The objective of this study was to assess three ECa sensors, commercially available, and evaluate their relationship with physicochemical soil properties, identifying the potential of them to map soil fertility spatial variability.

Material and Methods

The study was performed in a commercial sugarcane field (100 hectares) located at Santa Fe Mill (Nova Europa, São Paulo, Brazil – 21°38'16.06''S, 48°39'00.87''W). Apparent electrical conductivity (ECa) was measured by three commercially sensors (Figure 1). Two sensors work with resistivity principle, ARP® (Geocarta, France, Paris) and Veris 3100® (Veris technologies, Kansas, United States); the other works with electromagnetic induction principle, EM38-MK2® (Geonics, Toronto, Canada). The sensors are configured (default setting) for different depths of measurement. The ARP® was configured to measure at the depths 0.00 to 0.50 m, 0.00 to 1.00 m and 0.00 to 1.50 m; Veris 3100® at 0.00 to 0.30 m and 0.00 to 0.90 m and EM38-MK2® was configured to measure at 0.00 to 0.38 m and 0.00 to 0.75 m. For this study, we used only the first depth readings because the soil sampling was done within these depths. Measurements with sensors were made in parallel passes spaced by 10 m. All data were analyzed statistically with central tendency and dispersion, and a box-plot was constructed for outlier's identification. The Moran Index (MI) was calculated to assess the spatial autocorrelation in order to know the spatial structure of ECa readings. The limiting case, MI ≈ 1, shows a perfect spatial structure, while MI ≈ 0 shows a random spatial distribution. The sampling points were chosen based on the spatial distribution of ECa (Figure 2), taken at strategic places of the field, where the ECa presents differences within the mapped field and between the sensors used. In total 34 points were selected, corresponding, approximately, to 1 sample for 3 hectares (sample density usually adopted by the Mill). All soil samples were submitted to laboratory analysis to characterize the macro and micronutrients availability, pH, organic matter and clay content. The field elevation was also determined by a L1-band GNSS receiver (Figure 2 – detail). Soil ECa data were interpolated by ordinary kriging (Figure 2). ECa data were reduced to the sample point through the median of a 25 m radius buffer. The correlation between soil attributes *and* ECa was evaluated by Pearson's correlation at 5% of significance. The correlation between sensors was assessed comparing with 424 points distributed in the field in a regular grid (50 x 50 meters), that where measured at the beginning of the study, where the value at each point was obtained by a buffer of points inside the 50m. Finally, the principal component analysis (PCA) was used to evaluate the correlation of the main components of soil attributes with ECa sensors. This analysis, by dimensionality problem reduction, allows interpreting the correlation of soil attributes with ECa in a simpler and effective way, resulting in a robust application to identify the potential of the sensors evaluated.

Results

Except for the clay content and aluminum in the top soil layer, the other soil properties decreased its concentration while depth grow, and the phosphorus content reduced by half (10 to 5 mg dm^{-3}) (Table 1). The clay content of the area ranged from 212 to 494 g kg^{-1} in the surface layer and 261 to 513 g kg^{-1} in the subsurface layer. In general, the area is classified as a medium texture (≈ 321 g kg^{-1}). The soil shows highly acidic conditions (<5.0 $CaCl_2$), lying regions with very high acidity (<4.3 $CaCl_2$). Phosphorus and copper showed higher coefficients of variation in the surface layer, ranging from low values (4 and 0.3 mg dm^{-3} to P and Cu, respectively) to high (52 and 5.5 mg dm^{-3} to P and Cu, respectively). In the subsurface layer Al and Cu showed the highest coefficients of variation. The potassium content, in both layers, are laying at low levels (<1.5 $mmol_c$ dm^{-3}). The ARP® sensor showed that the most density measurements (≈ 2896 readings ha^{-1}), corresponding approximately to one measurement every 0.30 m (Table 2). Veris 3100® and EM38-MK2® showed a measurement density of approximately 401 and 721 points ha^{-1}, respectively. With the exception of electromagnetic induction sensor, resistivity sensors showed only positive measurements, with an average of 4.676 and 3.157 mS m^{-1} for the ARP® and Veris 3100®. The EM38-MK2® sensor ranged from -71.280 to 75.200 mS m^{-1}, presenting a coefficient of variation of -39.52%. The higher coefficient of variation was found in Veris 3100® sensor (60%) and the highest skewness and kurtosis for the ARP® sensor. The spatial correlation Moran Index was higher for the EM38-MK2® sensor (MI = 0.94), while for Veris 3100® sensor was equal to 0.33. The ARP® sensor showed an index equal to 0.68. Direct contact sensors showed a direct correlation (r = 0.45), while the EM38-MK2® and Veris 3100® sensors showed inverse correlation (r = -0.52), both significant at 5%. The EM38-MK2® and ARP® sensors were not statistically correlated (Table 3). The sensor for electromagnetic induction (EM38-MK2®) showed a strong direct correlation with the soil clay content (r = 0.83 for both layers), followed by direct contact sensor Veris 3100®, which showed moderate negative correlation (r = -0.48 and -0.51 for the surface and subsurface layers, respectively) (Table 4). Unlike other sensors did, ARP® sensor showed no significant correlation with clay content. The organic matter content also strongly correlated with the EM38-MK2® sensor (r = 0.73 and 0.77, respectively) and moderately with the Veris 3100® sensor (r = -0.50 and -0.53, respectively). The ARP® sensor showed evidence of correlation with the soil pH (r = 0.54 and 0.59) and the cations Ca^{2+} (r = 0.48 and 0.55) and Mg^{2+} (r = 0.42 and 0.40) in the surface and subsurface layers, respectively, and Boron in the surface layer (r = -0.56). The cation exchange capacity (CEC), copper and manganese contents were best reflected by electromagnetic induction sensor for the two layers of investigation. Through the application of principal component analysis (PCA) we found that the first two components explain for more than 60% of the total variability of the evaluated soil attribute data (65.35% and 63.52% for layers 0.00 to 0.25 and 0.25 to 0.50 m, respectively) (Figure 3). For both layers, the first principal component (PC 1), which explains the greater variability of data, is best represented by the clay, OM, Mn, Cu and CEC, and the correlation of these attributes with the PC1 is negative and positive for the surface and subsurface layers, respectively. The second main component (PC 2) best represents the attributes phosphorus and boron (positive correlation) to the first layer and the attributes phosphorus and Fe (negative correlation) to the second layer. The correlation of the first two principal components with ECa data of the three evaluated sensors (Table 5) show that the EM38-MK2® sensor correlated better with these components compared to other sensors, in the surface layer (r = -0.47 and 0.69 to PC1 and PC2, respectively) and subsurface layer (r = 0.60 and 0.52 for PC1 and PC2, respectively), both significant at 5%. The ARP® sensor correlated better with PC2, negatively in the surface layer (r = -0.44) and positively in the subsurface layer (r = 0.44). Veris 3100® sensor correlated better in the surface layer with PC2 (r = -0.49) and in the subsurface layer with the PC1 (r = -0.55).

Discussion

Intrinsically related to the clay content in the soil, organic matter content did not follow the same trends of this property and decreased in depth. The OM of an arable land tends to decrease in depth in soils cultivated with sugarcane, where in the first 0.40 m soil depth contain about 80% of crop roots (Otto et al., 2008ab), which contribute with organic matter soil reservoir. The OM content is within of the range for medium texture soils, ranging from 10 to 25 g dm^{-3} in the surface layer (Raij et al., 1997). The electromagnetic induction sensor showed this trend correlation between the properties of clay and OM, and the sensor that showed the best correlation with these properties. In fact, in tropical environments there is a direct correlation between the clay content and the OM (Raij et al., 1991), because the places with higher clay content its ability to save OM (protection of organic compounds soil between clay aggregates, reducing its consumption by microorganisms). The EM38-MK2® sensor also evidenced the availability of micronutrients such as Cu and Mn, also correlated with the organic matter content of the soil. The high capacity of the electromagnetic induction sensor to capture the variability in soil texture (r = 0.83) could reflect indirectly the soil properties related to the clay content. The case of OM and micronutrients Cu and Mn. Direct contact sensors reflected better elements such as pH, Ca and Mg, where the soil has, on average, high acidity (pH <5.0) and high concentrations of Ca (both layers) and Mg (the surface layer). These facts raise the hypothesis that the direct contact of the sensor with the soil (resistivity sensors) better reflects the places where the concentration of the latter elements in the soil is higher. Since the EMI based sensor to be highly influenced by the variability of texture (Castrignàno et al., 2012), the elements related to the concentration of salts in the soil, such as Ca, Mg and K, influenced least the sign of electromagnetic current induced by this sensor. A not expected result in this study was the differences between the ECa maps measured by the resistivity and electromagnetic induction principles. Although some areas of the field present similarities (plot located to the east of the field), the region located at north, place of lower altitude, showed completely different behavior, where the EM38-MK2® sensor showed higher ECa and the other two sensors showed lower ECa. Directly correlated to the clay content of the soil, the ECa presents greater in areas where the clay content is higher (Corwin and Lesch, 2005) as evidenced by the EM38-MK2® induction sensor. However, the direct contact sensors reflected an inverse behavior in the north region of the field, where may be assigned for other soil properties that directly affect the readings, such as soil compaction, soil type and/or soil porosity (Corwin and Lesch 2005; Kitchen et al., 1999; McBratney et al., 2005; Sudduth et al, 2001). The different depths of ECa measurements can be another factor that accounts for the difference found in the data. However, a more detailed research in the field scale is required to explain the causes of variability among ECa sensors evaluated. On the other hand, it is possible to observe a larger amount of noise present in the ECa data of direct contact sensors compared to the electromagnetic induction sensor. Moran's index highlights this fact, where the EM38-MK2® sensor (MI = 0.94) showed a high spatial structure highlighting an interesting attribute of management from the point of view of the precision agriculture. Soil properties, which present a low Moran index (MI ≈ 0), show a random distribution, indicating great difficulty managing located by AP techniques. The Veris 3100® sensor presented the lowest Moran index (MI = 0.33), suggesting that proper treatment of data must be applied for withdrawal of the noise (not performed in this study). The reduction of 14 soil attributes evaluated, by the principal component analysis, could explain approximately 60% of the variability of the data for both layers of soil, through the first two principal components. The first main component (PC1) is characterized mainly by the composition of clay, organic matter and CEC attributes to the two layers of soil evaluated, where these attributes are extremely important for the sugarcane crop management. The EMI sensor was that showed the best correlation with this component (PC1). The high spatial structure, and consequently a smaller amount of noise in the data, shows that ECa sensor based on EMI was able to detect, with greater accuracy, the spatial variability of soil properties, as evidenced by the correlation with the first principal component.

Conclusion

The apparent electrical conductivity sensors are sensible to different sources of variation, requiring further field investigation of the causes of this differences. Resistivity sensors are forced to deal with to a greater amount of noise. The electromagnetic induction sensor was able to better detect the spatial variability of soil fertility, with better correlations with clay and OM content in the field. By using commercially available ECa sensors, it is possible to quickly and efficiently, assess the spatial variability of the soil, supporting producers to have a powerful tool for local crop management.

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Table 1. Basic statistics of soil attributes at 0.00 to 0.25 m and 0.25 to 0.50m.

	N	Mean	Median	Min.	Max.	Var.	SD	CV	Skew.	Kurt.
					0.00 to 0.25 m					
Clay	34	321.71	274.00	212.00	494.00	8852.15	94.09	29.25	0.78	-1.04
OM	34	16.71	16.00	10.00	25.00	23.85	4.88	29.23	0.49	-1.08
pH	34	5.02	5.00	4.30	6.00	0.23	0.48	9.57	0.10	-1.14
P	34	10.00	6.00	4.00	52.00	107.64	10.37	103.75	2.82	8.58
K	34	1.10	1.09	0.26	2.33	0.21	0.46	41.48	0.38	0.21
Ca	34	13.84	11.83	4.62	32.45	52.35	7.24	52.26	0.84	-0.13
Mg	34	7.01	6.39	3.36	13.32	8.29	2.88	41.05	0.60	-0.69
Al	34	0.94	0.58	0.27	3.55	0.68	0.83	87.71	1.88	2.92
CEC	34	45.02	41.92	32.59	68.47	96.25	9.81	21.79	0.90	-0.16
BS	34	47.62	46.71	22.60	69.33	212.16	14.57	30.59	-0.12	-1.26
B	34	0.17	0.17	0.10	0.26	0.00	0.04	23.58	0.40	-0.51
Cu	34	1.71	0.70	0.30	5.50	2.74	1.66	97.10	1.04	-0.27
Mn	34	4.87	4.35	1.10	15.10	10.47	3.24	66.42	1.38	2.14
Fe	34	11.24	10.00	4.00	26.00	26.31	5.13	45.65	0.90	0.51
					0.25 to 0.50 m					
Clay	34	362.21	322.50	261.00	513.00	7307.08	85.48	23.60	0.69	-1.15
OM	34	12.29	11.50	8.00	18.00	10.46	3.23	26.30	0.45	-1.08
pH	34	4.68	4.60	4.20	5.90	0.21	0.45	9.69	1.10	0.77
P	34	5.00	4.00	3.00	15.00	4.00	2.00	40.00	3.98	19.55
K	34	0.63	0.63	0.20	1.51	0.07	0.27	42.72	1.36	3.04
Ca	34	6.52	5.60	2.27	15.35	10.53	3.25	49.76	1.22	1.23
Mg	34	4.97	4.74	1.88	10.40	5.42	2.33	46.82	0.79	-0.11
Al	34	1.59	0.96	0.26	4.89	1.78	1.33	83.72	1.10	0.03
CEC	34	37.22	36.53	28.37	49.06	26.52	5.15	13.84	0.36	-0.52
BS	34	32.93	33.00	12.54	59.93	173.88	13.19	40.05	0.21	-1.02
B	34	0.16	0.15	0.10	0.26	0.00	0.03	22.38	1.03	1.35
Cu	34	1.19	0.70	0.30	3.50	1.02	1.01	85.04	0.96	-0.47
Mn	34	3.40	2.30	0.70	10.30	7.15	2.67	78.67	1.22	0.48
Fe	34	5.74	5.00	2.00	11.00	3.47	1.86	32.49	1.19	1.87

Min. – Minimum Value; Max. – Maximum Value; Var. – Variance; SD – Standard Deviation; CV – Coefficient of Variation; Skew. – Skewness; Kurt. – Kurtosis.

Table 2. Basic statistics of Electrical Conductivity sensors.

	N	Mean	Median	Min.	Max.	Var.	SD	CV	Skew.	Kurt.	Moran's I
						ECa [mS m^{-1}]					
ARP®	289621	4.676	4.297	1.940	24.800	3.345	1.829	39.114	2.146	10.616	0.68
Veris 3100®	40114	3.157	2.900	0.225	7.670	3.616	1.901	60.231	0.538	-0.307	0.33
EM38-MK2®	72088	-59.963	-71.249	-71.280	75.200	561.737	23.701	-39.526	1.735	1.631	0.94

Min. – Minimum Value; Max. – Maximum Value; Var. – Variance; SD – Standard Deviation; CV – Coefficient of Variation; Skew. – Skewness; Kurt. – Kurtosis.

Table 3. Pearson's correlation matrix between ECa sensors.

	ARP®	Veris®	EM38-MK2®
ARP®	1.00		
Veris®	0.45*	1.00	
EM38-MK2®	-0.09	-0.52*	1.00

* Significant at 5%.

Table 4. Pearson's correlation matrix between ECa sensors and soil attributes at 0.00 to 0.25 m and 0.25 m to 0.50 m.

	Clay	OM	pH	P	K	Ca	Mg	Al	CEC	BS	B	Cu	Mn	Fe
							0.00 to 0.25m							
ARP®	0.07	-0.01	0.54*	0.16	-0.24	0.48*	0.42*	-0.27	0.19	0.55*	-0.56*	0.05	-0.06	-0.06
Veris®	-0.48*	-0.50*	0.32	0.15	-0.38*	0.13	0.02	0.02	-0.26	0.30	-0.29	-0.49*	-0.34*	0.12
EM38-MK2®	0.83*	0.73*	-0.26	0.21	0.29	-0.07	0.02	0.02	0.42*	-0.31	0.20	0.87*	0.77*	-0.31
							0.25 to 0.50m							
ARP®	0.07	0.03	0.59*	0.11	-0.38	0.55*	0.40*	-0.37	0.02	0.52*	-0.34*	-0.01	0.00	-0.36
Veris®	-0.51*	-0.53*	0.35	0.12	-0.37*	0.26	0.28	-0.12	-0.37	0.43	-0.01	-0.53*	-0.38*	-0.13
EM38-MK2®	0.83*	0.77*	-0.06	-0.09	0.20	-0.18	-0.32	-0.21	0.37*	-0.38	-0.08	0.83*	0.72*	-0.21

* Significant at 5%.

Table 5. Pearson's correlation matrix between ECa sensors and principal components PC1 and PC2 at 0.00 to 0.25 m and 0.50 m to 0.50 m.

	0.00 to 0.25 m		0.25 to 0.50m	
	PC 1	PC 2	PC 1	PC 2
ARP®	-0.33	-0.44*	-0.39*	0.44*
Veris®	0.22	-0.49*	-0.55*	-0.16
EM38-MK2®	-0.47*	0.69*	0.60*	0.52*

* Significant at 5%.

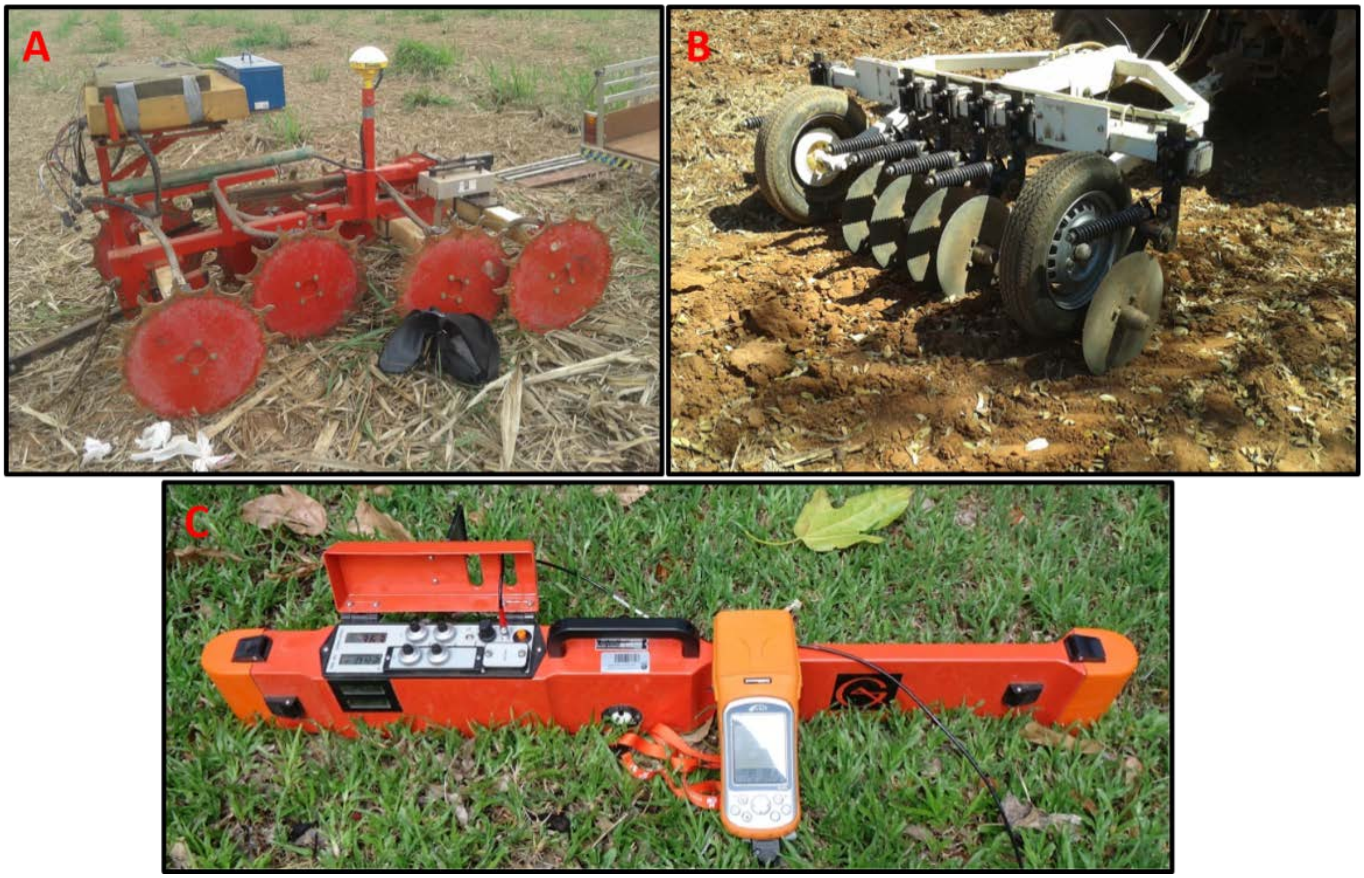

Fig 1. Electrical Conductivity sensors tested. (A) ARP® (Geocarta, France, Paris), (B) Veris 3100® (Veris technologies, Kansas, United States) and (C) EM38-MK2® (Geonics, Toronto, Canada).

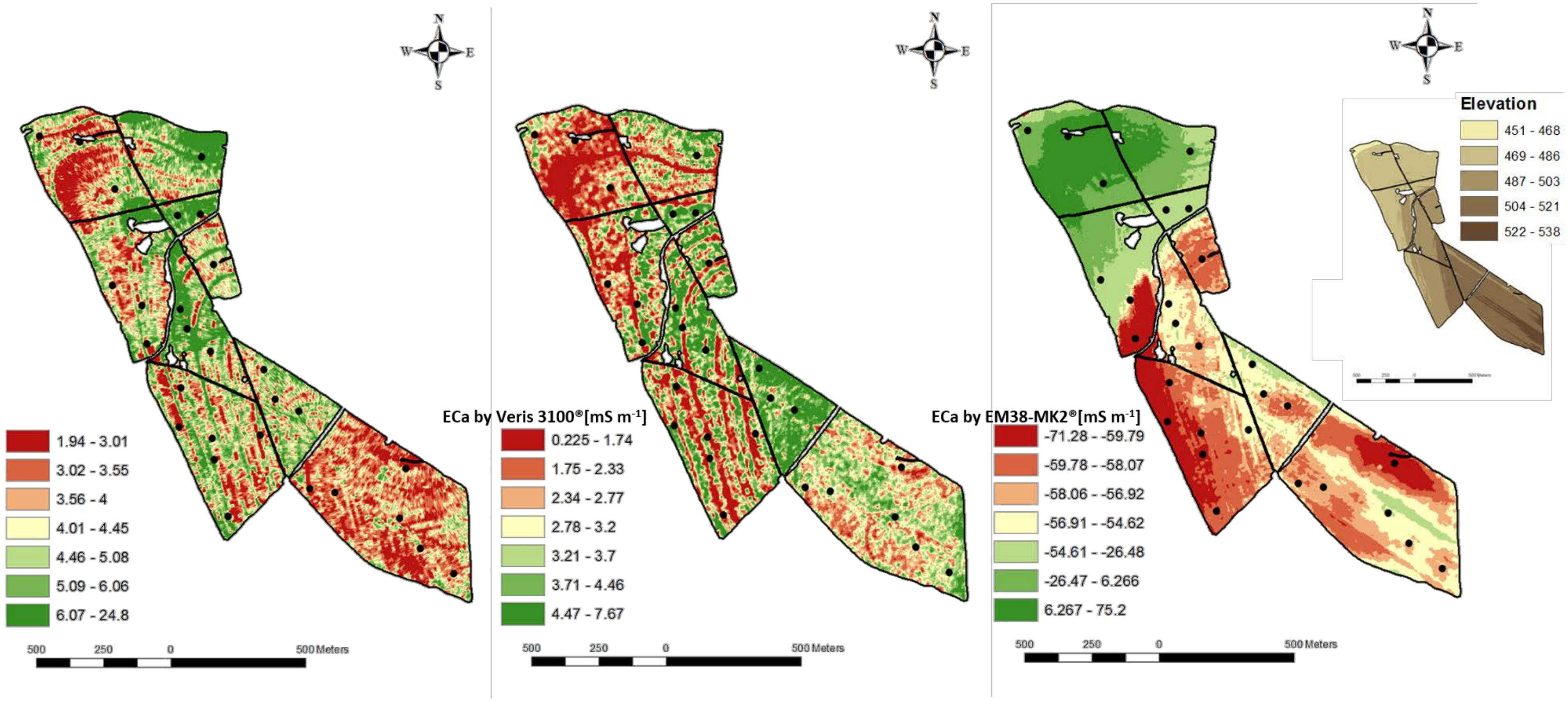

Fig 2. Electrical Conductivity [mS m^{-1}] maps by ARP® (left), Veris 3100® (middle) and EM38-MK2® (right) with soil samples (black dots) taken in strategic places of the field. Detail of the field elevation [m].

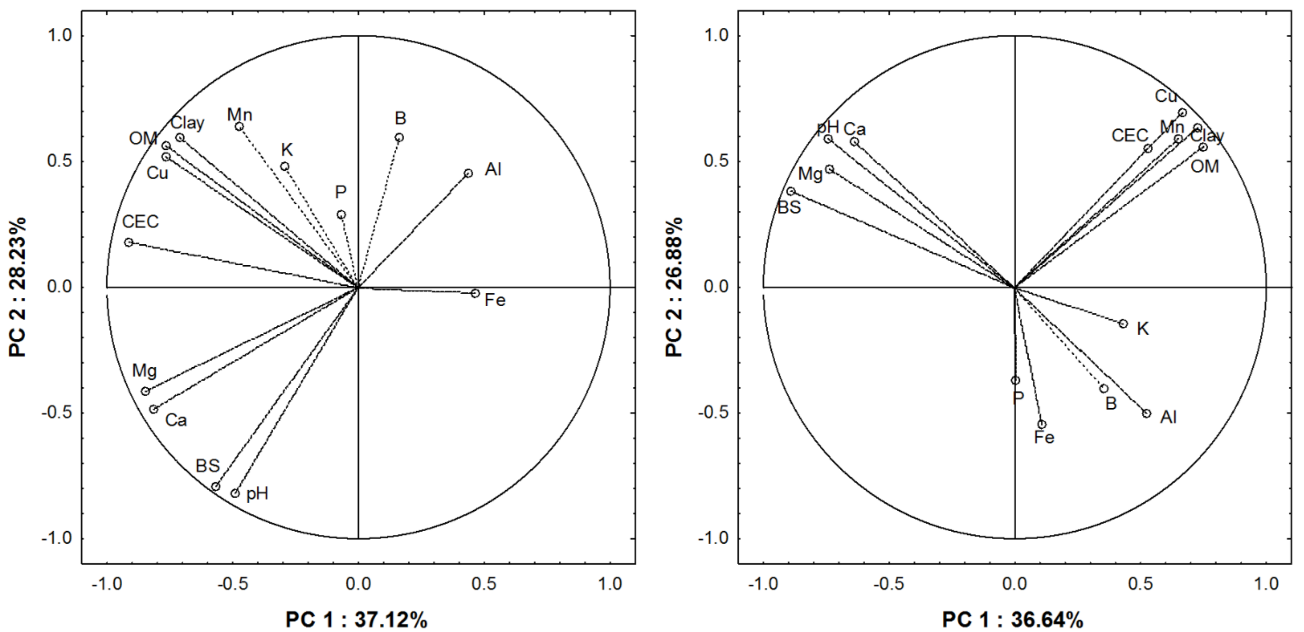

Fig 3. Projection of soil variables on the Component-Plane for PC1 and PC2 at 0.00 to 0.25 m (left) and 0.25 to 0.50 m (right).