Spatial distribution of soil apparent electrical conductivity measured by electromagnetic induction and sugarcane yield

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Abstract

The current agriculture requires the use of new technologies that allow the identification of soil and plant patterns, and the determination of their spatial variability. This work determined the spatial relationship between the sugar cane yield and soil apparent electrical conductivity (EC_a) measured by electromagnetic induction (EMI) and soil texture. The experimental area is located in Goiana (Pernambuco State, Brazil) (07°34'25"S, 34°55'39"W). The experimental area was 6.5 ha. Sugar cane yield and soil apparent electrical conductivity (EC_a) were measured at 90 sampling points randomly distributed in the study area. Maps of soil electrical conductivity (EC_a-V and EC_a-H) were similar to that of sugar cane yield. The linear correlation showed values of 0.74 (yield x EC_a-H) and 0.85 (yield x EC_a-V). The electrical conductivity measured by electromagnetic induction has been shown to be an important tool for predicting the yield of sugar cane. The textural properties (clay, silt and sand) showed high spatial variability.

Key words: geostatistics, precision agriculture, soil management zones.

1. INTRODUCTION

The agroindustrial complex of sugar cane, especially the alcohol production chain, places Brazil in the leading position in technological advance in the energy area from biofuel. In a global market with large and rapid flow of knowledge, maintaining competitiveness depends on an ongoing search for innovative technologies.

The National Supply Company (CONAB, 2012) provides for the 2012/2013 harvest an estimated planting area of 8,520.5 billion hectares, distributed in all producing states, representing an increase of 2.0% over the previous season. The average yield of the 2012/2013 harvest was 69.44 t ha^{-1} and a production of 595.13 million tons (CONAB, 2012). The Pernambuco State, according to CONAB (2012), has an area planted with sugar cane of 327.61 thousand hectares in the 2012/2013 season, with a yield of 45.5 t ha^{-1}, and a production 14,906.3 million tons.

The increased production of sugar cane creates the need to assess the economic, social and environmental impacts of this process, both for the country as a whole and for the producing regions. Thus, the current agriculture needs methodologies to promote changes in the technique for quantification of soil attributes in order to assist the characterization of the variability of these attributes rapidly and accurately (Siqueira et al., 2010). However, the costs involved, the high demand for time and labor and the need for human resources with high technical potential make unworkable the implementation of these detailed studies using numerical classification (Figueiredo et al., 2008).

Trying to solve this problem, researchers like Cunha et al. (2005), Campos et al. (2009) and Siqueira et al. (2010) used the numerical classification in cause and effect studies in soil science and associated these results to compartments identified based on concepts in geomorphology. These can be associated with agricultural suitability of different locations. Siqueira et al. (2010) designate these compartments

as site specific management zones. According to these authors, the identification of these specific management zones allows the application of technology to similar areas.

These compartments have been used for different purposes in soil science: sampling design (Montanari et al., 2005); dynamics of clay mineral formation (Camargo et al., 2008.); nutrient adsorption potential (Barbieri et al., 2008); soil loss (Campos et al., 2008); input application at varying rates (Barbieri et al., 2009); agricultural planning and implementation of sugar cane farming system (Campos et al., 2009), CO_2 emission (Brito et al., 2009), among others.

Among soil properties, the apparent electrical conductivity (EC_a) has been widely used due to its correlation with other soil properties and therefore with yield of crops (Lesch et al., 2005; Siqueira et al., 2009, 2013). According to McNeill (1980), Lesch et al. (2005), Sudduth et al. (2005), Kühn et al. (2009) and Siqueira et al. (2009), EC_a is related to the water content in the soil, texture, organic matter content, size and distribution of pores, salinity, cation exchange capacity and electrolyte concentration in the soil solution.

In this way, this study aimed to determine the spatial relationship between the sugar cane yield and the electrical conductivity of soil measured by electromagnetic induction and soil texture in a commercial production area under monoculture over 27 years, in Goiana, Pernambuco State, Brazil.

2. MATERIAL AND METHODS

The experimental area is located in the municipality of Goiana (Northern Zona da Mata, Pernambuco State, Brazil) at the coordinates 07°34'25"S latitude and 34°55'39"W longitude. The soils of the study region derive from the group Barreiras, consisting of sediments of continental origin of the late tertiary, texture sandy to clay, characterized by intense change (Brasil, 1969, 1972). Soil was classified as an OrthicPodzol (Soil Survey Staff, 2010), which is equivalent to an "Espodossolo Humilúvicoortico" following the Brazilian Soil Classification System (EMBRAPA, 2013), whose physical characterization is shown in table 1. Soil

texture (clay, silt and sand) was determined by the pipette method; bulk density and volumetric soil moisture were determined in the pedological profile using soil cores of 100 cm^3 as proposed by Camargo et al. (1986).

The climate, according to the Köppen Climate Classification, is humid tropical type As' or pseudo tropical, which is hot and humid, with rainfall in the fall and winter, with average annual temperatures around 24°C.

The study area is approximately 6.5 ha, at an average altitude of 8.5 m (Figure 1) and has been managed in the last 27 years with monoculture of sugarcane (*Saccharum officinarum* L.) with straw burning for harvesting. In the 2010/2011 growing season, the area was cleared, plowed, harrowed, and then grown again with sugar cane.

Sampling of sugar cane yield and the apparent soil electrical conductivity and texture was held on November 11st, 2011 at 90 sampling points in an uneven grid (Figure 2).

The study area is very important for the region, as the sugar cane is the main crop, located often in areas affected by salinity due to its proximity to the sea, especially in high tide periods, with more pronounced salinity in the lower sections. The area is located at about 10 km from the Atlantic Ocean on the east and 2.5 km to the northeast
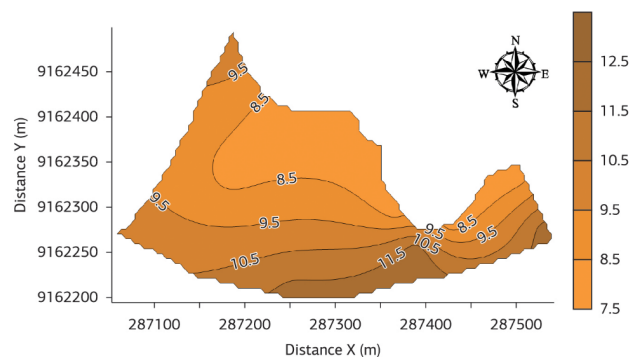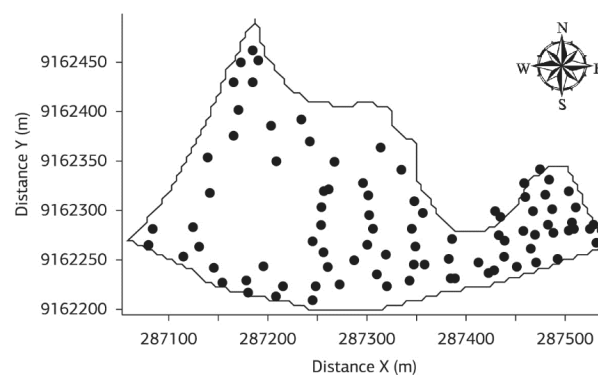

Figure 1. Topographic map of the study area.

Figure 2. Location of the sampling points in the study area.

Table 1. Physical propertie sof the OrthicPodzol

Layer (m)	--- Texture (g kg⁻¹) ---			Bulk density (kg dm⁻³)	Soilmoisture (m³ m⁻³)
	Clay	Silt	Sand		
0.0-0.3	44	26	930	1.52	0.345
0.3-0.60	43	25	932	1.54	0.368
0.6-1	44	26	930	1.60	0.426
> 1 m	32	40	928	1.66	0.472

from a river that flows into the ocean, suffering saline influence from two different sources.

Sugar cane yield was determined by the method proposed by Gheller et al. (1999), which estimates the total weight of the plot by multiplying the number of stems of the sampled area by the average weight of ten stems. At each sampling point, we chose three rows of sugar cane ten meters long, and counted the number of stems for calculating their average weight. Subsequently, ten stems were harvested at random among the three rows of each sampling point for weighing.

Thus, yield can be calculated as follows, as described by Gheller et al. (1999):

a) Average weight per stem:

$$Aps = \frac{ms}{tstems} \qquad (1)$$

where: ms is the weight of the bundle with 10 stems; $Tstems$ is the total of stems counted in the three rows.

b) Weight estimated at the sampling point:

$$Yield = \frac{Aps}{Tstems} \qquad (2)$$

With the average weight estimated in each sampling point, we can calculate the yield per hectare (t ha^{-1}).

The apparent soil electrical conductivity (EC$_a$, mS m^{-1}) was measured by electromagnetic induction with the equipment EM38 (Geonics®) at two depths: vertical dipole (effective depth of 1.5 m - EC$_a$-V) and horizontal dipole (effective depth of 0.4 m - EC$_a$-H). Values of EC$_a$ measured in the field (EC$_a$-V and EC$_a$-H) were then correlated with soil temperature, according to Huth & Poulton (2007). However, as it is a small area where it is possible to measure the EC$_a$ in a short time, the corrections of EC$_a$ values by soil temperature provided no consistent change in the original values, so we used the original values of EC$_a$.

Soil texture (clay, silt and sand) was determined at the layers 0.0-0.2 m and 0.2-0.4 m deep, according to Camargo et al. (1986).

The statistical parameters (mean, standard deviation, coefficient of variation, skewness and kurtosis) were determined for each sampling point. Coefficients of variation (CV, %) were used to determine the variability of the data, according to the classification Warrick & Nielsen (1980).

For the analysis of spatial variability, data were analyzed using geostatistical methods of semivariogram analysis, described by Vieira (2000), and based on the assumptions of stationarity of the intrinsic hypothesis. The spatial correlation between neighboring sites was calculated using the semi-variance γ(h), with the aid of the software GEOSTAT (Vieira et al., 2002).

Mathematical models were fitted to the semivariogram, which allowed the analysis of the spatial variation of variables. Criteria and procedures for semivariogram model fit were performed according to Vieira (2000), considering the methods of ordinary least squares and weighted least squares and cross-validation. From the fit of a mathematical model to the data, the semivariogram parameters were defined:

a) nugget effect (C_0), which is the value of γ when $h = 0$;

b) range of spatial dependence (a), which is the distance in which γ(h) remains approximately constant, after increasing with the increase of h;

c) sill ($C_0 + C_1$), which is the value of γ(h) from the range, which approximates the variance of the data, if any.

The preliminary geostatistical analysis indicated a trend in the data of sugar cane yield (t ha^{-1}), which was removed through the following equations for estimation of residuals:

1. Linear

$$m(x) = A_0 + A_1 x + A_2 y + A_3 xy \qquad (3)$$

2. Quadraticorparabolic

$$m(x) = A_0 + A_1 x + A_2 y + A_3 x^2 + A_4 y^2 + A_5 xy \qquad (4)$$

3. Cubic

$$m(x) = A_0 + A_1 x + A_2 y + A_3 x^2 + A_4 y^2 + A_5 xy + A_6 x^3 + A_7 y^3 + A_8 x^2 y + A_9 xy^2 \qquad (5)$$

The scaled semivariogram was constructed with the purpose of evaluating the spatial variability patterns between studied attributes (Vieira, 2000; Vieira et al 2002).

The analysis of the spatial dependence degree (SSD) of variables used the classification of Cambardella et al. (1994) considering the following relationship: $(C_0/C_0 + C_1)*100$, in which 0 to 25% (strong), between 25 and 75% (moderate) and >75% (poor).

The software SURFER (Golden Software Inc., 1999) was used for the construction of the contour maps for soil physical properties studied. Thus, the semivariogram fitting parameters were used to construct contour maps of the properties that presented spatial variability. For comparison between the properties, when detected the presence of pure nugget effect, contour maps were constructed using the default parameters of the software

SURFER, which is based on a linear kriging interpolation (Golden Software Inc., 1999).

3. RESULTS AND DISCUSSION

The average yield of sugar cane in the study area was 75.54 t ha^{-1} (Table 2). The yield in the area is about 66.02% higher compared to the average of the Pernambuco State for the growing season of 2012/2013 (CONAB, 2012). Domestic production in the 2012/2013 season (CONAB, 2012) was 69.44 t ha^{-1}, with a yield in the area 8.78% higher than the national average.

Mean values for the apparent soil electrical conductivity measured by electromagnetic induction in the vertical (EC$_a$-V) and horizontal (EC$_a$-H) dipoles were relatively similar (Table 2). This is probably because, at the time of sampling, the water table was close to the surface (Siqueira et al., 2013), which is the factor that interfered most with the readings taken with the EM38, corroborating Lesch et al. (2005). At the lower sections of the area, the water table was 0.2 m above the ground surface, moving away from the surface with increasing topography.

The yield showed the greatest variance of the data, since it varies considerably with soil changes across the landscape Coefficients of variation (CV, %) were classified as median (12-60%), according to Warrick & Nielsen (1980). There was an increase in CV values for EC$_a$-V (31.10%) and EC$_a$-H (40.60%). Siqueira et al. (2009) reports that the major differences in electrical conductivity measured by electromagnetic induction between the surface and the depth layers should be due to greater differences in water content in the surface layer, because in deep layers, such content becomes more stable. Confirmed by the analysis of the topographic map (Figure 1), since at the time of sampling the lower sections of the area were soaked, while at the higher sections, the water table was

more away from the surface, explaining the differences in EC$_a$ readings.

The textural properties (clay, silt and sand - g kg^{-1}) confirmed the sandy texture of the study area in the two studied layers (0.0-0.2 and 0.2-0.4 m), however the average of sand content (Table 2) found on the surface layer (0.0-0.2 m) and at the subsurface layer (0.2-0.4 m) was about 20% lower than the representative profile for the study area (Table 1). The coefficients of variation (CV, %) were low for all textural properties. This fact is related to the process of soil formation in the study area, which is based on sedimentation, making the finer particles to deposit in depth and the coarsest particles in the upper layer (Brazil, 1969, 1972).

The linear correlation between the properties (Table 3) showed the highest value between EC$_a$-V x EC$_a$-H (0.934). This high correlation is due to the nature of measuring both properties, since according to Lesch et al. (2005), up to 80% of the response obtained with the vertical dipole (EC$_a$-V) originates from the soil surface layer (EC$_a$-H). The linear correlation between yield and EC$_a$ was high, with values of 0.850 (yield x EC$_a$-V) and 0.740 (yield x EC$_a$-H).

Dantas et al. (2006) reported increased yield of sugar cane when there is no water deficit. In this way, high correlations between yield x EC$_a$-V (0.850) and yield x EC$_a$-V (0.740) are expected, since in higher areas, the yield is lower and hence EC$_a$ values, thus increase in yield an din EC$_a$ values are found in the lower sections of the area.

However, when correlating sugar cane yield with the content of clay, silt and sand in the layers of 0.0-0.2 m and 0.2-0.4 m (Table 3), the correlation values were low or zero, according to the classification proposed by Santos (2007). The same is true for the correlation between the textural properties and EC$_a$-V and EC$_a$-H. The occurrence of low linear correlation values between the textural properties and EC$_a$-V and EC$_a$-H was not expected, as the soil clay content is the property that interferes most

Table 2. Statistical parameters for the sugar cane yield (t ha^{-1}), the electrical conductivity of soil measured by electromagnetic induction (EC$_a$-V and EC$_a$-H, mS m^{-1}) and soil texture (g kg^{-1})

Parameter	Yield (t ha^{-1})	EC$_a$-V	EC$_a$-H	Texture (g kg^{-1})					
		------ (mS m^{-1}) ------		------- 0.0-0.2 m -------			------- 0.2-0.4 m -------		
				Clay	Silt	Sand	Clay	Silt	Sand
Mean	75.54	15.67	13.90	253.2	42.3	712.9	253.4	26.9	719.8
Variance	241.94	23.67	31.80	7.87	8.37	13.99	4.48	5.82	9.90
SD	15.55	4.86	5.64	2.81	2.89	3.74	2.12	2.41	3.15
CV (%)	20.60	31.10	40.60	0.11	0.68	0.05	0.08	0.90	0.04
Skewness	2.041	–0.081	0.087	–0.48	0.86	–0.24	0.15	1.05	–0.52
Kurtosis	9.112	–0.325	–0.349	0.54	–0.28	–0.20	0.42	1.01	0.33
D	0.141 n	0.076 n	0.084 n	0.14 n	0.19 n	0.13 n	0.12 n	0.16 n	0.11 n

SD = standard deviation. CV = coefficient of variation. D = 1% Error probability by Kolmogorov-Smirnov teste. n = normal. Ln = lognormal.

with the values of EC_a-V and EC_a-H (McNeill, 1980; Lesch et al., 2005; Sudduth et al., 2005; Kühn et al., 2009; Siqueira et al., 2009). This fact is related to water surplus in the study area, represented by the water table very close to the surface at the time of harvesting sugar cane and sampling other soil properties under study.

Negative linear correlation values between the textural properties were expected, since with the increase in sand content in the study area there is a reduction in the amount of clay and silt, with the highest correlation found for the silt × sand at the layer 0.2-0.4 m (–0.704).

The geostatistical analysis (Table 4) showed that the Gaussian model was the best fit to the data set. Siqueira et al. (2009) studied the spatial variability of soil electrical conductivity in area with topographic gradient and fitted the spherical model to EC_a at the surface and depth layers.

The fit of the Gaussian model to the data (Table 4) may be associated with the concave relief in the study area, coinciding with the areas with higher yields and consequently with higher EC_a values due to the greater water content in the soil when compared the higher sections of the area. Data of sugar cane yield presented a trend and we calculated the residuals through a linear equation. Siqueira et al. (2010) demonstrate how the geomorphology of the soil interferes with the identification of specific management zones, with the fit of different semivariograms

for each of the management zones. Different authors have justified the importance of soil geomorphology for sampling design (Montanari et al., 2005); dynamics of clay mineral (Camargo et al., 2008); nutrient adsorption potential (Barbieri et al., 2008); soil loss (Campos et al., 2008); input application at varying rates (Barbieri et al., 2009); agricultural planning and implementation of sugar cane farming system (Campos et al., 2009), CO_2 emissions (Brito et al., 2009), among othes.

The yield showed a range (a, m) of 110.00 m while EC_a-V and EC_a-H showed a value of 180.00 m (Table 4). This is because, among the plant attributes, yield is the most sensitive to soil changes. The spatial dependence was determined as proposed by Cambardella et al. (1994), indicating high correlation between samples (SSD ≤ 25.00%).

The scaled semivariograma showed the existence of a similar pattern of spatial variation between yield and EC_a-V and EC_a-H (Table 4). However, the pattern occurs at different levels of spatial variability, since the yiel dreaches higher values of C_0 and C_1, related to the higher variation in yield values across the area (variance = 241.94) when compared to EC_a-V (23.67) and EC_a-H (31.80, Table 2).

Additionally, the scaled semivariogram was modeled to check for a similar spatial pattern between semivariance pairs for yield, and the EC_a-V and the EC_a-H (Figure 3).

Table 3. Linear correlation between sugar cane yield (t ha⁻¹), soil electrical conductivity measured by electromagnetic induction (EC_a-V andEC_a-H,mS kg⁻¹) and soil texture (g kg⁻¹)

		Yield (t ha⁻¹)	EC_a-V	EC_a-H	\- Texture(g kg⁻¹) \-					
			\-\-\- (mS m⁻¹) \-\-\-		\-\-\-\-\-\-\- 0.0-0.2 m \-\-\-\-\-\-\-			\-\-\-\-\-\-\- 0.2-0.4 m \-\-\-\-\-\-\-		
					Clay	Silt	Sand	Clay	Silt	Sand
	Yield	1.000								
	EC_a-V	0.850	1.000							
	EC_a-H	0.740	0.934	1.000						
	Clay	0.133	0.100	0.115	1.000					
0.0-0.2 m	Silt	0.084	0.010	0.078	–0.207	1.000				
	Sand	–0.054	0.016	–0.060	–0.550	–0.529	1.000			
	Clay	0.115	–0.011	–0.026	0.461	–0.037	–0.288	1.000		
0.2-0.4 m	Silt	–0.007	0.161	0.164	0.040	–0.146	0.026	–0.039	1.000	
	Sand	–0.017	–0.115	–0.108	–0.341	0.137	0.173	–0.642	–0.704	1.000

Table 4. Semivariogramfitting parameters for the yield of sugar cane (t ha⁻¹), electrical conductivity of soil measured by electromagnetic induction (EC_a-V and EC_a-H, mS m⁻¹) and soil texture (g kg⁻¹)

| | Residuals Yield (t ha⁻¹) | EC_a-V | EC_a-H | \- Textura (g kg⁻¹) \- | | | | | |
		\-\-\-\-\-\-\-\- (mS m⁻¹) \-\-\-\-\-\-\-\-		\-\-\-\-\-\-\- 0.0-0.2 m \-\-\-\-\-\-\-			\-\-\-\-\-\-\- 0.2-0.4 m \-\-\-\-\-\-\-		
				Clay	Silt	Sand	Clay	Silt	Sand
Model	Gaussian	Gaussian	Gaussian				Exponential		
C_0	200	6	10				0.690		
C_0+C_1	580	28	35	PNE	PNE	PNE	3.926	PNE	PNE
a (m)	110	180	180				70.00		
SD	25.64	17.64	22.22				14.94		

SSD = spatial dependence degree (C_0/C_0+C_1) x 100. PNE =pure nugget effect.
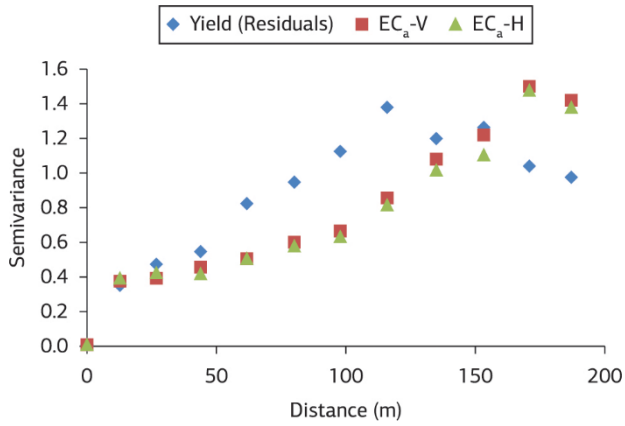
Figure 3. Scaled semivariogram for sugar cane yield (t ha^{-1}) and apparent soil electrical conductivity (EC$_a$-V andEC$_a$-H, mS m^{-1}) measured by electromagnetic induction.

The values of EC$_a$-V and EC$_a$-H show similar behavior for the pairs of semivariance, while the pairs of semivariance of soil yield (residuals) present a completely different behavior from EC$_a$-V and EC$_a$-H. As already discussed, this is due to the geomorphology of the area and the presence of higher moisture values in the lower sections of the landscape.

Maps of spatial variability confirm the similarity in the spatial distribution pattern for EC$_a$-V and EC$_a$-H (Figures 4a,b). As previously shown, this similarity is due to the higher values of soil moisture in the lower sections of the landscape, which, in turn favor a higher yield (Figure 4a). The greatest similarity between the analyzed properties occurs for thematic maps of EC$_a$ (Figures 4b,c).
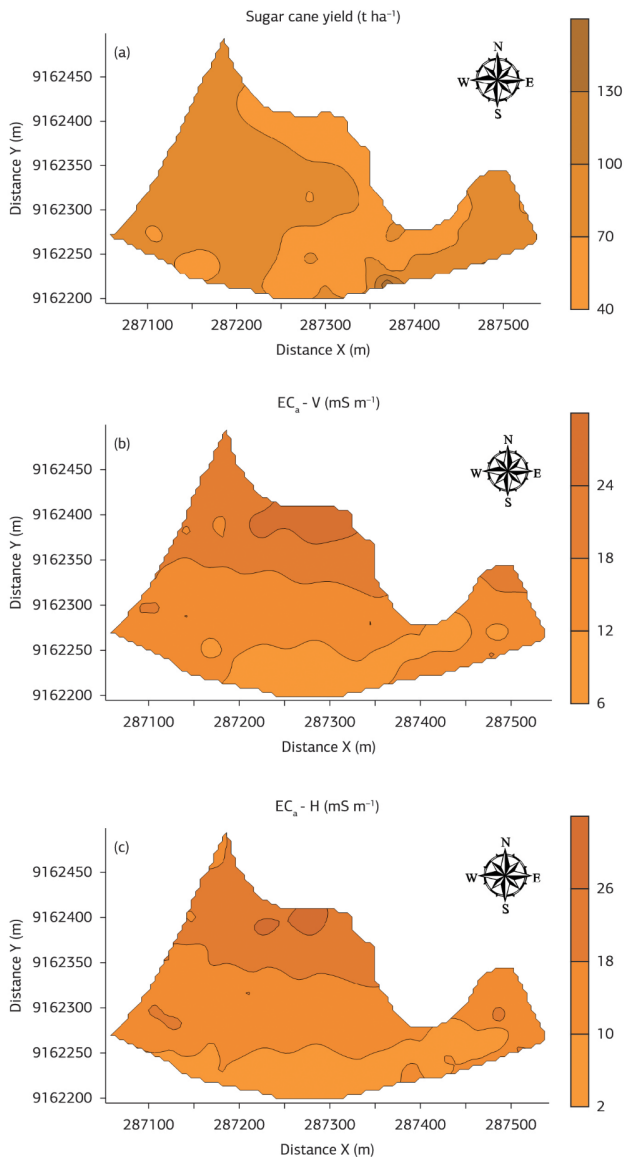
Figure 4. Thematic maps of spatial variability for: a) yield (t ha^{-1}); b) EC$_a$-V (mS m^{-1}); c) EC$_a$-H (mS m^{-1}).
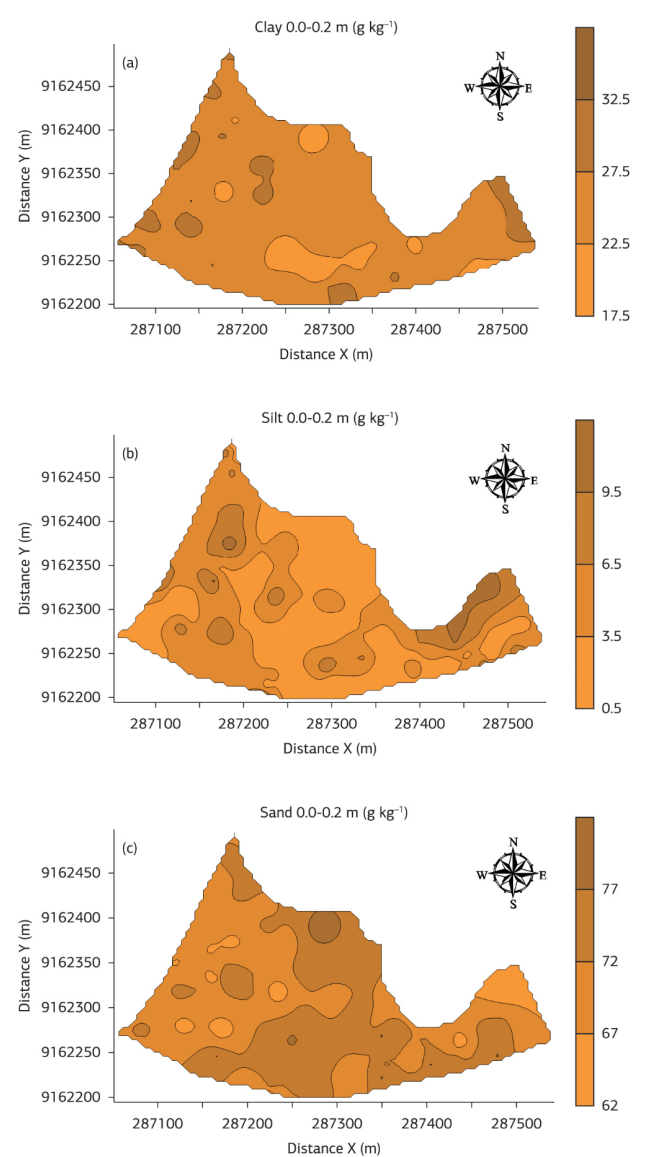
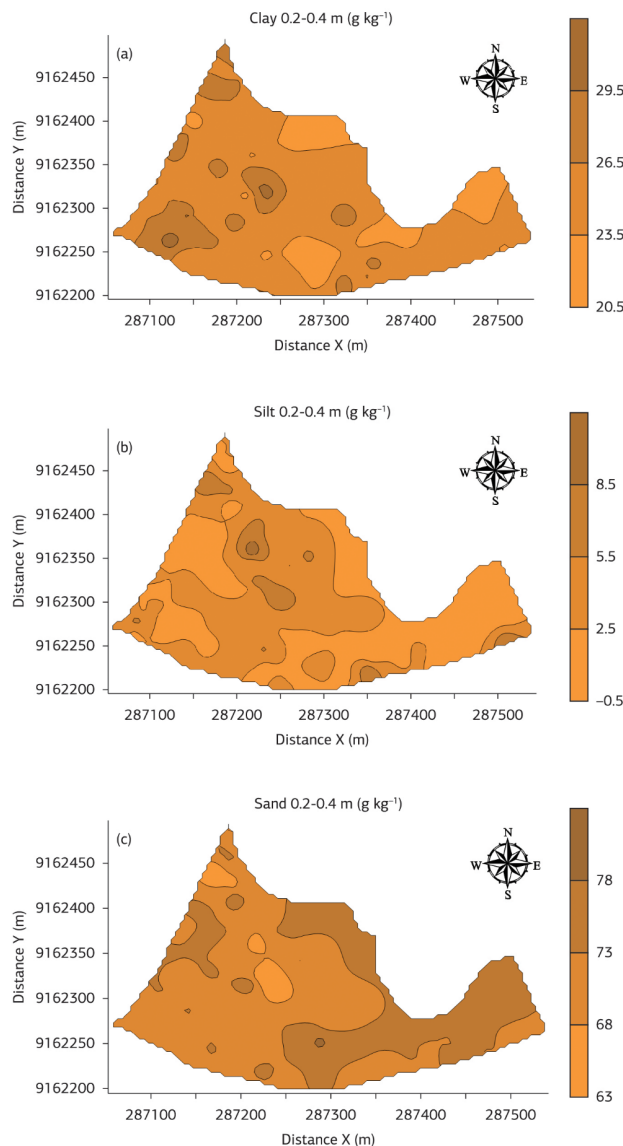**Figure 5.** Thematic maps of spatial variability for soil texture at the 0.0-0.2 m depth layer: a) clay (g kg^{-1}); b) silt (g kg^{-1}); c) sand (g kg^{-1}).

The yield of sugar cane showed high linear correlation with EC_a (Table 3), however, when analyzing the spatial variability maps (Figure 4), it is not possible to detect a clear relationship between the yield map (Figure 4a) and maps of EC_a (Figures 4b,c). The yield map (Figure 4a) shows, in most of the area, yield values greater than 75.54 t ha^{-1}, which represents the average yield of the area, reaching values of up to 160 t ha^{-1}, coinciding with concave zone and with higher values of moisture when compared to other zones, corroborating once again the relationship between water of the crop and its yield (Dantas et al., 2006).

Moreover, the lower yield values are situated in the part where the area has smaller width (Figure 4a) and its highest topographic elevation (Figure 1). Lower yield values were also registered also at the top left of the map, where the lowest topographic elevation is found, showing that excess moisture also influences the yield of sugar cane.

Maps of spatial variability of textural attributes (clay, silt and sand) at the 0.0-0.2 m layer (Figure 5) and 0.2-0.4 m layer (Figure 6) confirm that there is no relationship between maps of yield and EC_a-V and EC_a-H (Figure 4), corroborating the low linear correlation values shown in table 3. In general, maps of spatial variability of soil texture (Figures 5 and 6) indicated no similarity pattern in the arrangement of the contour lines of the textural classes. Nevertheless, in depth (Figure 6, 0.2-0.4m depth layer), there was an inverse relationship between the values of clay and sand (r = -0.642, Table 3) and between silt and sand (r = −0.704, Table 3).

4. CONCLUSION

The spatial variability maps present similar pattern for sugar cane yield and EC_a-V and EC_a-H. The electrical conductivity measured by electromagnetic induction has been shown to be an important tool for predicting the yield of sugar cane. The textural properties (clay, silt and sand) showed high spatial variability, demonstrating that the sampling design was not sufficient to determine the spatial distribution, whereas the relief and the water table are the factors that interfere most with the variability of all studied properties.

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Figure 6. Thematic maps of spatial variability for soil texture at the 0.2-0.4 m depth layer: a) clay (g kg^{-1}); b) silt (g kg^{-1}); c) sand (g kg^{-1}).

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