MULTIVARIATE GEOSTATISTICS AS A TOOL TO ESTIMATE PHYSICAL AND CHEMICAL SOIL PROPERTIES WITH REDUCED SAMPLING IN AREA PLANTED WITH SUGARCANE

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ABSTRACT

Precision Agriculture (PA) can be described as a set of tools and techniques applied to agriculture in order to enable localized production management, considering the spatial and temporal variability of crop fields. Among the numerous existing tools, one of the most important ones is the use of geostatistics, whose main objective is the description of spatial patterns and estimation data in non-sampled places. Nowadays, one of the most limiting factors to the use of PA is the number of samples required to represent the spatial soil attributes. Within this context, multivariate geostatistics emerges as a promising technique for mapping and quantification of soil attributes. One of the techniques, which minimize the number of samples needed, is the use of maps obtained by soil sensors equipment to identify points for sampling. The objective of this study was to map the spatial variability of chemical and physical soil properties, using a reduced number of samples, and applying kriging with external drift (KED) based on maps of apparent soil electrical conductivity (ECa). Samples were taken on a regular grid georeferenced at two depths. ECa soil readings in the whole area were made by means of a direct contact sensor. The results indicate that it is possible to obtain maps with acceptable precision in the spatial distribution of chemical (CEC, BS, SEB, K and pH) and physical attributes (clay) of soil from of 20 sampling points (0.4 samples ha^{-1})

determined based on the ECa. The methodology used to obtain the maps of spatial variability of chemical and physical soil properties indicate that it is possible to predict, with acceptable accuracy, maps that can be used for fertilizer recommendation at variable rate. This approach opens new possibilities for other important agronomical attributes that can be estimated over large areas from a small number of samples, assisting farmers in crop management.

Keywords: soil sensors, kriging with external drift (KED), *Saccharum spp.*, variable rate technology.

INTRODUCTION

Precision agriculture can be understood as a set of tools that aims to understand the spatial and temporal variability found in the field and thus take advantages, treating differently each portion of the field, aiming higher profitability and lower environmental impact. Despite constant advances, one of the factors that limit the use of AP is the sampling process required to represent the physical and chemical properties of soil and/or plant spatially (Bramley and Trengove, 2013). To obtain a proper mapping of the physical and chemical crop attributes dense sampling in the field is need, which involves manual sampling, sample pretreatment, chemical laboratory analysis and physical mapping, making the activity physically and economically impracticable (Peets et al., 2012). Moreover, the lack of a complete technology package makes the AP only a promising technology, which adopts the sugarcane sector, partly, in search of a sustainable management of the production of sugar cane (Silva et al., 2011). Although the yield monitor, the autopilot, the variable rate technology and some soil and plant sensors are part of the technology package of the AP, the appropriateness and applicability of the information to define methods and management models is the major challenge in this area. One of the current technologies to overcome this challenge is to use soil and/or plant sensors, which is a rapid, low cost and environmentally friendly method to describe the spatial variability (Peets et al., 2012). These devices are based on different principles and provide information that varies in precision and accuracy, enabling detect the spatial variability of the crop in relation to physical and/or chemical soil properties, the presence of water (Adamchuk et al., 2004) or biomass production. The sensors developed for measuring the soil and/or plant properties have the potential to provide benefits such as increased density measurements at a relatively low cost. Agriculture in many countries still, especially Brazil, is focused on areas treated as homogeneous, going to the concept of the average requirement for application of inputs, not considering the specific needs of different farming sites (Rossato, 2011). In this scenario, the correct distribution of fertilizers for plants, which ensures a lower environmental impact and increased profitability and productivity for farmers, makes the research in search for sensors to measure directly or indirectly the nutrients in the soil and/or plant increasingly intensified.

Within this context of need for available technologies for the acquisition of high quality information, aiming the adequate management of spatial variability of crops, the soil apparent electrical conductivity (ECa) has emerged as an effective method to evaluate quickly, high resolution and low cost of the overall soil fertility (Sudduth et al., 2005). Studies show that soil ECa is related to local topographic conditions, where areas with lower elevation present higher conductivity when compared the areas of higher elevation. These differences are attributed to the combined effects of the accumulation of water and salts in areas of lower slope (Fritz et al., 1999). Intrinsically related to moisture content, research shows that ECa is also able to detect variations in soil properties such as salinity, clay content, cation exchange capacity, size and pore distribution, organic matter and temperature (Corwin and Lesch, 2003; Kaffka et al., 2005; Kitchen et al., 2003; Sudduth et al., 2001). Another important question in the context of ECa variability along the field is its temporal stability, where studies have shown that, despite the magnitude of the temporal electrical conductivity (measurements vary with temperature and soil moisture), the spatial pattern of the soil ECa remains constant (Harstock et al., 2000).

As stated, several results in the literature show the relationship of ECa with soil properties, however, the response of these sensors to the spatial variability will always depend on the chemical and physical soil properties of the area, making the response of these sensor influenced, to a lesser or higher degree, for certain property. Although there is sufficient evidence in the literature that the ECa has great potential for mapping soil attributes, few studies have been focused on quantitative estimates (De Benedetto et al., 2011), mainly in the soil attributes of greatest agronomic interest. Considering the complexity of the relationships between different attributes on the nature in studies of spatial variability, several variables can be sampled simultaneously to best explanation of the phenomenon. Some of these variables can be subsampled and other over sampled. If subsampled and over sampled variables present some relationship, then over sampled variables can be used to make a better estimate of the subsampled variables (Isaacks and Srivastava, 1989). For this situation, geostatistics provides a set of tools to co-estimates, where the primary variables (greater interest) are subsampled and secondary variables (usually over sampled) are those that can be used to improve estimates of primary variables. Several estimation methods have been developed for fusion of primary and secondary information, such as the multivariate extension of kriging, known as cokriging (Goovaerts, 1997). However, these techniques assume stationarity intrinsic to both the variable of greatest interest and the secondary variable, and a strong correlation between them (Webster and Oliver, 2001). On the other hand, a different way to take into account the secondary variable is assuming that it presents a spatial trend, which is the significantly related with the primary variable (De Benedetto, 2011). Two non-stationary interpolation methods are possible, such as kriging with external drift (KED) (Wackernagel, 2003) and regression kriging (RK) (Goovaerts, 2000). Knowing that there exists a physical correlation between ECa and chemical and physical soil attributes, the propose of this study was to show that it is possible to obtain soil fertility maps based on a few soil samples taken at strategic points in the field, selected from spatial variability of ECa map.

MATERIALS AND METHOD

Study Area

The experiment has been conducted since 2010 in a commercial site of 50 ha in Serra Azul, São Paulo State, Brazil, which belongs to Pedra Sugar Mill. The climate is tropical to subtropical, and mean annual rainfall and temperature are 1560 mm and 22.9°C, respectively. The soil is a Typic Hapludox (Soil Survey Staf, 2010). It is clayey and its clay fraction being dominated by kaolinite, and iron and aluminium oxihydroxides mainly. The site had been under continuous sugarcane cultivation for 30 years. The area was divided into a regular 50 m grid (204 sample points) and points located in the field using a differential global positioning system (DGPS) (Ag114™, Trimble, Navigation Ltd, Sunnyvale, CA, USA). Soil sample was taken at two depths (0.00 to 0.20 m and 0.20 to 0.40 m) at each grid point and a wet-chemical analysis was done to determine soil physical and chemical attributes (macro and micronutrients) (Fig. 1). The point's elevation was also used to characterize the slope of the field. Apparent electrical conductivity (ECa) was measured at 0.30 m using the Veris (model 3100 sensor system, Veris Technologies of Salina, KS, USA). For the development of this work, targeting an initial investigation, we selected some attributes of agronomic interest, determined in both depths mentioned, as clay, pH, potassium (K), sum of exchangeable bases (SEB), Cation Exchange Capacity (CEC) and Base Saturation (BS).

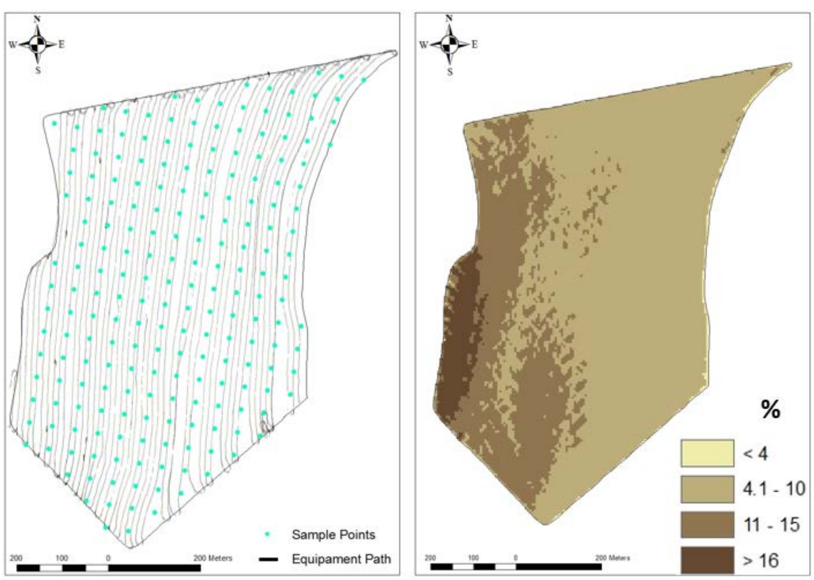

Fig. 1. Grid (204 points) and soil sensor path (black lines) for ECa soil data collecting (left) and slope (right).

Data Analysis

All the collected data were submitted to a statistical and geostatistical treatment. Measures of central tendency, dispersion and *Box plot* were evaluated. The *Box plot* allowed to evaluate the dispersion of the data and the existence of outliers in them. The data that have a high density, such as apparent electrical conductivity, were subjected to a pre-treatment in order to remove possible "*noise*" coming from the sensors and outliers. The pre-treatment was based on data standardization to mean zero and standard deviation 1 (one) by removing the normalized data outside the range of ± 3 of the normal distribution of data. Soil others data was also analyzed in order to eliminate the possible outliers arising of the readings in the field or laboratory errors. Spatial analysis of chemical and physical soil properties data was also performed to check the veracity of outliers. After that, the analyze was divided into two steps; in the first step (Fig. 2) we used Moran's I spatial autocorrelation to evaluate the spatial structure in all measured attributes. The limit case, $I \approx 1$, evidences perfect global spatial structure, indicating an attribute potentially valuable for PA. On the other hand, $I \approx 0$, evidence random spatial distribution, indicating an attribute with little utility for PA management. The Moran's index was calculated by eq. 1 (Cliff and Ord, 1973).

$$Ij = z_j^T L z_j \qquad \textbf{eq. 1}$$

Where $\mathbf{z_j}$ is the vector of the mean-centred normalized attribute estimated at grid points, $\mathbf{z_{i,j}} = (u_{i,j} - \bar{u}_j)/\sigma_j$.

Next, the experimental and theoretical semivariograms were constructed for data interpolation, using a regular grid of 5 meters and applying ordinary kriging. All these analyzes were performed using ArcGIS 10.2 (ESRI, Environmental Systems Research Institute, Redlands, CA, USA) using the Spatial Analyst Tools and Geostatistical Analyst Tools extensions. Subsequently the construction of thematic maps, a second step (Fig. 3) was performed. This step includes the determination of a reduced number of points in the area (20) to, using KED based on the ECa (secondary variable), reconstruct the thematic maps of soil attributes (primary variable). We used the software GeoMS (CERENA, Lisbon, Portugal) to performing KED. Finally, we performed the comparison of maps obtained in the original grid (204 points) with interpolated data by KED, using Pearson's correlation and kappa coefficient. Kappa index (eq. 2) can be used as a measure of agreement between model predictions and reality (Congalton, 1991) or to determine if the values contained in an error matrix represent a result significantly better than random (Jensen, 1996).

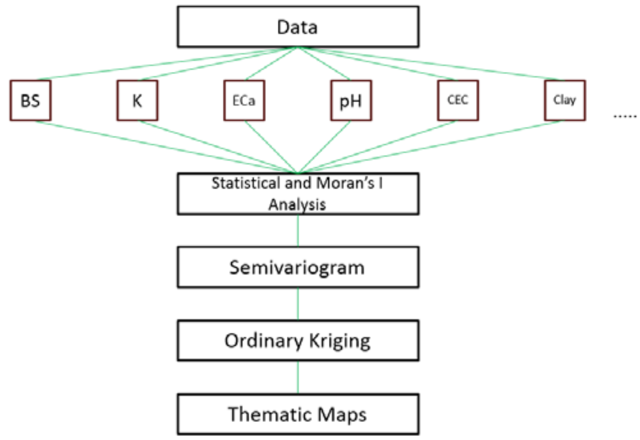

Fig. 2. Diagram of the first step in data analysis.

$$k = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} - x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} - X_{+i})} \qquad \textbf{eq. 2}$$

Where $\boldsymbol{N}$ is the total number of sites in the matrix, r is the number of rows in the matrix, $\boldsymbol{x_{ii}}$ is the number in row i and column i, $\boldsymbol{x_{+i}}$ is the total for row I and $\boldsymbol{x_{i+}}$ is the total for column I (Jensen 1996).

To calculate the Kappa Index a random sample of approximately 10% of the total estimated data was used. Landis and Koch (1977) suggest the following interpretation for the index (Table 1).

Table 1. Interpretation of the Kappa Index.(Landis & Koch 1977).

Values of Kappa	Interpretation
<0	No agreement
0-0.19	Poor agreement
0.20-0.39	Fair agreement
0.40-0.59	Moderate agreement
0.60-0.79	Substantial agreement
0.80-1.00	Almost perfect agreement

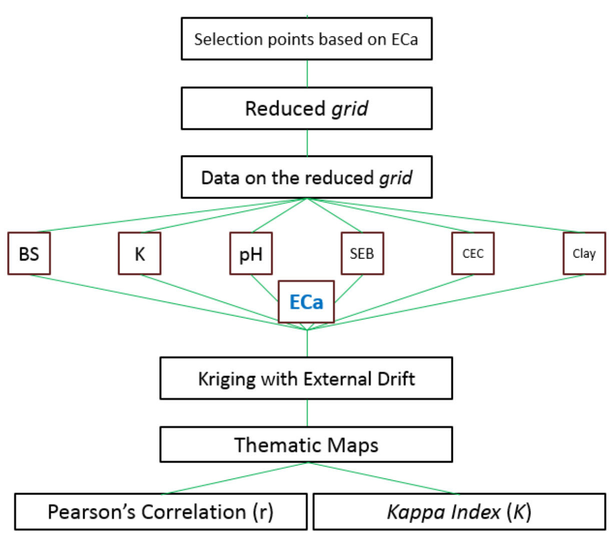

Fig. 3. Diagram of the second step in data analysis.

Kriging with External Drift

Aiming to make coestimates, KED estimates a primary variable Z(x) based on a secondary variable Y(x) correlated, with an insufficiently sampled primary variable while the secondary variable, which will assist in estimating the first, is more densely sampled. If Z(x) and Y(x) are correlated, according Wackernagel (1995), one may describe this correlation with a linear correlation:

$$E[Z(x)] = a_0 + b_1 Y(x) \qquad \textbf{eq. 3}$$

This means that the spatial variability of the secondary variable is related to the local trend of primary variable (Xu et al. 1992). The estimator of KED can be written as (Wackernagel, 1995):

$$Z^*_{KDE}(x_0) = \sum_{i=1}^{n} \lambda_i Z\,(x_i) \qquad \textbf{eq. 4}$$

Interesting to note from equation 4 is the fact that the secondary variable Y(x) does not enter directly in the estimate, such as with the cokriging estimators. This makes KED interesting when compared with other methods, once the estimated primary variable is made exclusively from observed values (eq. 5, Wackernagel, 1995):

$$\begin{cases} \sum_{j=1}^{n} \lambda_j C_R\left(x_i - x_j\right) - \mu_1 - \mu_2 y(x_i) = C_R(x_i - x_0)\ para\ i = 1, n \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \sum_{j=1}^{n} \lambda_j y\left(x_j\right) = y(x_0) \end{cases} \qquad \textbf{eq. 5}$$

Where $\boldsymbol{\mu_1}\ and\ \boldsymbol{\mu_2}$ are the Lagrange multipliers and $\boldsymbol{C_R\left(x_i - x_j\right)}$ is the covariance of the residues between $x_i\ and\ x_j$ points.

According to Xu et al. (1992) the advantages of KED is that it is easy to implement; it does not need the covariance $C_2(h)$ and $C_{12}(h)$; the system has dimension $(n+2)$ unlike $(n_1 + n_2)$ as in ordinary cokriging and maps Z(x) are very similar and follow the trend of the maps Y(x). Also according to the authors, the disadvantages of this method is that maps of Z(x) will be well correlated with Y(x), independent of the linear relationship is true or not; KDE does not capture the cross-correlation between Z(x) and Y(x), unlike cokriging; requires that the secondary data is at all sample points of the primary data and all nodes of the regular grid to be interpolated and requires the covariance of the residuals. The regionalized variable $Z(x)$ can be decomposed as $Z(x) = m(x) + R(x)$, where the $m(x)$ is the trend component and $R(x)$ the residual. The residual variogram is given by eq. 6 (Goovaerts 1997), subtracting the variogram of $Z(x)$ the average of the squared difference of trend components in the x and $x + h$ points, which are unknown.

$$2\gamma_R(h) = 2\gamma(h) - E\{[m(x) + m(x+h)]^2\} \qquad \textbf{eq. 6}$$

However, Landim and Yamamoto (2013) suggest that the term $E\{[m(x) + m(x+h)]^2\}$ is equivalent to the variogram of trend component, obtaining eq. 7.

$$2\gamma_R(h) = 2\gamma(h) - 2\gamma_M(h) \qquad \textbf{eq. 7}$$

Yet according to the authors, as the primary variable has a linear relationship with the secondary variable (eq. 3) the coefficients of the regression a_0 and b_1 can be easily calculated with the sampling points. Even as required by KED, know the values of the secondary variable on all nodes of the regular grid to be estimated, applying the coefficients of the regression line in the secondary variable results in the trend component, which shall be known in all the nodes of the regular grid. Finally the variogram trend component can be calculate, which subtracted from the variogram primary variable, resulting in residual variogram. The only restriction is that the variogram of the primary variable has a higher sill than the variogram trend, to obtain positive residuals.

RESULTS AND DISCUSSION

Initially, all data were normalized and plotted in a Box Plot in order to identify outliers that could cause detrimental bias to correlations and covariance (Fig. 4). Any entry deviating from the mean by more than three standard deviations (for a given attribute) was treated as outlier, but with some exceptions arising from the spatial analysis. A maximum of 4 % of data were removed as outliers from soil data and 1% for ECa data (Table 2).

Moderate spatial autocorrelation was detected for ECa, clay and pH, in the both layers and SEB only in the second layer, bean the highest value presented by clay, which was not unexpected due to its spatial variability intrinsically related to the characteristics of local relief and the type of soil. The high spatial autocorrelation value of ECa confirming its strong association with clay (Corwin & Lesch 2003; Kitchen et al. 2003; Machado et al. 2006). K, CEC and BS in two soil layers showed modest spatial structure (1.3-0.27). This could be explained by K being a cation of low concentration in the soil in relation to Ca, Mg and be absorbed in large quantities by sugarcane. Moran's Index is a good indicator of the quality of the data, showing whether they occur according to a trend or are spatially random. This fact contributes to the construction of the variables variogram, since random attributes tend to have high nugget effect, making it difficult to adjust to the theoretical model.

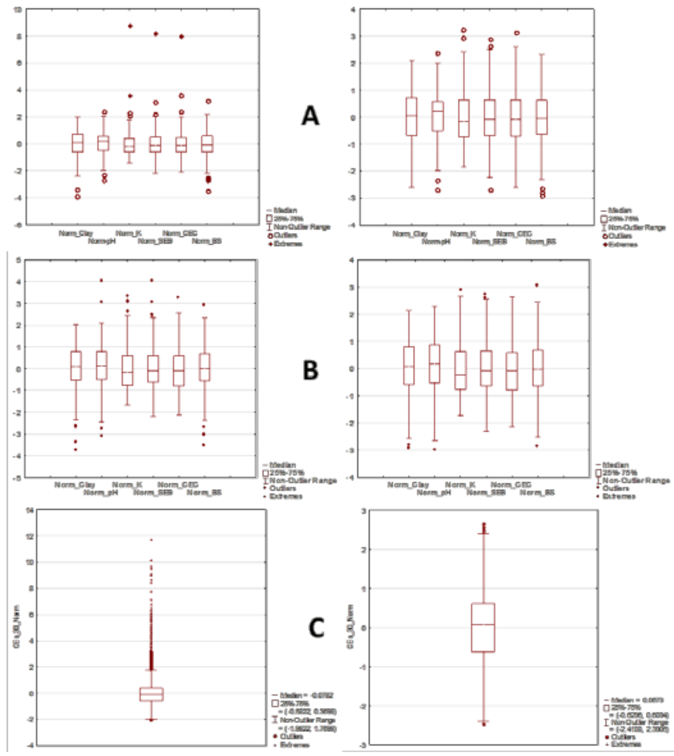

Fig. 4. Box plot of the analysed attributes in layers of 0.00 to 0.20m (A), 0.20 to 0.40m (B) and the ECa of 0.00 to 0.30m (C). Raw (right) and clean (left) data.

Variogram models were mostly exponential and anisotropy was founded for the data set with exception of clay that was fit to a spherical model showing a linear behavior at the origin and no anisotropy, confirming its stable and well-structured behavior along the field (Table 3). With the adjusted models, we proceeded to ordinary Kriging of the data using a minimum of 3 and a maximum of 6 points per neighbors quadrant to estimate the physical and chemical attributes and a minimum of 10 and a maximum of 20 neighboring points for ECa (Fig. 5 and 6). For the second stage of data analysis, based on thematic map of ECa, we manually select the reduced grid, at points with distinct values and spread inside the outline of the area (Fig. 6). Total 20 points were selected, corresponding to one sample per 2.5 hectare, which is reasonable from the economic point of view farmers wishing to employ PA.

Table 2. Descriptive analysis of the chemical and physical soil attributes at 0.00-0.20m and 0.20-0.40m, and ECa at 0.00-0.30m and Moran´s I.

	Valid N	Mean	Variance	Std. Dev.	Coef. Var.	Std. Error	Skewness	Kurtosis	Moran´s Index
					Depth 0.00 to 0.20m				
Clay	199	443.131	2023.209	44.980	10.151	3.189	-0.353	-0.305	0.664
pH	203	5.141	0.076	0.276	5.373	0.019	-0.106	-0.292	0.424
K	202	2.046	1.017	1.009	49.294	0.071	0.592	0.057	0.175
SEB	201	34.381	97.362	9.867	28.700	0.696	0.350	-0.100	0.134
CEC	201	64.835	102.358	10.117	15.605	0.714	0.423	0.233	0.273

BS	201	52.463	77.750	8.818	16.807	0.622	-0.247	-0.049	0.130
				Depth 0.20 to 0.40m					
Clay	199	451.692	2081.525	45.624	10.101	3.234	-0.504	0.202	0.675
pH	201	5.151	0.081	0.284	5.519	0.020	-0.344	-0.170	0.432
K	201	1.820	0.864	0.929	51.060	0.066	0.650	-0.220	0.175
SEB	202	22.913	36.064	6.005	26.209	0.423	0.313	-0.195	0.251
CEC	203	47.847	71.450	8.453	17.666	0.593	0.424	-0.344	0.484
BS	202	48.322	71.085	8.431	17.448	0.593	-0.006	0.265	0.184
				Depth 0.00 to 0.30m					
ECa (Raw)	12002	4.040	3.189	1.786	44.205	0.016	2.169	12.343	0.592
ECa (Clean)	11527	3.813	1.667	1.291	33.865	0.012	0.011	-0.207	

Table 3. Parameters of the theoretical models fitted to experimental data with verification of anisotropy.

Prop	Depth (m)	Model	LS	NL	N	R	PS	Anis.	MR	D
Clay	0.0 to 0.2	Sph.	50	10	0	345	2400	No	-	-
	0.2 to 0.4	Sph	50	10	0	440	2500	No	-	-
pH	0.0 to 0.2	Exp.	50	10	0.02	300	0.04	Yes	90	9
	0.2 to 0.4	Exp.	50	10	0	265	0.065	Yes	80	9
K	0.0 to 0.2	Exp.	50	10	0.2	260	0.78	Yes	70	9
	0.2 to 0.4	Exp.	50	10	0.2	260	0.8	Yes	120	9
SEB	0.0 to 0.2	Exp.	50	10	20	310	80	Yes	150	9
	0.2 to 0.4	Exp.	50	10	10	270	28	Yes	145	9
CEC	0.0 to 0.2	Exp.	50	10	20	410	80	Yes	85	9
	0.2 to 0.4	Exp.	50	10	10	470	50	Yes	120	9
BS	0.0 to 0.2	Exp.	50	10	10	240	70	Yes	70	9
	0.2 to 0.4	Exp.	50	10	20	330	50	Yes	80	9
ECa	0.0 to 0.3	Exp.	5	30	0	40	1.1	Yes	10	9

Prop – property; LS – leg size; NL – number of legs; N – Nugget; R – Range; PS – partial sill; Anis – Anisotropy; MR – minor range; D – direction; Sph – spherical; Exp – exponential.

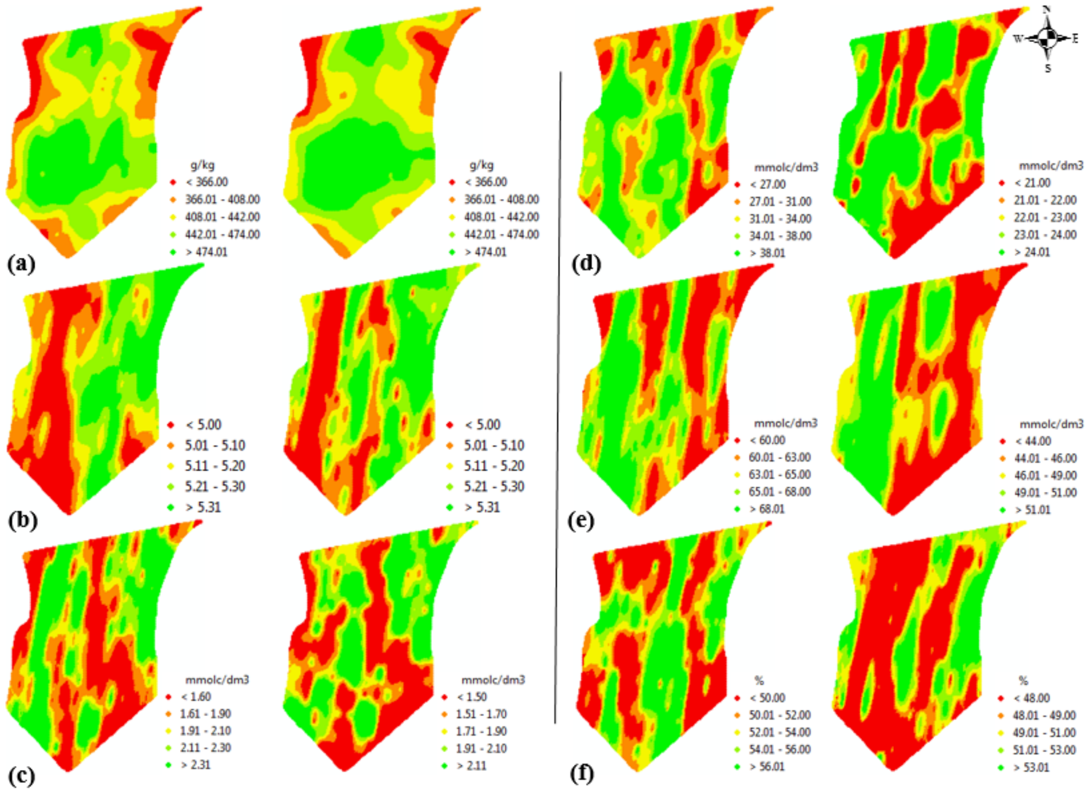

Fig. 5. Thematic maps generated by ordinary kriging (OK) of clay (a), pH (b), K (c), SEB (d), CEC (e), BS (f) in the layers 0.00 to 0.20m (left) and 0.20 to 0.40m (right).

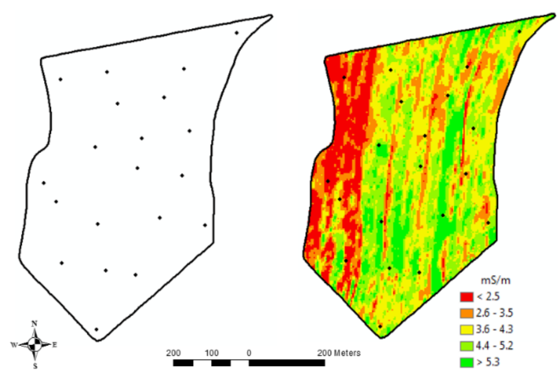

Fig. 6. Reduced grid with 20 sampling points (left) selected on the basis of thematic map generated by ordinary kriging (OK) of the ECa 0.30m (right).

The first step to perform KED was to determine the regression line between the attributes and ECa points in the reduced grid. This step is necessary to calculate the data variogram model, which in turn entailed the residual variogram, as proposed by Yamamoto & Landim (2013) (Table 4).

Table 4. Best-fitting equations and their coefficients of determination (R^2) for relating attributes and apparent electrical conductivity in the reduced grid.

	R^2	Equation y(x)	R^2	Equation y(x)

Depth (m)	0.00 to 0.20		0.20 to 0.40	
Clay	0.5956	33.668*x + 315.16	0.4647	32.240*x + 325.88
pH	0.3616	0.1228*x + 4.743	0.3681	0.1966*x + 4.283
K	0.2244	0.4199*x + 0.146	0.4296	0.5420*x - 0.503
SEB	0.5601	7.8903*x + 1.478	0.4434	2.9375*x + 12.35
CEC	0.6847	7.6825*x + 31.726	0.2454	3.1152*x + 37.822
BS	0.6942	5.9538*x + 28.535	0.2723	3.2467*x + 35.291

With the exception of K, the other attributes showed a better fit in the topsoil, showing the possibility of ECa measured at 0.30m better reflect the surface layer. The pH showed similar results in both layers. The residual variogram was calculated as the difference between the variogram of the primary variable with the variogram of trend component, been the variogram of the primary variable adjusted for the reduced grid points. Special attention was given in the calculation of the variogram trend component to find smaller sill than the variogram of primary variable, in order to obtain positive residuals. Thus, since it is an irregular grid with few sample points, fitting the model to the data needs a prior knowledge about the drift or trend of the variables that are being studied. For KED a minimum of two and maximum of four neighboring points was used within data interpolation (Fig. 7).

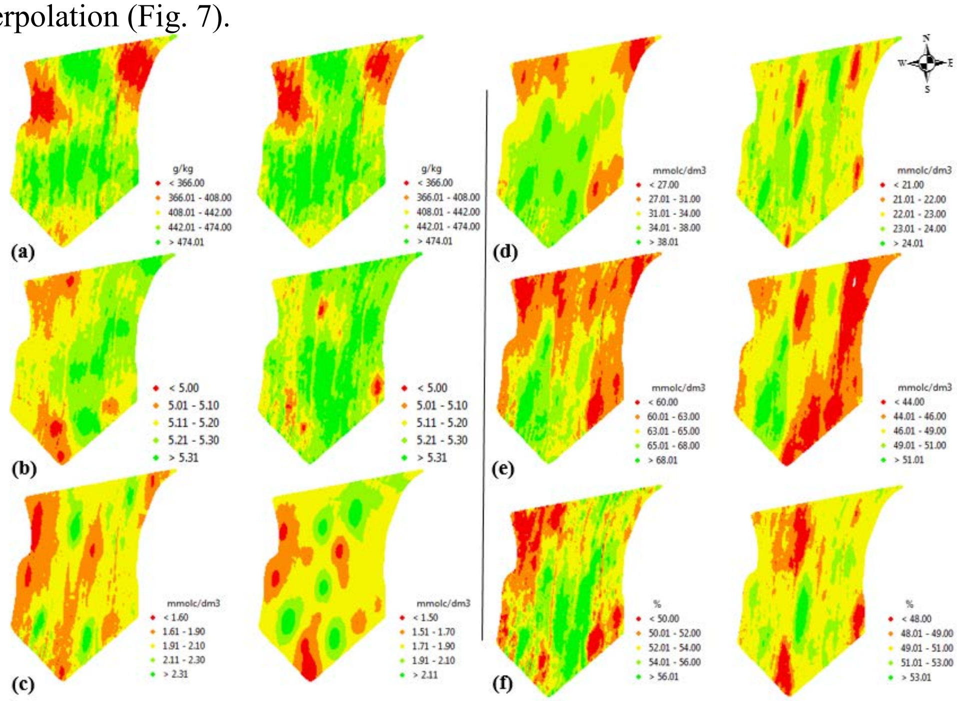

Fig. 7. Thematic maps generated by kriging with external drift (KED) of clay (a), pH (b), K (c), SEB (d), CEC (e), BS (f) layers 0.00 to 0.20 (left) and 0.20 to 0.40 (right).

A comparison of the OK and KED results using Person´s correlation coefficient reveals that there is a 50–75% agreement when combined ECa and selected soil attributes, with the exception of K. Kappa Index showed a poor agreement for BS, SEB and K, fair agreement for CEC e pH and moderate for clay. The prediction of soil map using KED generated reliable soil maps, and the method appears to deserve more research effort, given the reliability and low cost of the resulting information. On the other hand, the estimation of K with a better correlation remains a challenge. Moreover, new soil sensors can be integrated with the ECa in order to improve spatial distribution estimation of this element.

Table 5. Pearson's correlation and Kappa Index for the studied attributes in layers of 0.00 to 0.20m and 0.20 to 0.40m.

Depth (m)	Clay	pH	K	SEB	CEC	BS
			Pearson's Correlation			
0.00 to 0.20	0.759	0.739	0.347	0.546	0.545	0.489
0.20 to 0.40	0.776	0.469	0.564	0.427	0.759	0.444
			Kappa Index			
0.00 to 0.20	0.356	0.246	0.117	0.160	0.223	0.163
0.20 to 0.40	0.401	0.136	0.171	0.089	0.230	0.070

CONCLUSIONS

The spatial distribution of clay and some soil chemical attributes can be estimated by kriging with external drift using reduced targeted soil sampling based on ECa. We concluded that this kriging technique, which uses dynamic secondary information, has the clear advantages of using fewer sampling points, even though the Person´s correlation coefficient is not high. To improve prediction uncertainties, one can try to add more information using other soil sensors in the trend model. This offers good perspective for other attributes that need to be estimated over large areas based on a small number of soil samples, assisting farmers in crop management and ensuring higher economic returns and sustainability of the production system.

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