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Spatial patterns of soil attributes in a fluvent in the semiarid region, Brazil

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Spatial variability studies on soil attributes are fundamental for adoption of best agricultural practices concerned with irrigated agricultural sustainability. This study aims to infer the spatial variability patterns of soil moisture, soils salinity and soil texture in an irrigated area of Pernambuco State (Brazil) under cultivation of carrot (*Daucus Carota* L.), during the dry period of 2012. The area is a typical system in the semiarid under small scale agricultural practices. For the study, it was adopted a 4 × 4 m regular mesh, with 49 sampling points collected at 0-0.2 m and 0.2-0.4 m layers. Data were submitted to classical statistical procedure, followed by geostatistical analysis. For soil moisture at 0.2-0.4 m layer and clay content, the degree of variability was considered low. For soil moisture at 0-0.2 m the degree of variability was moderate, while the electrical conductivity showed a high degree of variability. Occurrence of soil salinity is higher at the soil surface. Water flow occurs from the borders to the central plot, as evidenced by contour maps. Geostatistics allowed the characterization of the spatial variability patterns for the main soil attributes in an irrigated plot in the semiarid of Brazil, and it has been shown as an important tool for the prediction of soil attributes. Such results are important for issuing guidance for sustainable small scale agriculture practices in the region.

Key words: Geostatistics, soil moisture, salinity, texture, communal farming.

INTRODUCTION

Inadequate soil and water management has led many irrigated areas to become non-productive all around the world. When croplands are intensively explored, spatial and temporal variations of the various soil attributes may occur, and the agricultural economy becomes dependent on these changes (Scherpinski et al., 2010). The spatial variability studies of soil properties are fundamental to evaluate the management effectiveness, concerned with the sustainability and environmental quality (Darwish et al., 2015). Producing maps of soil properties requires a

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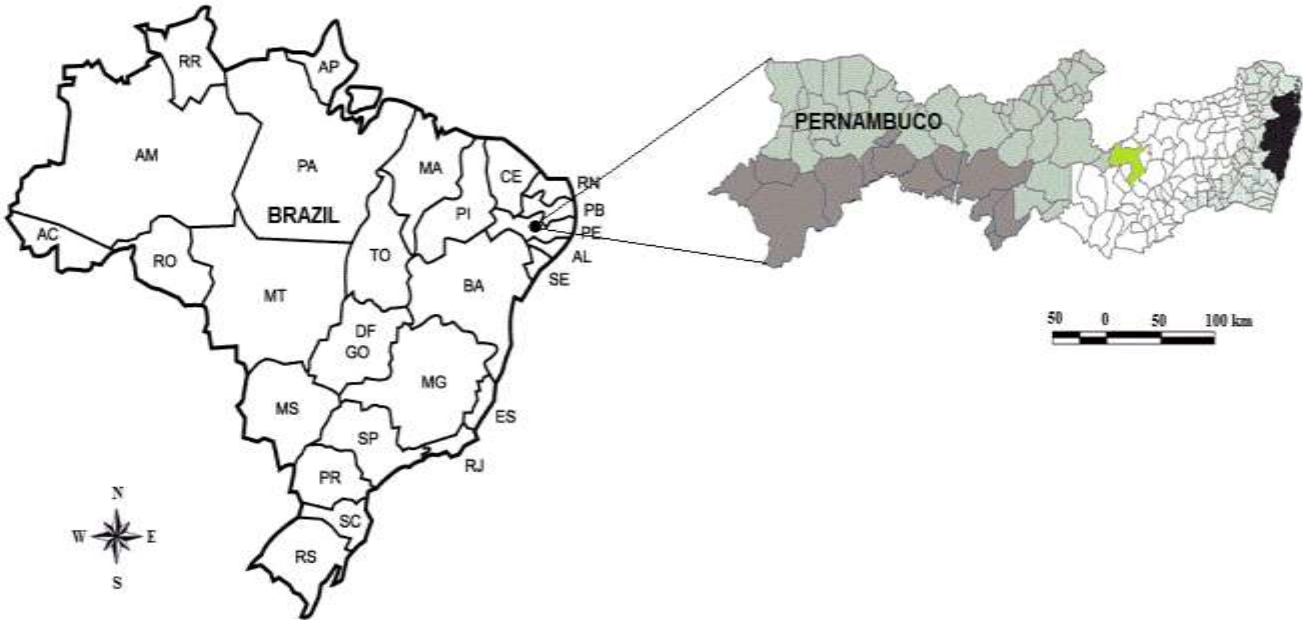

Figure. 1. Map of Brazil, Pernambuco State and Pesqueira city (green) (Source: Modified from https://portal.macamp.com.br).

large effort of sampling and evaluation of these properties, resulting in high investment of time and cost. Hence, the definition of an ideal sampling design and technique is a fundamental criterion for mapping. One tool that can assist in studies is the precision agriculture (Triphati et al., 2015). Studies that aim to understand the distribution of soil attributes minimize time and cost of sampling,and the maps can be applied in scientific areas, for example, in hydrological and climatic studies, as well as operational applications, such as decision making in agricultural practices. Among the various soil attributes, water content, electrical conductivity and soil texture can be considered as main quality indicators and their determinations have a high importance in many scientific fields and operational applications (Brocca et al., 2012; Darwish et al., 2015; Triphati et al., 2015). There are several recent studies about the spatial variability of soil attributes: spatial and temporal variability of soil moisture in the surface layer of the Loess Plateau in China (Hu et al., 2008); spatial variability of soil physical properties in a semiarid alluvial valley at Pernambuco State (Souza et al., 2008); spatial variability of hydraulic conductivity and water infiltration in the soil at Paraná State (Scherpinski et al., 2010); study in a catchment scale of soil moisture spatial–temporal variability in central Italy (Brocca et al., 2012); spatial distribution analysis of soil variables for agronomic development in North-Coastal of Egypt (Darwish et al., 2015); and spatial variability analysis of soil properties in salt affected coastal India using geostatistics and kriging (Triphati et al., 2015). Although there are many applications related to the study of the spatial variability of soil attributes, there are still few studies carried out in semiarid Brazilian regions, such as the present study.

Among management tools for sustainable development of irrigated areas, those based on the understanding of the spatial variability pattern of different soil attributes are very important. Geostatistics techniques, which can be defined as tools for studying and predicting the spatial patterns of several variables, allow understanding spatial variability in a change of natural phenomena (Jackson et al., 2007), as well as the spatial properties of soil attributes (Cambardella et al., 1994). Geostatistics offers a set of statistical tools that include the spatial coordinates of soil samples in data processing, allowing a description of spatial patterns, prediction at unsampled locations, and evaluation of the uncertainty associated to these predictions (Triphati et al., 2015). This work aims to study the spatial variability of soil moisture, salinity and texture in an irrigated area of Pernambuco State (Brazil) under cultivation of carrot (*Daucus carota* L.), during the dry period of 2012. This is a typical system in the semiarid under small scale agricultural practices.

MATERIALS AND METHODS

Study area

The study was conducted at Nossa Senhora do Rosário Farm, located in Pesqueira city, Pernambuco State (Brazil), with 08°10' S and 35°11' W coordinates and altitude of 650 m (Figure 1). The study area is within a rural settlement installed by the State Government, where small scale agriculture is practiced. The predominant soil in the region is Fluvent. The climate is BSsh (extremely hot, semiarid), according to the Köppen classification,

Table 1. Annual (1961-1990) climate normal in Pesqueira (Source: http://www.inmet.gov.br).

P_{cum} (mm)	P (mm)			E_t (mm)	T_m (°C)	RH_m (%)	W_s (ms^{-1})
	3 days	5 days	10 days				
701.5	30	20.4	9.3	1589.8	22.7	73.1	3.61

P_{cum}, Cumulative precipitation; P, Number of periods with 3 or more, 5 or more and 10 or more consecutive days without precipitation; E_t, total evaporation; T_m, Mean temperature; RH_m, mean relative humidity; W_s, wind speed.

Table 2. Physical characteristics of Fluvent at 0-0.2 and 0.2-0.4 m layers.

Layer (m)	Sand	Silt	Clay	Ds (g cm^{-3})	Dp (g cm^{-3})	P (%)
		(%)				
0 - 0.2	56.31	22.12	21.37	1.59	2.5	36.4
0.2 - 0.4	56.61	20.74	22.53			

Ds, Bulk density; Dp, particle density; P, porosity.

with an annual mean precipitation of 607 mm (Scherpinski et al., 2010). The annual climatological Normal for the period 1961 to 1990 in Pesqueira is presented in Table 1. The experimental area consists in a one hectare plot cultivated with carrot (*Daucus Carota* L.). The area is irrigated during 1.5 hours per day and the micro sprinkler system has a flow rate of 105 L h^{-1}, with a control of the applied water depth. Groundwater is used for irrigation, with electrical conductivity (EC) of 0.57 dS m^{-1}.

Samples

For the spatial analysis, it was adopted an irrigated plot of 576 m² under carrot cultivation (*Daucus carota* L.). In order to characterize the spatial dependence, a regular grid of 4 × 4 m was established, comprising 49 sampling points. The samples at 0-0.2 m and 0.2-0.4 m layers were transported to the laboratory and were air dried for 72 h and separated through sieve with a 2 mm diameter. Physical characteristics (Table 2), soil moisture evaluating, electrical conductivity and texture were performed according to Embrapa (2011). According to the textural classification of the Brazilian Society of Soil Science, the Fluvent was classified as sandy clay loam texture.

Statistical and geostatistical analysis

Data were initially analyzed using descriptive statistics, by evaluating central tendency (mean, median and mode) and dispersion measures (standard deviation, variance and coefficient of variation); and values of kurtosis, and skewness. Normal distribution was tested according to the Kolmogorov Smirnov test at 5% significance level. Spatial dependence was analyzed by fitting experimental semivariograms based on the assumption of intrinsic stationarity hypothesis (Journel and Huijbregts, 1978) to different theoretical variogram models. Coefficients of variation were observed, as suggested by Warrick and Nielsen (1998), which considers low variability when CV < 15%; moderate for 15 < CV < 50% and high variability when CV > 50%. Semivariance analysis was applied to estimate the range over which samples of the soil parameters were related. The semivariance, γ(*h*), of all observed values of a variable separated by a vector *h* were defined as:

$$\gamma(h) = \left[\frac{1}{2N(h)}\right] \sum_{\infty=1}^{N(h)} [Z_i - Z_{i+h}]^2 \quad (1)$$

where Z_i and Z_{i+h} are experimental estimates of any two points separated by the vector *h*, and N (*h*) is the number of experimental pairs separated by *h* (Goovaerts, 1999). For construction of the experimental semivariograms, the software GS+ tool (Gamma Design, 2004) was used, adopting the classic semi-variance estimator (Journel and Huijbregts, 1978). The Gaussian, exponential and spherical models were tested with the experimental data to fit the mean close to zero and standard deviation close to one, using the technique of cross-validation Jack – Knifing. The coefficients of the best fit model were then estimated. The degree of spatial dependence was observed according to the classification of Cambardella et al. (1994), where the degree of dependence lower than 25% characterizes strong spatial dependence, between 25 and 75% moderate spatial dependence, while higher than 75%, weak dependence. For the construction of contour maps, the software Surfer 9.0 was used (Golden Software, 2009).

RESULTS AND DISCUSSION

The results of statistical analysis for soil moisture, electrical conductivity and clay content at 0-0.2 m and 0.2-0.4 m layers are presented in Table 3. Kolmogorov Smirnov test indicated that the data of moisture and clay content at 0-0.2 m and 0.2-0.4 m, and soil electrical conductivity of 0-0.2 m follow Normal distribution, after removing outliers (Hoaglin et al., 1983). Electrical conductivity at 0.2-0.4 m follows a Normal behavior. Additionally, the mean, median and mode for the analyzed variables have similar values (Table 3), suggesting a symmetrical distribution. Such result indicates that the measures of central tendency are not dominated by atypical distribution values (Cambardella et al., 1994), as all the variables follow a Normal distribution. Soil moisture presented values of skewness consistent with a Normal distribution. In effect, the skewness coefficient should approach 0. It is noted that for the moisture and clay content, the values of these coefficients approached the standards required, with an electrical conductivity parameter which is distanced a

Table 3. Descriptive statistics for the soil moisture, electrical conductivity and clay content.

Descriptive statistics	Soil moisture 0-0.2 m (%)	Soil moisture 0.2-0.4 m (%)	EC 0-0.2 m (dS m^{-1})	EC 0.2-0.4 m (dS m^{-1})	Clay Content 0-0.2 m (%)	Clay content 0.2-0.4 m (%)
Mean	12.3	10.65	2.05	1.57	21.37	22.42
Median	12	11	1.61	0.95	21.48	22.64
Mode	13	11	-	-	22.64	22.64
SD	1.93	0.92	1.52	1.25	2.67	2.28
CV	15.72	8.65	74.24	79.64	12.48	10.15
Skewness	0.09	-0.47	1.23	1.10	0.03	-0.08
Kurtosis	0.21	-0.5	0.98	0.25	-0.81	0.05
1º Quartile	11	10	1.05	0.59	18.64	20.64
2º Quartile	12	11	1.61	0.95	21.48	22.64
3º Quartile	13	11	2.59	2.45	23.04	24.46
Variance	3.75	0.85	2.32	1.56	7.11	5.18

EC, Electrical conductivity; SD, standard deviation; CV, coefficient of variation.

little from zero. Variables showed a positive asymmetry, indicative that the most data tends to the minimum values. Soil moisture at 0-0.2 m, EC in both depths and clay content at 0.2-0.4 m had a positive kurtosis, which indicates that the data are dispersed, and that the distribution presents elevation (leptokurtic). Soil moisture at 0.2-0.4 m and clay content at 0-0.2 m showed negative kurtosis, where it is found that the curve is flatter than normal (platykurtic).

Other authors have studied the spatial variability of water content in different soil types and also found normality for this attribute (e.g. Hu et al., 2008; Brocca et al., 2012; García et al., 2014). Geostatistics allows the spatial dependence analysis, from the group of experimental semivariogram, according to a mathematical model, and the characterization of variability by estimating without tendency, estimating values at non-sampled locations. For setting semivariograms, normality of data is not required, but desirable. If the distribution is not normal, but is reasonably symmetrical, it may be sufficient for accepting the hypotheses for the semivariogram construction. Soil moisture at 0.2-0.4 m layer and clay content at both layers showed low degree of variability, with values respectively of 8.65, 12.48 e 10.15%. Souza et al., (2008) also found low variability degree for the clay fraction at 0-0.2 m layer in a Fluvent soil. Soil moisture at 0-0.2 m layer had a moderate degree of variability, with 15.72%. The low or moderate degree of variability found may have been influenced by irrigation performed in the study area a day before sampling. There was no antecedent precipitation in three days and the sampling and measurements were performed during the dry season in the region. Hu et al. (2008) also found moderate variability for water content in a soil in the Loess Plateau of China at 0-0.6 m layer. Brocca et al. (2012) studying the spatial and temporal variability of soil moisture at the catchment scale, found low variability at 0-0.15 m layer. According to the authors, these results can be used to estimate the average conditions of variation in a desired range and consequently, the number of required samples for spatial analysis. This was not the focus of this study, but may be further investigated. Darwish et al. (2015) studying a seacoast to the Libyan plateau, found low degree of variability for clay content.

Electrical conductivity at 0-0.2 m and 0.2-0.4 m layers showed a high degree of variability, since the coefficients of variation were respectively 74.24 and 79.64%. Other authors also found high variability for this attribute as Souza et al. (2000) working on an alluvial soil in the state of Paraíba (Brazil) and Darwish et al. (2015) studying a seacoast to the Libyan plateau. According to Souza et al. (2000), the high variability is related to the heterogeneity of these soils, caused by factors such as the processes of accumulation and distribution of its particles, they are topographically positioned in an alluvial valley, in addition to management they are subjected to, among other factors. It was observed correlation between the mean soil moisture and its standard deviation, in agreement with other recent studies (Gao et al., 2011; Brocca et al., 2012; Gao et al., 2013; Zhang et al., 2013). A positive correlation was also observed between soil moisture and the coefficient of variation, in which the decrease in the mean soil moisture along the layers reduced the spatial variability (Table 3), in agreement with Gao et al. (2011), Gao et al. (2013) and Zhang et al. (2013). The decrease on the moisture variation along the soil layer is because the subsurface layers are usually less influenced by agricultural practices, which occur at the first soil layer, mainly irrigation practices.

Except for the clay fraction at 0.2-0.4 m layer, for which the best fit was to the Gaussian model, for all other attributes the semivariogram showed pure nugget effect, indicating the randomness of the data. The pure nugget

Table 4. Parameters of semivariogram models fitted to experimental data of the study variables and parameters obtained by the validation technique.

Parameter	Soil moisture 0-0.2 m (%)	Soil moisture 0.2-0.4 m (%)	EC 0-0.2 m (dS m^{-1})	EC 0.2-0.4 m (dS m^{-1})	Clay content 0-0.2 m (%)	Clay content 0.2-0.4 m (%)
Nugget effect$_{(C0)}$	3.95	0.92	2.15	1.45	6.77	3.24
Sill$_{(C0+C1)}$	3.95	0.92	2.15	1.45	6.77	6.56
Range (A)	13.71	13.74	13.73	13.75	13.74	7.95
GD $_{(C0/\ C0+C1)\ x\ 100}$	100	100	100	100	100	49.39
Model	PNE	PNE	PNE	PNE	PNE	Gaussian
Mean	-	-	-	-	-	0.018
SD	-	-	-	-	-	0.954

EC, Electrical conductivity; GD, degree of dependence; SD, standard deviation, PNE, pure nugget effect.

effect variogram indicate that there is no spatial correlation between the variables at the sampled distance (Cambardella et al., 1994). Additionally, the nugget effect (C_0) indicates the discontinuity of a phenomenon. According to Vieira (2000), high nugget values are indicative of variation detected by the sampling process. Souza et al. (2008) set the Gaussian model for all variables, which were the soil fractions and electrical conductivity. Results of geostatistical analysis showed that the values of soil moisture, electrical conductivity at 0-0.2 and 0.2-0.4 m layers and clay content at 0-0.2 m, had weak spatial dependence, since the relationship between the nugget and the sill was equal to 100% (Table 4). The clay content at layer 0.2-0.4 m showed moderate dependence, with 49.39%. Other authors found moderate dependence on soil moisture, with values of spatial dependence of 40, 19 and 29% to layers 0-0.15, 0.15-0.30 and 0.30-0.45 m, respectively, in an irrigated Fluvisol at same region of this study, with similar hydrological characteristics (Santos et al., 2012). However, other authors found strong spatial dependence for this variable (Yang et al., 2011). Souza et al. (2008), studying a Fluvent found high spatial dependence for sand, silt and clay fractions, and moderate dependence for electrical conductivity. Authors cite Grego and Vieira (2005) and associate the strong spatial dependence of granularity fractions to excessive movement in the soil surface, which causes a change of its original structure and makes it similar nearby points. An important aspect to be highlighted is that the degree of spatial dependence considers both the variability between sampling points, as the uncertainty of the determination method in the laboratory (Silva et al., 2010). The range indicates the extent to which the studied variable is correlated, that is, represent the radius in which an area can be considered homogeneous in relation to the parameters studied (Lima et al., 2006). Semivariogram ranges found in this study were 13.71; 13.74; 13.73; 13.75; 13.74 e 7.95 m for soil moisture, electrical conductivity and clay at 0-0.2 and 0.2-0.4 m layers, respectively. For the clay content, Silva et al. (2010) studied the spatial variability of growth parameters of castor bean and physical-chemical properties in the same study area, found a range of 11.82 at 0-0.2 m. However, Souza et al. (2008) also analyzing the clay content at 0-0.2 m found a range of 50 m. These differences can be attributed degree of soil weathering and possible movement of clay in the profile. According to Montanari et al., (2008) an important concept in soil genesis is that the high degree of weathering in the surface layers are due to their greater exposure to occurrence of the weathering process. Semivariogram model fitted for clay at 0.2-0.4 m produced estimated errors with average 0.018 and standard deviations with 0.954, respectively, indicating a good fit confirmed by cross validation. In Figure 2, semivariograms with nugget effect and the Gaussian model are presented. Maps based on the respective semivariograms are shown in Figure 3.

In the contour maps the darker areas show higher values of the evaluated data. Maps for soil moisture at 0-0.2 and 0.2-0.4 m layer show that there is higher soil moisture in the surface layer, probably due to irrigation in the area prior to sample collection. The subsurface layer had low water contents. According to Santos et al. (2012), a way of maintaining the high water levels in the soil in the region would be mainly with the addition of a continuous vegetation cover on the soil, such as mulching. Soil moisture is related to many attributes and soil conditions, such as texture, density and organic matter (Busscher et al., 1997). Cohesion is a characteristic that also changes the soil moisture. Thus, when the soil is dry or has a low water content, particles are often highly aggregated, being difficult to separate them by an external force. Additionally, for soils with loam texture, water loss occurs more rapidly due to high hydraulic conductivity, related to an in efficient water retention. It can be observed that the central regions have lower soil moisture than the borders of the area, indicating that the water movement occurs from borders to the central regions. The darker areas of the maps (left) indicate values with higher soil moisture.

Regarding the maps of soil electrical conductivity, it can

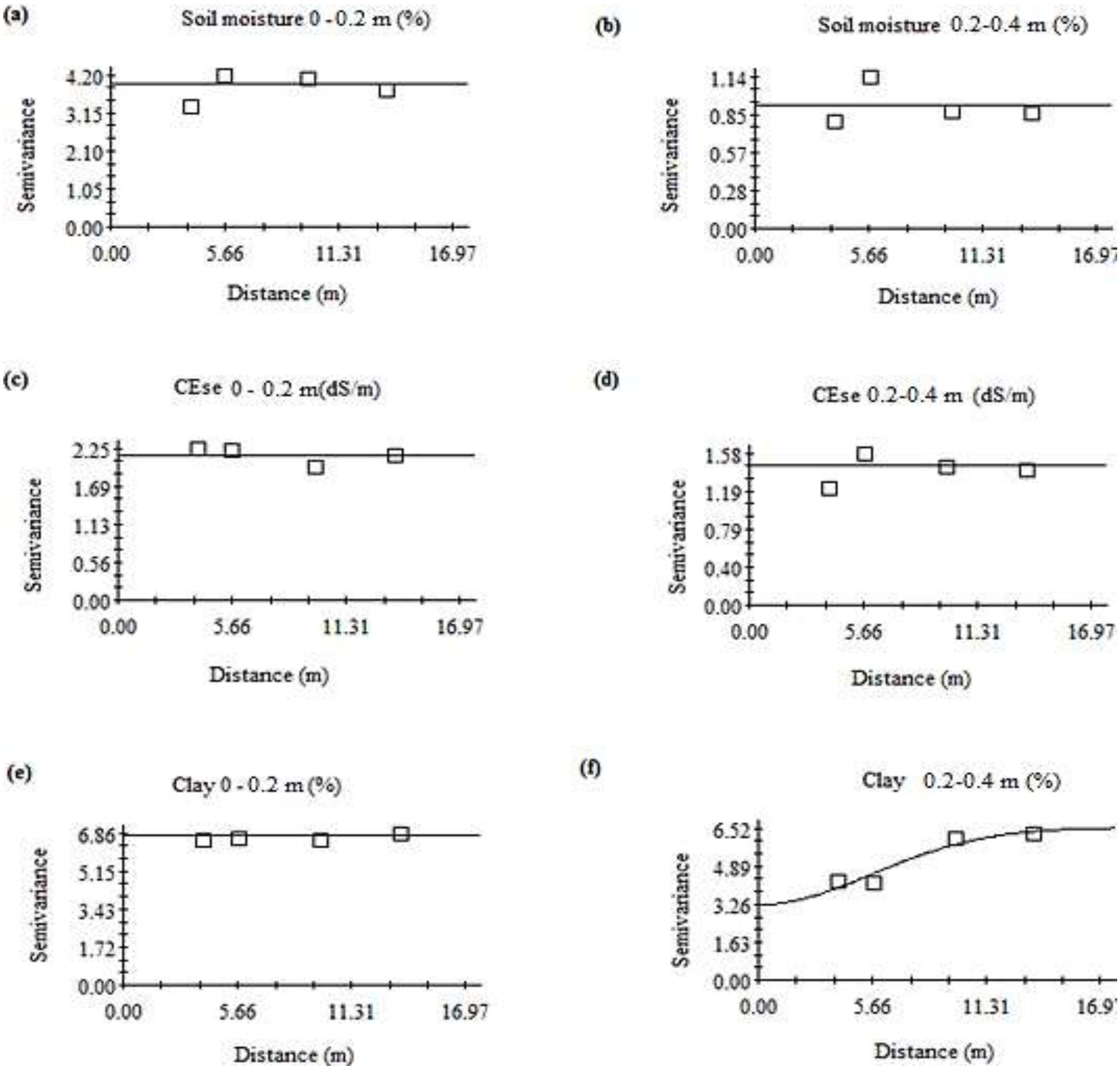

Figure 2. Semivariograms: (a) soil moisture at 0-0.2 m (%); (b) soil moisture at 0.2-0.4 m (%); (c) EC at 0-0.2 m (dS m^{-1}); (d) EC at 0.2-0.4 m (dS m^{-1}); (e) clay content at 0-0.2 m (%) and (f) clay content at 0.2-0.4 m (%).

be seen that the values are also higher in the most extreme and surface areas. According to Silva et al. (2013), the soil exposition to insolation induces capillary ascension, and consequently increases salt concentration in surface layers. Soils with high moisture have lower electrical conductivities. As commented above, the determining factor was soil moisture, because it influenced the electrical conductivity values in the soil profile. The electrical conductivity and moisture contour maps show homogeneity, have revealed a similar pattern of spatial variability. According to Fritz et al. (1998), the electrical conductivity is influenced by the water content, dissolved salts, topography, and the source material in the soil formation. In a study conducted by Silva (2016) with spatial variability of soil electrical conductivity in a cultivated area of sugarcane, the determining factor was soil moisture, because it influenced the EC values in the soil profile, as relief and the water level were the factors

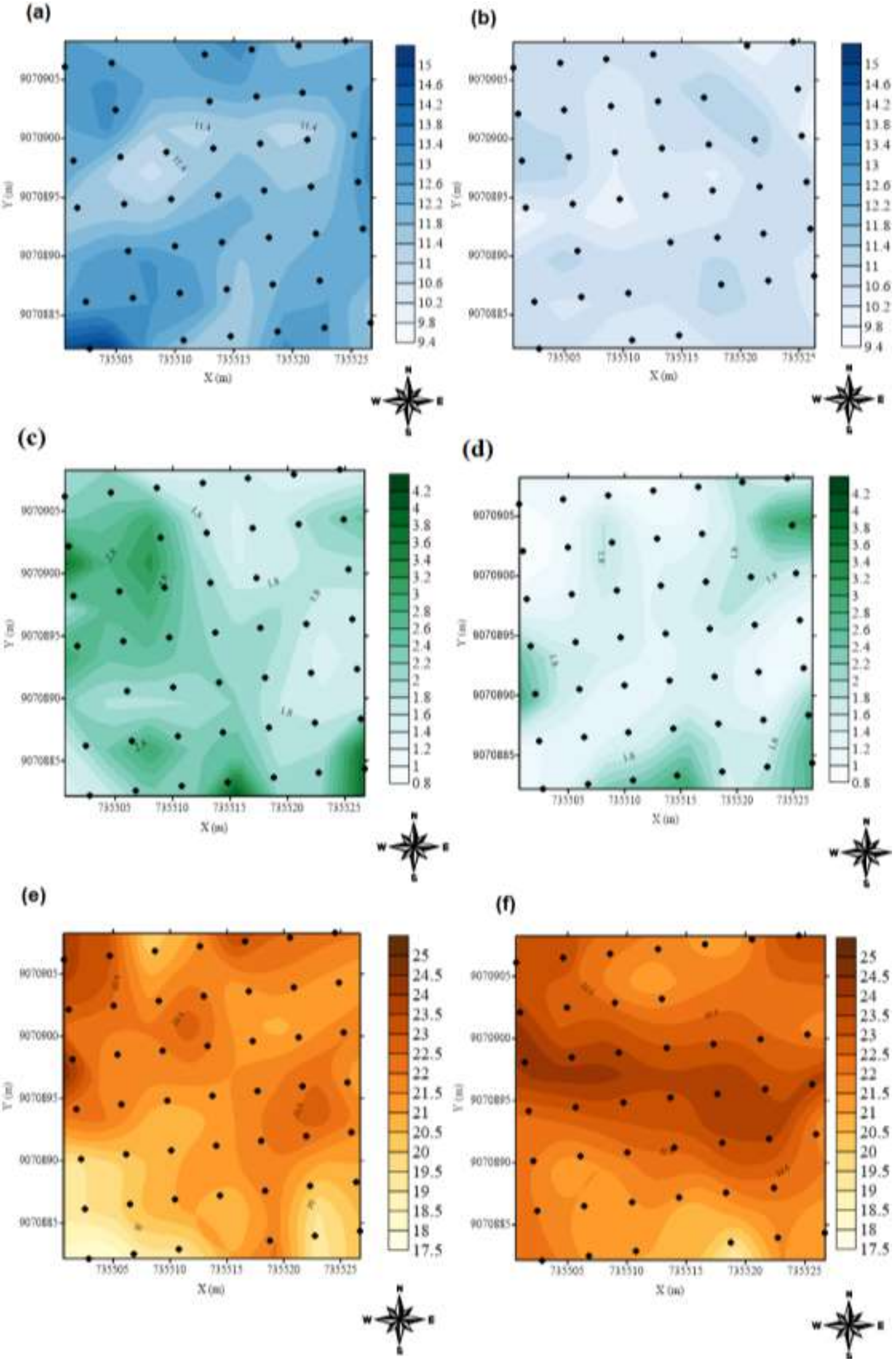

Figure 3. Maps for: (a) soil moisture at 0-0.2 m (%); (b) soil moisture at 0.2-0.4 m (%); (c) EC at 0-0.2 m (dS m^{-1}); (d) EC at 0.2-0.4 m (dS m^{-1}); (e) clay content at 0-0.2 m (%) and (f) clay content at 0.2-0.4 m (%)

that interferes with the spatial distribution of all studied attributes. Values of electrical conductivity at 0-0.2 m layer were higher than 0.2-0.4 m. It can be observed that the map 3c has less amount of clear areas in relation to the map 3d. These results are indicative that the surface layer (0-0.2 m) has higher salinity than the deeper layer (0.2-0.4 m) and this may be attributed to agriculture practiced by the local management, as well as high rates of evaporation and effect of the severe drought in the region. Considering the mean values, the average electrical conductivity of the saturation extract (EC) was equal to 2.05 dS m^{-1} at 0-0.2 m, and 1.57 dS m^{-1} for the 0.2-0.4 m layer. Silva et al. (2010) found in the same study area and before the rainy season, EC values of 1.48 dS m^{-1} and 0.65 dS m^{-1} for the 0-0.2 and 0.2-0.4 m, respectively. These results confirm that the higher salts content is in the surface layer, even using sprinkler irrigation system. Additionally, one can affirm that do not occur salinity problems in the soil, since EC values between 0-4 dS m^{-1} are classified as non-saline according Richards (1954). However, there are areas where EC values are at the limit, and so these areas can easily become saline. The carrot tolerance limits checked by Kotuby-Amacher et al. (2000) are 1.0 dS m^{-1}, with losses of 10, 25 and 50% when EC is 1.7, 2.8 and 4.6 dS m^{-1}, respectively. Also, according to the FAO (2016), the threshold is 1 dS m^{-1}, wherein carrot falls within the rating S (sensitive) salinity tolerance table. The results show that many areas of the map, due to salt levels, may can cause crop development limitations and compromise the agricultural production. Regarding the clay fraction, there is a more homogeneous distribution in the surface layer (0-0.2 m), also due to cultivation practices performed in the area, while at 0.2-0.4 m layer there is a higher amount of this fraction in the central region, also where the electrical conductivity is lower (Figures 3e, f and d). Observing Figure 3f, the clay concentration at the central region can characterize an impediment layer, with areas of lower permeability and higher water retention, soil characteristics with higher clay content. Leão et al. (2010) found that texture variability is related to the rates flow even in a small scale.

Conclusions

Geostatistics allowed the characterization of the spatial variability patterns of the main soil attributes in an irrigated plot in the semiarid of Brazil. It has been shown as an important tool for the prediction of soil attributes. The results may help to issue guidelines for agricultural management. The main results were:

1 The electrical conductivity and moisture contour maps show homogeneity, and revealed a similar pattern of spatial variability.
2 The electrical conductivity of both layers presented a high degree of variability.
3 Occurrence of soil salinity is higher at the soil surface.
4 Water flow occurs from both ends to the central plot, as evidenced by the maps.

Conflict of Interests

The authors have not declared any conflict of interests.

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REFERENCES

Brocca L, Tullo T, Melone F, Moramarco T, Morbidelli R (2012). Catchment scale soil moisture spatial–temporal variability. J. Hydrol. pp. 422-423:63-75.
Busscher WJ, Bauer PJ, Camp CR, Sojka RE (1997). Correction of cone index for soil water content differences in a coastal plain soil. Soil Tillage Res. 43:205-217.
Cambardella CA, Moorman TB, Novak JM, Parkin TB, Karlen DL, Turco RF, Konopka AE (1994). Field scale variability of soil properties in Central Iowa soils. Soil Sci. Society Am. J. 58:1501-1511.
Darwish KM, Rashad M, Mohamed SZ, Gad A (2015). Spatial distribution analysis of soil variables for agronomic development in El-Omayed Area, North-Coastal of Egypt. Environ. Earth Sci. 74:889-901.
FAO - Food and Agriculture Organization (2016). Agricultural Drainage Water Management in Arid and Semiarid Areas. Annex 1. Crop salt tolerance data. 24 p.
Fritz RM, Maio DD, Schumacher TE, Clay DE, Carlson CG, Ellsbury MMM, Dalsted KJ (1998). Field comparison of two soil electrical conductivity measurement systems. In: International Conference on Precision Agriculture, 4, Proceedings, St. Paul: ASA; CSSA; SSSA pp. 1211-1217.
Gamma Design. GS+ version 7.0. (2004). Plainwell, Michigan: Gamma Desing Software. 1 CD-ROM.
Embrapa. Empresa Brasileira de Pesquisa Agropecuária (2011). Manual de métodos de análises de solo. Rio de Janeiro 225 p.
Gao XD, Wu PT, Zhao XN, Shi YG, Wang JW, Zhang BQ (2011). Soil moisture variability along transects over a well-developed gully in the Loess Plateau, China. Catena 87:357-367.
Gao X, Wu P, Zhao X, Zhang B, Wang J, Shi Y (2013). Estimating the spatial means and variability of root-zone soil moisture in gullies using measurements from nearby uplands. J. Hydrol. 476:28-41.
García GM, Pachepsky YA, Vereecken H (2014). Effect of soil hydraulic properties on the relationship between the spatial mean and variability of soil moisture. J. Hydrol. 516:154-160.
Golden Software (2009). Surfer 9.0 - User’s Guide. Colorado: Golden Software 56 p.
Goovaerts P (1999). Geostatistics in soil science: state-of-the-art and perspectives. Geoderma 89:1-45.
Grego CL, Vieira SR (2005). Variabilidade espacial de propriedades físicas do solo em uma parcela experimental. Rev. Bras. Ciênc. do Solo 29:169-177.
Hoaglin DC, Mosteller F, Tykey JW (1983). Análisis exploratória de datos: Técnicas robustas, un guia. Lisboa: Salamandra 446p.
Hu W, Shao MA, Wang QJ, Reichardt K (2008). Soil water content temporal spatial variability of the surface layer of a Loess Plateau hillside in China. Sci. Agríc. 65:277-289.

Jackson RD, Bell MM, Gratton C (2007). Assessing ecosystem variance at different scales to generalize about pasture management in southern Wisconsin. Agricultural Ecosystem Environment. 122:471-478.

Journel AG, Huijbregts J (1978). Mining geostatistics. London: Academic Press 600p.

Kotuby-Amacher J, Koenig R, Kitchen B (2000). Salinity and plant tolerance. Utah State University Extension, Electronic Publishing, AG-SO-03.

Leão MGA, Marques-Júnior J, Souza ZM, Pereira, GT (2010). Variabilidade espacial da textura de um Latossolo sob cultivo de Citrus. Ciênc. agrotécnica 34(1):121-131.

Lima JAG, Mendes AMS, Duda GP, Ferreira CV (2006). Variabilidade espacial de características físico-hídricas de um Cambissolo cultivado com mamão no semiárido do RN. Caatinga 19:192-199.

Montanari R, Pereira GT, Marques-Júnior J, Souza ZM, Pazeto RJ, Camargo LA (2008). Variabilidade espacial de atributos químicos em Latossolo e Argissolos. Ciênc. Rural. 38:1266-1272.

Richards LA (1954). Diagnosis and improvement of saline and alkali soils. Washington D.C., U.S. Salinity Laboratory, (USDA Agriculture Handbook, 60). 160 p.

Santos KS, Montenegro AAA, Montenegro SMGL, Andrade TS, Fontes-Júnior RVP (2012). Variabilidade espacial de atributos físicos em solos de vale aluvial no semiárido de Pernambuco. Rev. Bras. Engenharia Agríc. Ambient. 16:828-835.

Scherpinski C, Uribe-Opazo MA, Boas MAV, Sampaio SC, Johann JÁ (2010). Variabilidade espacial da condutividade hidráulica e da infiltração da água no solo. Acta Sci. Agron. 32:7-13.

Silva JJN, Montenegro AAA, Silva EFF, Fontes-Júnior RVP, Silva APN (2010). Variabilidade espacial de parâmetros de crescimento da mamoneira e de atributos físico-químicos em Neossolo. Rev. Bras. Engenharia Agríc. Ambient. 14:921-931.

Silva JS, Montenegro AAA, Silva EFF, Andrade CWL, Silva JRL (2013). Distribuição espacial da condutividade elétrica e matéria orgânica em Neossolo Flúvico. Rev. Bras. Geografia Física 6(4):764-776.

Silva JS (2016). Variabilidade espacial e temporal da salinidade do solo e da produtividade de cana-de-açúcar em área de sequeiro. Thesis (Doctorate) Federal Rural University of Pernambuco. Recife, Brazil 116 p.

Souza ER, Montenegro AAA, Montenegro SMGL, Santos TEM, Andrade TS, Pedrosa ER (2008). Variabilidade espacial das frações granulométricas e da salinidade em um Neossolo Flúvico do semiárido. Ciênc. Rural. 38:698-704.

Souza LC, Queiroz JE, Gheyi HR (2000). Variabilidade espacial da salinidade de um solo aluvial no semiárido paraibano. Rev. Bras. Engenharia Agríc. Ambient. 4:35-40.

Triphati R, Nayak AK, Shahid M, Raja R, Panda BB, Mohanty S, Kumar A, Lal B, Gautam P, Sahoo RN (2015). Characterizing spatial variability of soil properties in salt affected coastal India using geostatistics and kriging. Arab J Geosci. 8:10693-10703.

Vieira SR (2000). Geoestatística em estudo da variabilidade espacial do solo. In: Novais RF, Alvarez VVH, Schaefer CEGR (ed.) Tópicos Ciência do Solo. Sociedade Brasileira de Ciência do Solo. Campinas: Sociedade Bras. Ciênc. Solo pp. 1-54.

Warrick AW, Nielsen DR (1998). Spatial variability of soil physical properties in the field. In: Hillel, D. Environmental soil physics (655-675). New York: Academic.

Yang Z, Ouyang H, Zhang X, Xu X, Zhou C, Yang W (2011). Spatial variability of soil moisture at typical alpine meadow and steppe sites in the Qinghai-Tibetan Plateau permafrost region. Environ. Earth Sci. 63:477-488.

Zhang M, Li M, Wang W, Liu C, Gao H (2013). Temporal and spatial variability of soil moisture based on WSN. Math. Comput. Model. 58:826-833.