Original Article

SPATIAL VARIABILITY STRUCTURE OF THE SURFACE LAYER ATTRIBUTES OF GLEYSOLS FROM THE COASTAL PLAIN OF RIO GRANDE DO SUL

ESTRUTURA DE VARIABILIDADE ESPACIAL DOS ATRIBUTOS DA CAMADA SUPERFICIAL DE GLEISSOLOS DA PLANÍCIE COSTEIRA DO RIO GRANDE DO SUL

Dioni Glei Bonini BITENCOURT[1]; Luís Carlos TIMM[2]; Ednaldo Carvalho GUIMARÃES[3]; Luiz Fernando Spinelli PINTO[4]; Eloy Antonio PAULETTO[4]; Letiane Helwig PENNING[5]

1. Professor Adjunto do Departamento de Aquicultura, Universidade Federal do Pampa, Uruguaiana, RS, Brasil. dioniglei@gmail.com; 2. Professor Associado do Departamento de Engenharia Rural, Faculdade de Agronomia Eliseu Maciel, Universidade Federal de Pelotas - UFPel, Capão do Leão, RS, Brasil; 3. Professor Associado do Departamento de Matemática, Faculdade de Matemática, Universidade Federal de Uberlândia, Uberlândia, MG, Brasil; 4. Professores Associados do Departamento de Solos, Faculdade de Agronomia Eliseu Maciel - UFPel, Capão do Leão, RS, Brasil; 5. Mestranda em Manejo e Conservação do Solo e da Água, Faculdade de Agronomia Eliseu Maciel - UFPel, Capão do Leão, RS, Brasil.

ABSTRACT: The spatial variability structure of soil attributes in a certain area might influence the semivariogram fitting model and, consequently, the attribute behavior mapping in this area leading to different decisions regarding crop management. This study aimed to identify, characterize and quantify the spatial variability of chemical attributes and the clay content in the superficial layer of a Gleysoils mapping unit (MU) at reconnaissance scale in the coastal plain of Rio Grande do Sul, through descriptive statistics and geostatistics and compare the results taking into consideration the existence of three Gleysoils mapping units at semi-detailed scale through the scaled semivariogram technique. A 403 ha area located in the Rio Grande do Sul Coastal Plain, in the city of Jaguarão was sub-divided into three mapping units (GL-mo, GL-mo.lv and GL-lv), a sampling grid with 403 points, 100 m far one from another was established. In a 5 m radius around each sampling point, 10 sub-samples of disturbed soil were collected from the 0-0.20 m layer, making up a soil compound sample, and the following attributes were determined for each sample: pH in water, organic carbon, phosphorus, potassium, sodium, calcium, magnesium, aluminum, potential acidity and clay content. The cation Exchange capacity (pH=7.0) and base saturation were also calculated. The identification, characterization and quantification of the spatial variability of attributes from the soil Ap horizons were carried out through descriptive statistics and geostatistics, considering the mapping unit at the reconnaissance scale and the three units at the semi-detailed scale. In the geostatistics analysis, the scaled semivariogram technique was employed aiming to compare the spatial variability structure for each soil attribute in the total area and in the three MUs at the semi-detailed scale. Regarding the descriptive statistics, the Ap horizon attributes behavior in GL-lv was similar to that in the total area of the soil layer under analysis; however, when considering the spatial coordinates, the spatial variability structure of the GL-mo.lv attributes was the one that best described the attributes variability in the total area. The scaled semivariogram technique revealed that the spatial behavior of the attributes pH and exchangeable sodium was similar, regardless of the evaluation scale adopted or the factor used for the scaled semivariogram.

KEYWORDS: Geostatistics. Scaled semivariograms. Wetlands. Soil map units. Precision farming.

INTRODUCTION

Learning about the spatial variability of soil attributes, at the field or water basin level, is essential for a better farming management practice as well as to evaluate the farming impact on the environment (CAMBARDELLA et al., 1994). In Brazil, however, most of its territory has only information generated in low intensity exploratory or reconnaissance surveys, made up by highly heterogeneous mapping units (associations), which are not enough for this kind of evaluations (STRECK et al., 2008).

Criticism to the qualitative character of the conventional pedologic surveys, based on a mental model (soil-landscape relation), allied to the advent of new technologies (remote sensing, GPS, SIG, digital elevation model, etc.) led to the development of new quantitative methods to carry out the soil pedologic survey taking into consideration its spatial distribution. McBratney et al. (2003) pointed out that in response to these criticisms, quantitative methods have been used to describe, classify and study the soil spatial distribution pattern more objectively. The authors also emphasize that these methods are categorized within a soil science emerging area known as Pedometry, and the ones

Received: 11/03/15
Accepted: 10/06/15

most commonly used to analyze the soil spatial distribution are geostatistics, classical statistics and the combination of both.

Geostatistics has been used successfully to evaluate, identify and map the spatial variability of soil attributes (LARK, 2012; TRANGMAR et al., 1985) and its tools have been employed in Precision Farming aiming at soil sampling, attributes estimate and mapping, fertilizers variable application rate, among others (OLIVER, 2010). Some authors have suggested to consider the soil mapping units in its interpretation as advantageous (COUTO et al., 1997; ROGOWSKI; WOLF, 1994).

Wu et al. (2008) used geostatistics to estimate the concentration of four heavy metals (copper, zinc, lead and cadmium) in three soil mapping units. Those authors concluded that the kind of soil was one of the factors that most affected these metals concentration and, therefore, the metal spatial variability would be better characterized if the soil mapping units were taken into consideration.

Liu et al. (2006), comparing ordinary kriging combined with soil map design, concluded that the soil map conventional design can be used to improve its attributes spatial interpolation. Duffera et al. (2007), studying the relation between vertical and horizontal spatial variability of physical attributes within three mapping units in a 12 ha area (scale 1:2400), found that the spatial variability structure of some physical attributes (texture, water available to the plants and soil resistance to penetration) were captured by the units but others (soil density, total porosity and water conductivity in saturated soils) were not.

Nielsen et al. (1996) carried out a detailed soil survey (scale around 1:15.000) from a 100 ha area within a single mapping unit at the reconnaissance scale, identifying seven mapping units, named 'pedotops' (mapping unit including a taxonomic unit at its lowest level) by the authors. After that, they measured the water infiltration rate in the soil at 293 sites (separated by 60 m intervals) and estimated it by using regression equations based on the soil superficial layer texture. The authors concluded that in the situation in which the units ('pedotops') were not considered, there was no correlation between the measured values and those estimated for the infiltration rate; however, when they were considered, the data correlation became quite high ($\mathbf{r^2 = 0.936}$).

The hypothesis of this study is that the mapping units associated to the scale of soil survey might influence the semivariogram fitting model and, consequently, the spatial variability structure, leading to different decisions regarding crop management. In this sense, the objective of this study was to identify, characterize and quantify the spatial variability of chemical attributes and clay content in the superficial layer of a Gleysoil mapping unit at the low intensity reconnaissance scale, used with flooded rice in the Coastal Plain of Rio Grande do Sul, through descriptive statistics and geostatistics and to compare the results taking into consideration the existence of three Gleysoil mapping units at the semi-detailed scale through the scaled semivariogram technique.

MATERIAL AND METHODS

The study was carried out in a 403 ha area, inside the "Formiga" mapping unit in the Reconnaissance Survey in the State of Rio Grande do Sul (BRASIL, 1973; STRECK et al., 2008) (Figure 1). The area is located in Granja Bretanhas farm, in the Coastal Plain of Rio Grande do Sul, municipality of Jaguarão - Brazil. The area central point geographical coordinate is 32°32'45"S and 53°05'45"W and the relief is plain, with altitude ranging from 5 to 7 m above the sea level. According to the Köppen climate classification, it has a Cfa climate, with a maritime subtropical environment, sub-humid summer and humid or super-humid climate throughout the other seasons (MOTA, 1983).

Initially, a previous recognition of the soil was carried out in the area, involving photo-interpretation (aerial photos scale 1:20000), transections and field observation via borehole, according to Embrapa regulations (1995). After checking, the total area was subdivided into three more homogeneous areas which were characterized, according to Lemos; Santos (1996) and Embrapa (1997) in the Brazilian Soil Classification System as: Gleissolo Melânico Ta eutrófico chernossólico, Gleissolo Melânico Ta eutrófico luvissólico, and Gleissolo Háplico Ta eutrófico luvissólico (Figure 2), corresponding to Mollic Gleysol (GL-mo), Luvic Mollic Gleysol (GL-mo.lv), and Luvic Gleysol (GL-lv), respectively, according to the World Reference Base classification (WRB, 2014).

Throughout the 1999 to 2005 crops, the crop system adopted in the study area was flooded rice followed by soybeans. In the years 1998 and 1999, the area was systematized and since then the non-tillage system has been employed. In the experimental area, the sampling grid had 403 points established, spaced 100 m, with the aid of a GPS (Figure 2).

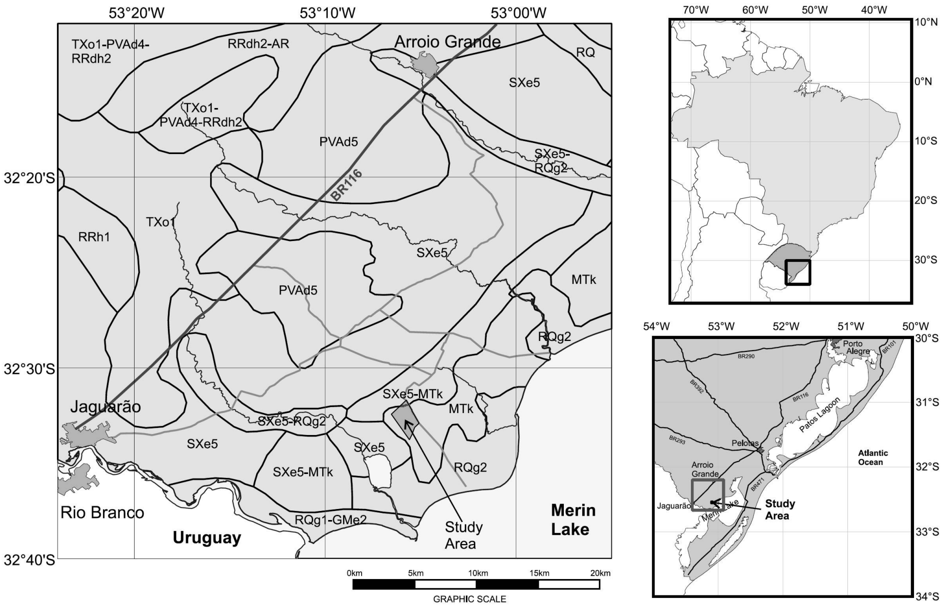

Figure 1. Location of the study area and the semi-detailed survey in relation to the soil reconnaissance survey in the State of Rio Grande do Sul (STRECK et al., 2008), municipality of Jaguarão, Rio Grande do Sul.

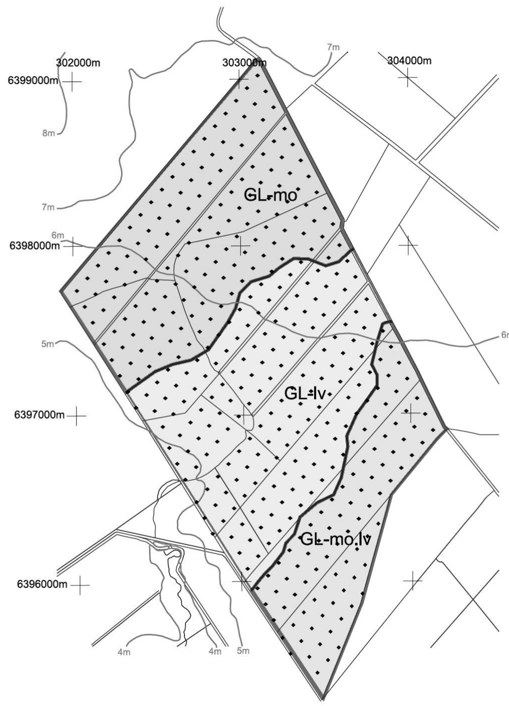

Figure 2. Georeferenced points in the study area and its homogeneous areas.

In a 5 m radius around each sampling point, 10 sub-samples of disturbed soil from the 0-0.20 m layer were collected in order to produce a compound sample from each sampling point. Each soil sample had the following attributes determined: clay content, pH in water, organic carbon, exchangeable phosphorus, potassium, sodium, aluminum, calcium and magnesium and potential acidity. The cation exchange capacity (pH=7.0) and the base saturation were also calculated. All methodologies are described by Tedesco et al. (1995).

The identification, characterization and quantification of spatial variability of the soil superficial horizon (Ap) attributes were carried out through descriptive statistics and geostatistics, considering the total area (low density reconnaissance mapping unit) and, also, considering its semi-detailed mapping units. For the exploratory analysis of data, the following statistics were calculated: arithmetic mean, maximum value, minimum value and coefficient of variation. The Wilding; Drees (1983) criterion was adopted to classify the soil attribute variability based on the coefficient of variation: low – CV ≤ 15 %, moderate – 15 < CV ≤ 35 % and high variability - CV > 35 %. The Kolmogorov-Smirnov (MASSEY, 1951) adherence test was applied at 5% significance level, in order to verify the normality of the data set, aiming to help the selection of the semivariance estimator for the geostatistical analysis.

Two semivariance estimators were used in the geostatistics analysis: the classical estimator (MATHERON, 1962), when the variable under study presented normal distribution, and the Cressie; Hawkins (1980) robust estimator, when it did not. The experimental and theoretical semivariogram adjustments with the respective parameters (nugget effect "Co", sill "C+Co" and range "a") were carried out based on the ordinary least square method implemented in the software R. The spatial dependence degree (SDD) of each attribute [SDD=(Co/C+Co)*100] was classified according to Cambardella et al. (1994) as: strong SDD ≤ 25 %; moderate – 25 % < SDD ≤ 75 %; and weak – SDD > 75 %. The scaled semivariogram technique proposed by Vieira et al. (1997), in which each experimental semivariance value was divided by the most suitable scale factor (sampling variance or the adjusted theoretical model sill), was applied aiming to compare the spatial variability structure of each soil attribute in the total area and its mapping units.

All the statistical procedures were carried out aided by the software R, and the descriptive statistics was used with the Rcmdr packet (FOX, 2005), the adherence tests employed the fBasics packet (WUERTZ, 2012) and the experimental and theoretical semivariograms were built with the geoR packet (RIBEIRO JÚNIOR; DIGGLE, 2001). In order to compare the results of this study considering the existence of different areas, it was used the scaled semivariogram technique proposed by Vieira et al. (1997).

RESULTS AND DISCUSSION

The results of applying descriptive statistics to the soil Ap horizon attributes in the total area (low density reconnaissance scale) and in the soil mapping units classified as Mollic Gleysol (GL-mo), Luvic Gleysol (GL-lv) and Luvic Mollic Gleysol (GL-mo.lv) are presented in Table 1.

Table 1. Results of applying descriptive statistics to the soil attributes under evaluation in the total area and in the soil mapping units classified as Mollic Gleysol (GL-mo), Luvic Gleysol (GL-lv), and Luvic Mollic Gleysol (GL-mo.lv).

Soil attributes												
Total area												
Est.	pH	C	Ca	Mg	Na	S	H+Al	CTC	V	Clay	P	K
Average	6.1	1.4	9.1	2.9	0.5	12.6	2.2	14.9	84.1	28	7.0	62
Min.	5.3	0.7	3.4	1.8	0.3	5.7	0.9	8.7	64.7	17	1.9	33
Max.	7.5	2.2	16.8	4.8	1.6	21.8	4.9	22.9	96.0	46	23.6	102
CV	6.7	18.7	33.4	20.6	37.6	27.7	32.1	22.4	7.3	15.8	49.0	23.4
KS	0.00*	0.20	0.00*	0.00*	0.00*	0.06	0.00*	0.07	0.31	0.00*	0.00*	0.12
GL-mo												
Average	6.3	1.5	11.7	3.1	0.5	15.4	2.2	17.6	87.3	30	6.9	70
Min.	5.3	0.7	7.2	2.0	0.3	10.0	0.9	13.1	69.2	19	1.9	37
Max.	7.5	2.1	16.8	4.8	1.1	21.8	4.9	22.9	96.0	46	19.3	102
CV	7.2	19.5	18.5	18.9	25.6	16.6	38.3	12.8	6.1	12.4	50.1	17.1
KS	0.07	0.72	0.75	0.25	0.00*	0.88	0.00*	0.63	0.20	0.01*	0.01*	0.58
GL-lv												
Average	6.1	1.3	7.9	2.9	0.5	11.5	2.3	13.8	82.9	27	6.9	58
Min.	5.4	0.8	5.2	1.8	0.3	7.7	1.2	10.2	68.6	20	1.9	33
Max.	7.0	1.8	13.0	4.7	1.6	18.4	4.4	19.8	93.0	46	23.6	90
CV	6.1	17.3	21.4	21.7	49.0	20.8	30.5	16.2	6.9	15.1	54.2	24.0
KS	0.03*	0.13	0.04*	0.02*	0.00*	0.17	0.00*	0.15	0.77	0.00*	0.00*	0.16

GL-mo.lv												
Average	5.9	1.3	5.7	2.5	0.5	8.8	2.2	11.0	79.5	25	7.3	52
Min.	5.4	0.9	3.4	1.8	0.3	5.7	1.4	8.7	64.7	17	3.0	35
Max.	6.5	1.6	9.2	3.7	1.3	13.4	3.1	15.1	88.7	46	17.6	86
CV	3.9	13.2	20.6	13.8	33.6	16.2	18.1	11.8	6.0	14.5	37.8	19.4
KS	0.00*	0.37	0.53	0.21	0.00*	0.72	0.06	0.35	0.93	0.00*	0.05	0.81

Est.= descriptive statistics, pH= water pH, C= organic carbon content (%); Ca= calcium content ($cmol_c.dm^{-3}$), Mg = magnesium content ($cmol_c.dm^{-3}$), Na= sodium content ($cmol_c.dm^{-3}$), H+Al= potential acidity ($cmol_c.dm^{-3}$), S= base sum ($cmol_c.dm^{-3}$), CTC= cation Exchange capacity at pH 7.0 ($cmol_c.dm^{-3}$), V= base saturation (%), clay = content in %, P= phosphorus content ($mg.dm^{-3}$), K= potassium content ($mg.dm^{-3}$), Min.= minimum value; Max. = maximum value, CV = coefficient of variation (%), KS= Kolmogorov-Smirnov test probability value p, * significant at the 5% level of probability.

According to the Soil Fertility and Chemistry Committee (CQFSRS/SC, 2004), the pH and V% average values in the total area and the GL-mo and GL-lv (Table 1) soils mapping units were classified as high, while in GL-mo.lv they were considered medium; organic matter content (carbon content x 1.724) are in accordance with the medium classification for the GL-mo unit and low for the remaining ones (< 2.5 %); the Ca and Mg average content are classified as high in all cases; regarding CTC pH 7.0, it can only be considered high in the GL-mo (> 15.0 $cmol_c\ dm^{-3}$).

Considering total area and the soil mapping units, the phosphorus average content (Table 1) regarding the clay class (class 3-21 to 40%) is in the agronomy interpretation band regarded as low; while the potassium average content referring to the CTC (pH 7.0) (from 5.1 to 15.0 $cmol_c\ dm^{-3}$), is in the high band in the total area and GL-mo and medium in GL-lv and GL-mo.lv. In general (Table 1), it could also be observed that the majority of medium content of the attributes under analysis were found in GL-mo, following a tendency of reduction in the average content as a function of the systematization plan adopted in the area, since the larger volume of soil section was observed in GL-mo.lv. Regarding the Na high average content observed in Table 1, it is believed to result from the use of saline water to irrigate the area, which comes from the **Mirim** Lake.

By analyzing data dispersion around the average (Table 1), expressed by the coefficient of variation (CV), the pH and V values in the total area were verified to present low variability (CV ≤ 15 %), while the C, Ca, Mg, S, H+Al, CTC, Clay and K data variability is classified as moderate (15 < CV ≤ 35 %), according to the classification proposed by Wilding; Drees (1983). While the Na (CV = 37.6 %) and P (CV = 49.0 %) data dispersion is considered high (CV > 35 %). The same behavior can be observed regarding the data set evaluated in GL-lv (Table 1). On the other hand, the data sets evaluated in the soil mapping units GL-mo and GL-mo.lv presented distinct behavior in relation to the CV behavior, and the data low variability was predominant in GL-mo.lv (50% of the soil attributes evaluated) and the moderate data variability in GL-mo (8 out of 12 data sets evaluated).

By analyzing the data in Table 1, it was seen that the P data sets presented the highest CV values when compared to the remaining sets, varying from 37.8 % (GL-mo.lv) to 54.2 % (GL-lv). Such results indicate that, for the dimensioning of samples with non spatial statistical methodology, when considering the total area as an experimental unit, sample sizes can be over or under estimated in some units, that is, units with high variability might have an underestimate of the sample size while more homogeneous units might be using a sampling effort above the necessary to represent the area. Descriptive statistics also indicates that the use of uniform management in the whole experimental area might lead to results which do not meet the agricultural needs of the soil under study, that is, the need to apply Precision Farming is verified and, consequently, the analysis of the soil mapping units influence in the soil attributes spatial variability.

Based on Kolmogorov-Smirnov adherence test and considering a 5% p value for probability (Table 1), the pH, Ca, Mg, Na, H+Al, Clay and P data distribution in the total area and in the GL-lv was not verified to tend to normality, confirming the attribute behavior previously seen in relation to data variability around the average. In GL-mo, the Na, H+Al, Clay and P data distribution did not follow normal behavior, while in GL-mo.lv the pH, Na and Clay values did not tend to normality, indicating that these attributes presented distribution localized in the area (GREGO et al., 2006) and that the arithmetic average cannot be considered as the distribution center (NIELSEN; WENDROTH, 2003).

The spatial variability structure of all attributes in the total area and in the soil mapping units was evaluated through the construction of experimental isotropic semivariograms. The adjustment parameters "Co", "C+Co" and "a" for the theoretical models were only obtained for the attributes that presented semivariograms in which the intrinsic hypothesis (semivariogram with a defined sill in the sampling space evaluated) was confirmed (Table 2). For data that followed normal distribution (Table 1), the semivariances were calculated via Matheron (1962) estimator, while for data that did not, they were calculated through the Cressie; Hawkins (1980) robust estimator, according to Webster; Oliver (2007). Table 2 shows that the experimental semivariograms were adjusted, for most of the soil attributes, to the spherical model regardless of the evaluation scale under analysis (Table 2). The spatial dependence degree of the attributes under evaluation in the total area was classified as moderate (25 % < SDD ≤ 75 %), while in the soil mapping units GL-mo, GL-lv and GL-mo.lv most of their SDD was classified as strong; the degree of spatial dependency is the relationship, in percentage terms, of the nugget (Co) to sill (Co + C), i.e. the relationship between the unexplained variance or random, caused by measurement errors or the micro-variability of the property under study which cannot be detected in the sample scale used by the total variance of the sample for stationary data (TRANGMAR et al., 1985). The magnitude of the nugget variance is important in kriging because it sets a lower limit to the size of estimation variance and, therefore, to the precision of the interpolation (TRANGMAR et al., 1985). Thus, kriging and the mapping carried out when considering total area must present lower precision in relation to the individual areas mapping. This fact is very relevant for the management systems that involve precision farming technology. According to Cambardella et al. (1994), variables that present strong SDD (SDD ≤ 25 %) are more influenced by soil composition characteristics such as original material, relief, climate, organisms and time. Thus, the semi-detailed mapping units, which are more homogeneous compared to the reconnaissance mapping unit, with fewer inclusions of different types of soils, tend to have lower variability of their physical and chemical properties, thereby influencing the degree of spatial dependence of the soil properties.

The comparison of spatial variability structures of the attributes pH, Mg, Na, H+Al, V, Clay, P and K in the total area and in the soil mapping units was carried out through the scaled semivariogram technique (Figure 3), and in the scaled semivariogram estimated via Matheron (1962), the data sample variability was adopted as scale factor and in the scaled semivariograms built by the Cressie; Hawkins (1980) estimator, the sill "C+Co" (Table 2) was adopted as scale factor.

When Figure 3 is analyzed, the attributes pH and Na are observed to have shown higher coalescence of scaled semivariance values when compared to the other attributes, indicating the possibility of adjustment of an only semivariogram model regardless of the factor used for the scaling and the evaluation scaling under analysis, thus, characterizing more similarity in the spatial dependency structure. Montanari et al. (2012) pointed out that the adjustment of an only semivariogram model would provide an only sampling scheme for these attributes. The Mg, H+Al, V, Clay, P and K attributes spatial variability in GL-mo.lv were observed to be similar to the scaled semivariogram model structures in the total area, this result is not in accordance with the descriptive statistics result (Table 1), but indicates the distribution of high and low values in the total area similar to that in the soil mapping unit GL-mo.lv, altering the magnitude of values and, therefore, influencing the descriptive analysis.

The greatest difference in behavior between scaled semivariograms can be seen through the potential acidity (H+Al) as a function of the soil mapping units, followed by the semivariogram behavior for clay content (Figure 3) indicating that estimate errors when considering total area might be more accentuated for these attributes. This more marked difference for these attributes can derive from the cut and fill performed in the surface layer by the land leveling, which brought to the surface the lower parts of the A horizon or even the top of the B horizon in some parts of the area, with different physical and chemical properties compared to the natural surface more organic horizon.

Table 2. Experimental and theoretical semivariograms with respective adjustment parameters (nugget effect Co, sill C+Co and range a) and residual sum of squares (RSS) and the spatial dependence degree (SDD) of the attributes evaluated in the total area and in the soil mapping units.

Attribute	Estimator	Model	Co	C+Co	a (m)	RSS	SDD	Classification
Total area								
pH	C-H	Spherical	0.0402	0.1515	844	$9x10^{-04}$	27	Moderate
C	M	Spherical	0.0497	0.0752	1923	2x10-04	66	Moderate
Mg	C-H	Spherical	0.1252	0.3425	578	0.0011	37	Moderate
Na	C-H	Spherical	0.0082	0.0212	348	$1x10^{-04}$	39	Moderate
H+Al	C-H	Spherical	0.1394	0.4758	652	0.0327	29	Moderate
V	M	Spherical	15.0133	38.0342	1221	5.7695	40	Moderate
Clay	C-H	Spherical	8.4754	23.9584	3038	4.637	35	Moderate
P	C-H	Spherical	4.3199	9.5365	416	0.857	45	Moderate
K	M	Spherical	84.2681	218.7875	1093	197.8968	39	Moderate
GL-mo								
pH	M	Spherical	0.0346	0.279	1267	$7x10^{-04}$	12	Strong
C	M	Spherical	0.0539	0.0815	462	$2x10^{-04}$	66	Moderate
Ca	M	Exponential	0.7859	5.6288	991	0.2629	14	Strong
Mg	M	Gaussian	0.1216	0.3388	337	0.0037	36	Moderate
Na	C-H	Spherical	0.00	0.0138	394	0.00	0	Strong
S	M	Spherical	2.1180	6.8417	490	0.3951	31	Moderate
H+Al	C-H	Spherical	0.0401	1.0267	1421	0.1049	4	Strong
CTC	M	Spherical	1.6303	5.1745	394	1.0261	32	Moderate
V	M	Spherical	3.6761	42.5317	1386	34.1432	9	Strong
Clay	C-H	Exponential	0.00	11.9709	434	2.5009	0	Strong
P	C-H	Spherical	0.00	10.4926	301	6.5441	0	Strong
K	M	Exponential	12.6895	143.6447	290	641.9771	9	Strong
GL-lv								
pH	C-H	Spherical	0.0346	0.1484	660	0.0011	23	Strong
Ca	C-H	Spherical	1.3684	2.7472	513	0.4947	50	Moderate
Mg	C-H	Exponential	0.0487	0.4088	696	0.0023	12	Strong
Na	C-H	Spherical	0.0060	0.0431	437	$1x10^{-04}$	14	Strong
S	M	Exponential	1.0897	5.9395	395	0.9158	2	Strong
H+Al	C-H	Spherical	0.1840	0.5099	981	0.0087	36	Moderate
CTC	M	Exponential	0.00	5.3045	261	1.2187	0	Strong
V	M	Spherical	15.0483	35.2714	920	55.1256	43	Moderate
Clay	C-H	Spherical	3.7707	12.2613	677	3.7598	31	Moderate
P	C-H	Spherical	2.6805	11.8215	519	17.6584	23	Strong
K	M	Exponential	59.4077	195.5589	525	752.0699	31	Moderate
GL-mo.lv								
pH	C-H	Spherical	0.0179	0.0555	699	$8x10^{-04}$	32	Moderate
C	M	Spherical	0.0076	0.0316	308	$1x10^{-04}$	24	Strong
Ca	M	Spherical	0.00	1.4138	208	0.2906	0	Strong
Mg	M	Spherical	0.0232	0.1266	255	0.0027	18	Strong
Na	C-H	Spherical	0.0045	0.0153	308	0.00	30	Moderate
S	M	Spherical	0.00	2.0929	213	0.931	0	Strong
H+Al	M	Spherical	0.00	0.1681	240	0.0021	0	Strong
CTC	M	Spherical	0.00	1.7392	200	0.5432	0	Strong
V	M	Spherical	0.00	23.1434	227	100.2178	0	Strong
Clay	C-H	Spherical	3.2205	7.8884	512	13.2396	41	Moderate
P	C-H	Spherical	0.00	6.3273	167	2.324	0	Strong
K	M	Spherical	30.2698	111.7447	544	1225.684	27	Moderate

pH= water pH, C= organic carbon content (%), Ca= calcium content ($cmol_c\ dm^{-3}$), Mg= magnesium content ($cmol_c\ dm^{-3}$), Na= sodium content ($cmol_c\ dm^{-3}$), H+Al= potential acidity ($cmol_c\ dm^{-3}$), S= base sum ($cmol_c\ dm^{-3}$), CTC= cation Exchange capacity at pH 7.0 ($cmol_c\ dm^{-3}$), V= base saturation (%), Clay= Clay content(%), P= phosphorus content ($mg\ dm^{-3}$), K= potassium content ($mg\ dm^{-3}$), C-H= Cressie and Hawkins robust estimator, M=Matheron classical estimator, SDD = [(Co/C+Co)*100]: strong - SDD ≤25 %; moderate – 25 % <SDD ≤75 %; and weak – SDD >75 %.

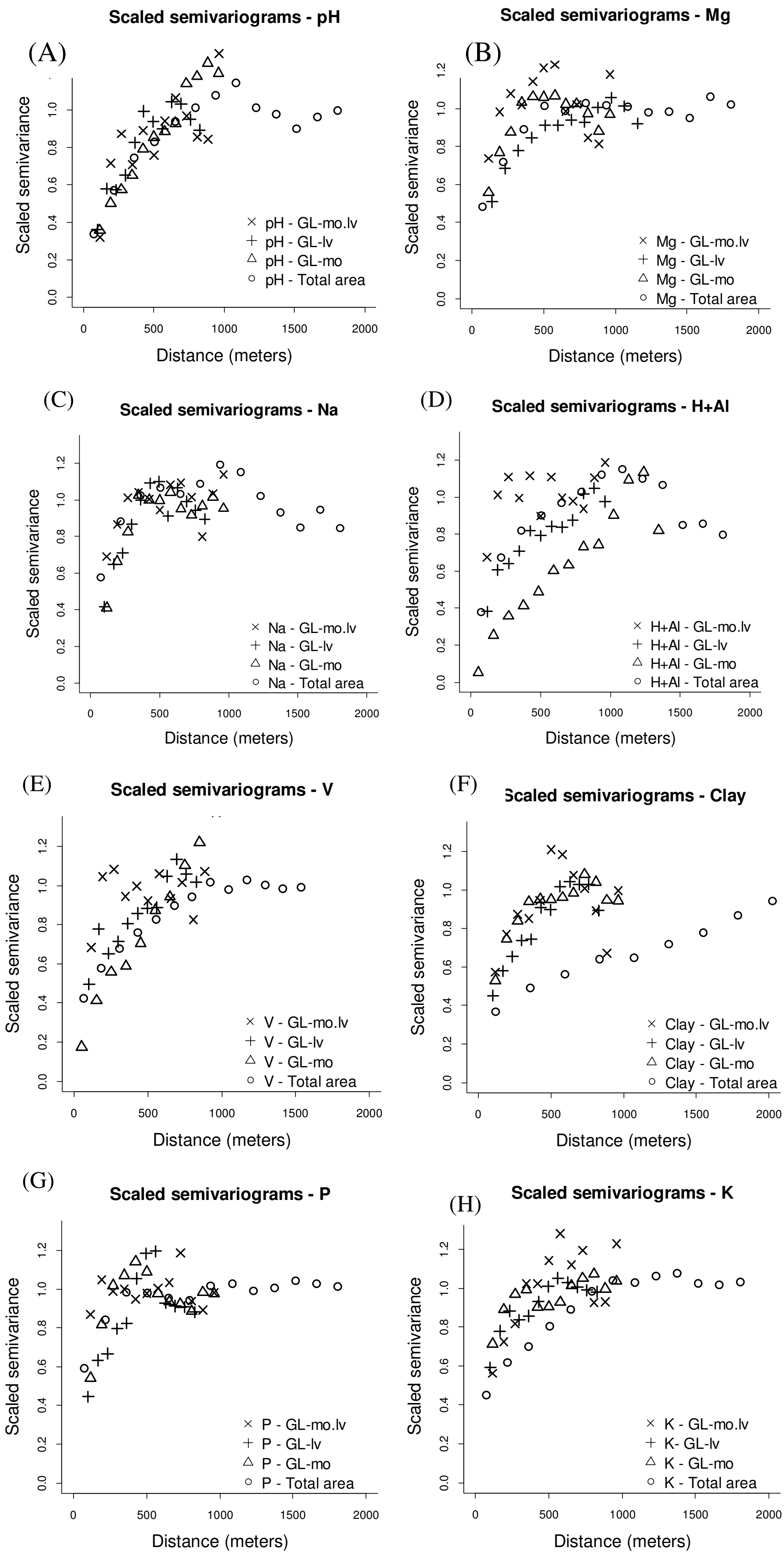

Figure 3. Scaled isotropic semivariograms of the soil attributes evaluated in the total area and the soil mapping units: Mollic Gleysol (GL-mo), Luvic Gleysol (GL-lv) and Luvic Mollic Gleysol (GL-mo.lv). (A)= Water pH, (B)= magnesium, (C)= Sodium, (D)= Potential acidity, (E)= Base saturation, (F)= Clay, (G)= Phosphorus, (H)= Potasssium.

CONCLUSIONS

There is no correspondence in the attributes spatial distribution and structure between the semi-detailed mapping units and the reconnaissance mapping unit in which they are included.

The use of non-spatial statistics in the management decisions might lead to unsuitable recommendations to the crop if spatially different soil mapping units are present in the area.

The scaled semivariogram technique allows the identification of similar or different spatial behaviors between the soil mapping units, contributing to the attributes sampling plan.

ACKNOWLEDGEMENTS

To Granja Bretanhas for the general support throughout the development of the study, to CAPES and CNPq for the Master's and research productivity grants.

RESUMO: A estrutura de variabilidade espacial dos atributos do solo em determinada área pode influenciar o modelo de ajuste do semivariograma e, consequentemente, o mapeamento do comportamento do atributo nesta área induzindo a decisões diferenciadas de manejo agrícola. O objetivo deste trabalho foi identificar, caracterizar e quantificar a variabilidade espacial de atributos químicos e do teor de argila da camada superficial de uma unidade de mapeamento de Gleissolos em escala de reconhecimento na Planície Costeira do Rio Grande do Sul, por meio da estatística descritiva e da geoestatística e comparar os resultados levando em consideração a existência de três unidades de mapeamento de Gleissolos em escala de semi-detalhe por meio da técnica de escalonamento de semivariogramas. Uma área de 403 ha localizada na Planície Costeira do Rio Grande do Sul, no município de Jaguarão, foi subdividida em três unidades de mapeamento (GMve1, GMve2 e GXve), sendo estabelecida uma malha total de amostragem de 403 pontos, distanciados entre si de 100 m. Em um raio de 5 m em torno de cada ponto amostral, foram coletadas 10 sub-amostras deformadas de solo na camada de 0-0,20 m, constituindo uma amostra composta de solo, sendo determinados os seguintes atributos das amostras: pH em água, carbono orgânico, fósforo, potássio, sódio, cálcio, magnésio, alumínio, acidez potencial e o conteúdo de argila. Calculou-se também a capacidade de troca de cátions (pH=7,0) e a saturação por bases. A identificação, caracterização e quantificação da variabilidade espacial dos atributos dos horizontes Ap dos solos foram realizadas por meio da estatística descritiva e da geoestatística, considerando a unidade de mapeamento em escala de reconhecimento e as três unidades em escala de semi-detalhe. Na análise geoestatística foi usada a técnica de escalonamento dos semivariogramas, com a finalidade de comparar as estruturas de variabilidade espacial de cada atributo do solo na área total e nas três UMs em escala de semi-detalhe. Em relação à estatística descritiva, o comportamento dos atributos do horizonte Ap na GXve é semelhante ao da área total na camada de solo avaliada; entretanto, ao considerar as coordenadas espaciais, a estrutura de variabilidade espacial dos atributos na GMve2 é a que melhor descreve a variabilidade dos atributos na área total. A técnica de escalonamento dos semivariogramas mostra que o comportamento espacial dos atributos pH e sódio trocável é semelhante, independente da escala de avaliação adotada e do fator usado para o escalonamento dos semivarigramas.

PALAVRAS-CHAVE: Geoestatística. Escalonamento de semivariogramas. Áreas de várzeas. Unidades de mapeamento de solo. Agricultura de precisão.

REFERENCES

BRASIL. Ministério da Agricultura. Departamento Nacional de Pesquisa Agropecuária. Divisão de Pesquisa Pedológica. Levantamento de Reconhecimento dos Solos do Estado do Rio Grande do Sul. Recife, 1973. 431 p. (Boletim Técnico n° 30)

CAMBARDELLA, C. A.; MOORMAN, T. B.; NOCAK, J. M.; PARKIN, T. B.; KARLEN, D. L.; TURCO, R. F. KONOPKA, A. E. Field-scale variability of soil properties in central Iowa soils. **Soil Sci. Soc. Am. J.** v. 58, p. 1501-1511, out. 1994. http://dx.doi.org/10.2136/sssaj1994.03615995005800050033x

COMISSÃO DE QUÍMICA E FERTILIDADE DO SOLO - CQFSRS/SC. Recomendações de adubação e calagem para os estados do Rio Grande do Sul e Santa Catarina. 3.ed. Passo Fundo: SBCS - Núcleo Região Sul/ UFRGS, 2004. 400 p.

COUTO, E. G.; STEIN, A. KLAMT, E. Large area spatial variability of soil chemical properties in central Brazil. **Agric. Ecosyst. Environ.** v. 66, p.139-151, dez. 1997. http://dx.doi.org/10.1016/S0167-8809(97)00076-5

CRESSIE, N.; HAWKINS, D. M. Robust estimation of the variogram: I. **Math. Geol.** v. 12, p. 115-125, jan. 1980. http://dx.doi.org/10.1007/BF01035243

DUFFERA, M.; WHITE, J. G.; WEISZ, R. Spatial variability of southeastern U.S. Coastal Plain soil physical properties: Implications for site-specific management. **Geoderma.** v. 137, p. 327 -339, jan. 2007. http://dx.doi.org/10.1016/j.geoderma.2006.08.018

EMPRESA BRASILEIRA DE PESQUISA AGROPECUÁRIA - EMBRAPA. Centro Nacional de Pesquisa de Solos. **Manual de Métodos de Análise de Solo**. 2. ed. Rio de Janeiro: Embrapa Solos, CNPS, 1997. 212 p.

EMPRESA BRASILEIRA DE PESQUISA AGROPECUÁRIA - EMBRAPA. Centro Nacional de Pesquisa de Solos. **Procedimentos normativos de levantamentos pedológicos**. 1. ed. Brasília: Embrapa-SPI, 1995. 116 p.

FOX, J. The R Commander: A Basic Statistics Graphical User Interface to R. **J. Stat. Softw.** v. 9, p. 1-42, jan. 2005.

GREGO, C. R.; VIEIRA, S. R.; LOURENÇÃO, A. L. Spatial distribution of Pseudaletia sequax Franclemlont in triticale under no-till management. **Sci. Agric.** v. 63, p. 321-327, ago. 2006.

LARK, R.M. Towards soil geostatistics. **Spatial Stat.** v. 1, p. 92-99, mai. 2012.

LEMOS, Raimundo Costa; SANTOS, Raphael David. **Manual de descrição e coleta de solo no campo.** 3. ed. Campinas: Sociedade Brasileira de Ciência do Solo, 1996. 84 p.

LIU, T.L.; JUANG K.W.; LEE D.Y. Interpolating soil properties using Kriging combined with categorial information of soil maps. **Soil Sci. Soc. Am. J.** v. 70, p. 1200-1209, jul. 2006. http://dx.doi.org/10.2136/sssaj2005.0126

MCBRATNEY, A. B.; ODEH, I. O. A.; BISHOP, T. F. A.; DUNBAR, M. S.; SHATAR, T. M. An overview of pedometric techniques for use in soil survey. **Geoderma**. v. 97, p. 293–327, set. 2000. http://dx.doi.org/10.1016/S0016-7061(00)00043-4

MCBRATNEY, A. B.; MENDONÇA-SANTOS, M. L.; MINASNY, B. On digital soil mapping. **Geoderma.** v. 117, p. 3-52, nov. 2003. http://dx.doi.org/10.1016/S0016-7061(03)00223-4

MASSEY, F. J. The Kolmogorov-Smirnov Test for Goodness of Fit. **J. Am. Stat. Assoc.** v. 46. p. 68-78, mar. 1951. http://dx.doi.org/10.1080/01621459.1951.10500769

MATHERON, G. Traite de Geostatistique Appliquee, Memoires du Bureau de Recherches Geologiques et Minieres. 1. ed. Paris: Technip, 1962. 333 p.

MONTANARI, R.; SOUZA, G. S. A.; PEREIRA, G. T.; MARQUES JUNIOR, J.; SIQUEIRA, D. S.; SIQUEIRA, G. M. The use of scaled semivariograms to plan soil sampling in sugarcane fields. **Precis. Agric.** v. 13, p. 542-552, out. 2012. http://dx.doi.org/10.1007/s11119-012-9265-6

MOTA, F. S. Meteorologia agrícola. 7. ed. São Paulo: Nobel, 1983. 376 p.

NIELSEN, D. R.; KUTILEK, M.; PARLANGE, P. Surface soil water content regimes: opportunities in soil science. **J. Hidrol.** v. 184, p. 35-55, out. 1996.

NIELSEN, D.; WENDROTH, O. Spatial and temporal statistics: sampling field soils and their vegetation. 1.ed. Reiskirchen: CatenaVerlag GMBH, 2003. 416 p. http://dx.doi.org/10.1016/0022-1694(95)02967-2

OLIVER, M. Geostatistical applications for Precision Agriculture. 1. ed. London: Springer, 2010. 331 p. http://dx.doi.org/10.1007/978-90-481-9133-8

RIBEIRO JÚNIOR, P. J.; DIGGLE, P. J. GeoR: a package for geostatistical analysis. **R-News.** v. 1, p. 15-18, jun. 2001.

ROGOWSKI, A. S.; WOLF, J. K. Incorporating variability into soil map unit delineations. **Soil Sci. Soc. Am. J.** v. 58, p. 163-174, jan. 1994. http://dx.doi.org/10.2136/sssaj1994.03615995005800010024x

STRECK, E. V.; KAMPF, N.; DALMOLIN, R. S. D.; KLAMT, E.; NASCIMENTO, P. C.; SCHNEIDER, P.; GIASSON, E.; PINTO, L. F. S. Solos do Rio Grande do Sul. 2.ed. Porto Alegre: EMATER/RS, ASCAR, 2008. 222 p.

TEDESCO, M. J.; GIANELLO, C.; BISSANI, C. A.; BOHNEN, H.; VOLKWEISS, S. J. Análises de solo, plantas e outros materiais. 2. ed. Porto Alegre: Departamento de Solos, Universidade Federal do Rio Grande do Sul, 1995. 174 p.

TRANGMAR, B. B.; YOST, R. S.; UEHARA, G. Application of geostatistics to spatial studies of soil properties. In: BRADY NYLE (Ed.). Advances in Agronomy. Florida: Academic press, 1985. p. 45-94.

VIEIRA, S. R.; NIELSEN, D. R.; BIGGAR, J. W.; TILLOTSON, P. M. Scaling of semivariograms and the kriging estimation of field-measured properties. **R. Bras. Ci. Solo.** v. 21, p. 525-533, dez. 1997. http://dx.doi.org/10.1590/S0100-06831997000400001

WEBSTER, R.; OLIVER, M. Geostatistics for Environmental Scientists. 2. ed. Chichester: Wiley, 2007. 325 p. http://dx.doi.org/10.1002/9780470517277

WILDING, L. P.; DREES, L. R. Spatial variability and pedology. In: WILDING, L. P.; SMECK, L. E.; HALL, G.F. (Ed.). Pedogenesis and soil taxonomy I. concepts and interactions. Amsterdam: ELSEVIER, 1983. p. 83-116. http://dx.doi.org/10.1016/S0166-2481(08)70599-3

WORLD REFERENCE BASE FOR SOIL RESOURCES 2014 - WRB: International soil classification system for naming soils and creating legends for soil maps. Rome: FAO, 2014. 191p. (World Soil Resources Reports 106)

WU, C.; WU. J.; LUO, Y.; ZHANG, H.; TENG, Y. Statistical and geostatistical characterization of heavy metal concentrations in a contaminated area taking into account soil map units. **Geoderma.** v. 144, p. 171-179, mar. 2008. http://dx.doi.org/10.1016/j.geoderma.2007.11.001

WUERTZ, D. Package “fBasics”. 2012. Disponível em: <http://cran.r-project.org/web/packages/fBasics/fBasics.pdf>. Acesso em: 10 dez. 2012.