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TECHNICAL PAPER

TRANSITION FROM SYSTEMATIC TO DIRECTED SOIL SAMPLING DESIGNS IN AN AREA MANAGED WITH PRECISION AGRICULTURE

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KEYWORDS

sampling costs,
sampling grids,
spatial variability,
management zones.

ABSTRACT

In agricultural areas with a historical of systematic soil sampling, alternative methodologies such as directed sampling design based on management zones (MZ) have been proposed to reduce sampling costs. The aim of this study was to evaluate the technical and economic impacts of replacing a dense systematic soil sampling design (cell size of 0.5 ha) by a systematic sampling with a smaller number of samples (cell size ranging from 1 to 4.5 ha), directed or conventional sampling design on the mapping of soil plant-available phosphorus (P), exchangeable potassium (K), and pH_{water}. The study was carried out in an agricultural area of 120 ha with soil classified as an Oxisol. The directed sampling designs were based on MZ delimited from data of elevation and overlapping of crop yield maps. Our finding revealed that systematic samplings with grids larger than 2 ha were not efficient to detect the spatial variability of soil P, K and pH_{water}. Larger systematic grid sizes, directed and conventional sampling design resulted in more generalist thematic maps, losing information about spatial variability of the soil attributes. Thus, from a technical point of view, soil sampling designs with a low density were little efficients, particularly for mapping P and K, due to their higher spatial variability. However, because soil P and K contents were close to or above critical levels and soil acidity was low (average pH close to 5.5), the different sampling designs presented little influence on fertilizer and liming recommendations. Therefore, we concluded that systematic soil sampling design may be replaced by soil sampling directed based on MZ or even by conventional sampling in soils with high fertility to reduce sampling costs. Nevertheless, crop responses must be monitored to validate fertilization management based on these simplifications on soil sampling procedure.

INTRODUCTION

Historically, soil fertility management has been performed based on conventional soil sampling design, which does not consider the spatial variability of soil attributes (CQFS-RS/SC, 2016). However, the modernization of agriculture and implementation of precision agriculture (PA) tools have shown that soil nutrient levels, nutrient amounts removed by plants, and nutrient losses are not uniformly distributed in the field (Molin, 2002, Mallarino & Wittry, 2004, Santi et al., 2012). Thus, geo-referenced soil sampling for recognizing the spatial variability of soil attributes and application of variable rates of fertilizers and correctives has been widely adopted in Brazil (Corá & Beraldo, 2006, Soares Filho & Cunha, 2015, Baio et al., 2017). Soil fertility mapping can optimize the use of agricultural inputs, increase crop yield, promote higher profitability for farmers and mitigate environmental impacts derived from agriculture (Mallarino & Wittry, 2004, Baio et al., 2017).

Systematic soil sampling by grid sampling is the most widespread methodology for mapping soil fertility attributes (Cherubin et al., 2016). However, some

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methodological procedures remains unclear (Siqueira et al., 2014), such as the size of cells and consequently the number of soil samples per hectare (Nanni et al., 2011, Souza et al., 2014, Bottega et al., 2014, Cherubin et al., 2014, 2015). The difficulty in defining the dimension of the grid cells is associated with the different patterns in the spatial variability of each of the soil chemical properties within the field and between fields (Mallarino & Wittry, 2004, Nanni et al., 2011, Souza et al., 2014, Cherubin et al., 2014, 2015). Under contrasting soil conditions in Brazil, studies that considered only technical aspects have suggested the adoption of grid sampling with cells smaller ≤ 1 ha (Nanni et al., 2011, Souza et al., 2014, Cherubin et al., 2014, 2015). However, the high number of samples and its costs associated with sampling and laboratory analysis have been the main obstacles to expand the adoption of systematic soil sampling in Brazil (Souza et al., 2014, Oliveira et al., 2015).

The economic viability of using systematic soil sampling designs with a high density of samples is maximized in fields with high spatial variability of soil attributes and nutrient contents below the critical levels for suitable crop development (Schmidt et al., 2002, Nanni et al., 2011, Cherubin et al., 2014, Siqueira et al., 2014). In high-fertility areas (contents above the critical level), as expected for areas with long-term management using PA tools, crops usually present a low responsiveness to fertilization (CQFS/RS-SC, 2016) and, therefore, alternative and simplified soil sampling designs may be economically attractive to farmer. Among these alternative designs, directed soil sampling stands out based on the establishment of management zones (MZ), defined as subareas of the field with similar characteristics, which allows carrying out an uniform management of soil fertility within each MZ (Molin, 2002, Molin et al., 2015).

In a study conducted in Iowa, the United States, Mallarino & Wittry (2004) compared the use of systematic soil sampling with MZ delineated by soil type surveys and found that systematic sampling design showed higher accuracy on detecting spatial variability of soil attributes in most of fields. Although the adoption of soil sampling based on MZ is consistently supported by the theory (Molin, 2002, Suszek et al., 2011, Santi et al., 2012, Molin et al., 2015), no studies have been conducted in Brazil to prove its efficiency in guiding soil samplings. In this sense, we conducted a study in a commercial field with long-term soil fertility management based on PA principles to evaluate the technical and economic viability of replacing a dense systematic soil sampling design (cell size of 0.5 ha) by a systematic sampling with a lower sampling density (cell size ranging from 1 to 4.5 ha), directed or conventional sampling design for mapping soil phosphorus (P), potassium (K), and pH_{water}.

MATERIAL AND METHODS

The study was conducted in an area of 120 ha located in Boa Vista das Missões, RS (central coordinates of 27°43′12″ S and 53°20′13″ W). The area has a soft wavy relief with a Rhodic Acrudox (Oxisol) according to Soil Taxonomy (Soil Survey Staff, 2014) and "Latossolo Vermelho distrófico típico" according to the Brazilian System of Soil Classification (Santos et al., 2013) with clay texture (> 600 g kg^{-1}). The experimental area has been managed under the no-tillage system for more than 20 years using PA tools since 2009, such as autopilot use, systematic soil sampling using a grid sampling of 1 ha (2009 and 2012), variable rate applications of fertilizers and correctives, and crop yield mapping.

First, the field perimeter was demarcated using a GPS (Garmin®, Legend model) portable navigation device (accuracy of 3–5 m). Subsequently, a grid sampling with cells of 0.5 ha was overlaid on the area and soil samples were collected in May 2015, using a quadricycle equipped with a screw auger at a depth of 0.00–0.10 m. Fourteen soil subsamples, collected in the perimeter from a radius of 10 m from the central point of each cell were combine to compose a sample. After sampling, these samples were identified and sent to the laboratory for analyzing the available P and exchangeable K (Mehlich 1) contents and pH_{water} values.

The systematic point elimination technique was used from the initial grid sampling design of 0.5 ha (cell sizes of 70.71 × 70.71 m, 243 points) to simulate larger grids of 1 ha (141.42 × 70.72 m, 119 points), 2 ha (141.42 × 141.42 m, 60 points), 3 ha (212.14 × 141.42 m, 42 points), and 4.5 ha (212.14 × 212.14 m, 29 points) (Figure 1).

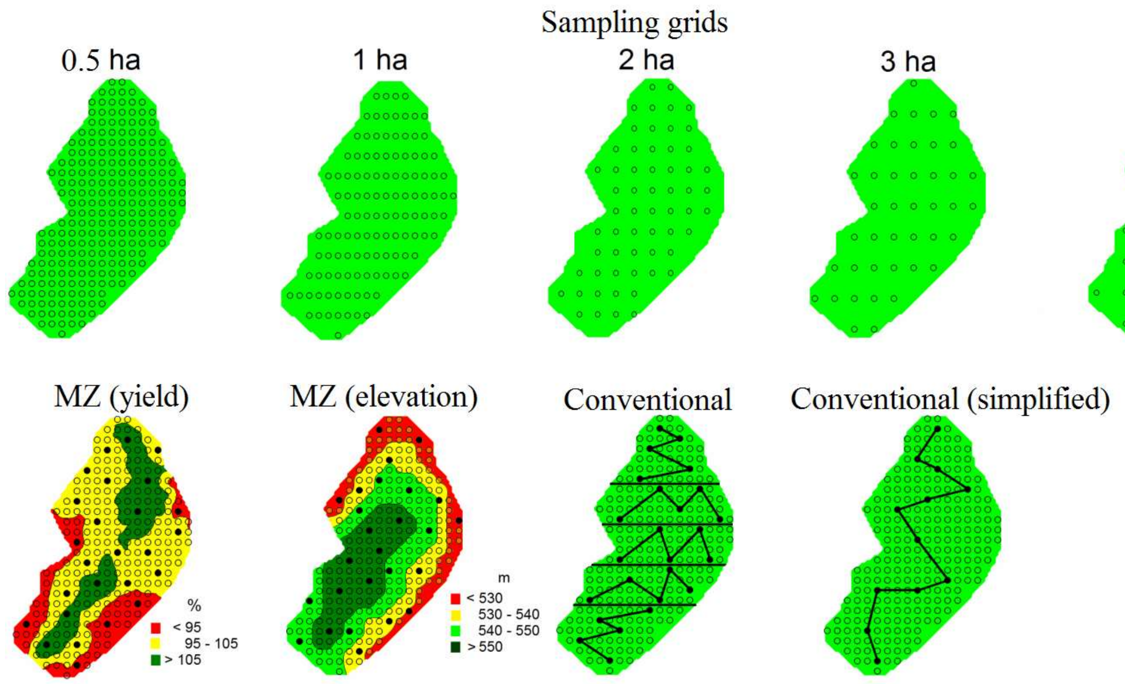

FIGURE 1. Location of sampling points for mapping soil fertility defined through different sampling designs, such as systematic sampling with grids of 0.5, 1, 2, 3, and 4.5 ha, directed sampling based on management zones (MZ) established by crop yield maps (yield) and elevation data (elevation), conventional, and simplified conventional (simplified) sampling.

The MZ were delimited using two criteria: overlapping grain yield maps and field elevation data (Figure 1). Each MZ was represented by the mean of points, arranged one every 4.5 ha, approximately. The delimitation of MZ from grain yield was carried out based on data from the follow crop seasons: black oat (2010), soybean (2010/11 and 2014/15), and wheat (2013). First, yield data were filtered to remove errors and then, the data of each map were relativized by their mean value (Suszek et al., 2011). The temporal stability of grain yield in the area was confirmed by the coefficient of temporal variation of grain yield (Molin, 2002, Suszek et al., 2011), which averaged 12.3%. Subsequently, the relativized maps were overlapped and three MZ were defined: low (*i.e.* yield value lower than 95% of the mean yield of the field), medium (95–105%), and high yield (>105%), as described by Santi et al. (2012). The field elevation data were obtained from DGPS integrated with a Case® harvester. The field presented elevation ranging from 518 to 560 m, being this amplitude subdivided into four MZ (*i.e.*, <530 m, 530-540 m, 540-550 m and >550 m).

For the simulation of conventional sampling, the area was divided into five plots so that a sample represented less than 30 ha. A sampling point was demarcated every 4.5 ha within each 30-ha plot to create a composite sample. In addition, the use of a simplified conventional sampling was simulated, in which a sample composed of the mean of 12 sampling points arranged in a zig-zag scheme represented the entire field (120 ha).

The data were subjected to statistical analysis, obtaining measurements of position (minimum, mean, and maximum) and dispersion (coefficients of variation, CV). CV values were classified as of low (<10%), medium (10–20%), high (20–30%), and very high (>30%) variability (Pimentel-Gomes & Garcia, 2002). Descriptive statistical analysis was performed using the Statistical Analysis System – SAS 9.3 software (SAS Inc., Cary, USA).

The data from the systematic sampling in grids were analyzed using geostatistical procedures. The semivariogram adjustment was performed by GEOEST software (Vieira et al., 2002) where spherical, exponential, and Gaussian theoretical models were tested. The choice between models was based on the highest coefficient of determination (R^2) and the lowest sum of squares of residuals (SSR) obtained by the cross-validation technique. From the models, the geostatistical parameters range (a), nugget effect (C_0), contribution (C_1), and sill (C) were obtained. The degree of spatial dependence (DSD) was estimated from equations developed by Seidel & Oliveira (2014) and classified as strong, moderate, and weak according to the suggestions for each theoretical model presented by Seidel & Oliveira (2016). Thematic maps were elaborated using the software Surfer 9 (Golden Software, Inc.). The ordinary kriging was used as an interpolator for the data with defined spatial structure (Vieira, 2002) and inverse-square distance for the data with no satisfactory adjustment to any of the tested theoretical models (*i.e.* pure nugget effect).

To evaluate the influence of soil sampling schemes on the accuracy of mapping, two methods were used: the Pearson's simple linear correlation matrix ($p<0.01$) and coefficient of relative deviation (CRD). In order to have only estimated values in all sampling designs, a grid with cell sizes of 0.16 ha (40 × 40 m) was initially overlaid under the area, resulting in 722 points, and then, estimated values were extracted from each soil map elaborated based on different sampling designs. CRD expresses the dissimilarity of two maps, in module, existing between the sampling points on each map, according to Equation (1) (Cherubin et al., 2015).

$$CRD = \sum [(Ncij - Nciref) / Nciref] \times (100 / n) \quad (1)$$

Where,

n is the number of interpolated points (n = 722 points);

$Ncref$ is the nutrient reference content at point i obtained on the map generated by the grid sampling with cell sizes of 0.5 ha (reference), and

$Ncij$ is the nutrient content at point i in the different soil sampling methods.

Fertilizer recommendation was performed only for correcting nutrient contents to critical levels (correction fertilization), being 9 mg dm^{-3} of P and 90 mg dm^{-3} of K for this soil (CQFS-RS/SC, 2016). Soil clay contents and cation exchange capacity (CEC) values at pH 7.0, auxiliary parameters used to interpret P and K contents, respectively, were higher than 60% and between 7.6 and 15 cmol$_c$ dm^{-3} in the entire field. Liming was recommended based on the SMP index (data not shown) (CQFS-RS/SC, 2016), which presented a mean value of 5.74 (minimum and maximum value of 5.2 and 6.2, respectively) and CV of 3.3% in the sampling grid of 0.5 ha. Fertilizer and liming rates were defined according to soil fertilization guidelines for the Rio Grande do Sul and Santa Catarina states (CQFS-RS/SC, 2016).

Rates of fertilizers and liming obtained from data collected using the different sampling designs were compared to those obtained from the grid with cell sizes of 0.5 ha, which was considered as a reference. Therefore, the area in which the recommended rates were above and below those recommended for the reference was calculated for all other sampling design. Subsequently, the total deviation on fertilizer and lime rates (kg) and its associated costs (R$) were calculed. For this, the mean market costs practiced during 2016 (CONAB, 2016) were used for triple superphosphate (41% of P_2O_5) (R$ 1.63 kg^{-1}) and dolomitic limestone with an effective calcium carbonate equivalent of 75% (R$ 123.75 Mg^{-1}). Since soil K contents were above the critical level (90 mg dm^{-3}) in all points evaluated, the field did not require fertilization. Costs associated with soil sampling and analysis were determined according to values practiced by service providers in the studied region. The established values were R$ 70.00 per soil sample for the grid of 0.5 ha, R$ 80.00 for the grid of 1 ha, R$ 90.00 for the grid of 2 ha, R$ 95.00 for the grid of 3 ha, R$ 100.00 for the grid of 4.5 ha, R$ 150.00 for the conventional sampling and MZ based on the elevation and R$ 200.00 for the MZ based on crop grain yield and simplified conventional sampling.

RESULTS AND DISCUSSION

The mean values of P and K at all sampling schemes were close to 13 and 190 mg dm^{-3}, respectively (Table 1), being classified as high and very high by CQFS/RS-SC (2016). These results showed that the different sampling designs would not result in significant differences in the fertilizers recommendations, if fixed rates were applied.

However, a high difference was observed in the minimum and maximum values between the sampling designs, mainly between directed and conventional samplings compared to systematic sampling designs. According to increase the size of grid cells the amplitude of data decreases (Table 1). This reduction in data amplitude leads to the underestimation of the real spatial variability in the area, causing errors of interpretation and, consequently, negatively affecting the fertilizer recommendations. Our results were in accordance with those reported by Cherubin et al. (2015), who concluded that grids with smaller cell sizes and consequently, larger number of samples allowed detecting subareas with soil P and K contents very low, which may potentially reduce crop yields.

TABLE 1. Descriptive statistical analysis of soil phosphorus (P), potassium (K), and pH$_{water}$ sampled using different sampling designs, such as systematic (grids), directed by management zones (MZ) delimited by grain yield (Yield) and field elevation data (Elevation), conventional (Conv), and simplified conventional (Simp Conv).

Statistical parameter	Sampling grids (ha)					MZ		Conv	Simp Conv
	0.5	1	2	3	4,5	Elevation	Yield		
N[1]	243	119	60	42	29	4	3	5	1
Soil P content (mg dm^{-3})									
Minimum	3.30	5.60	5.60	5.60	5.60	10.03	11.45	10.54	-
Mean	12.82	13.11	12.92	12.76	12.91	12.20	13.46	12.85	14.04
Maximum	22.00	22.00	22.00	22.00	20.00	13.29	15.80	16.00	-
CV[2]	30.90	30.12	31.46	31.27	29.74	16.61	16.31	16.76	-
Soil K content (mg dm^{-3})									
Minimum	96.00	102.00	107.00	107.00	115.00	184.13	173.86	158.40	-
Mean	194.58	191.05	191.02	190.10	204.59	190.64	185.34	203.88	176.50
Maximum	353.00	338.00	315.00	336.00	338.00	198.57	198.33	251.80	-
CV	27.09	26.58	27.69	30.19	28.92	3.64	6.64	18.37	-
Soil pH$_{water}$									
Minimum	4.50	4.80	4.80	4.90	4.80	5.29	5.28	5.26	-
Mean	5.31	5.30	5.30	5.27	5.26	5.37	5.33	5.36	5.33
Maximum	6.10	5.70	5.70	5.80	5.60	5.46	5.38	5.44	-
CV	4.21	3.76	3.68	4.17	4.22	1.86	0.94	1.21	-

[1] N: Number of observations (soil samples); [2] CV (%): Coefficient of variation.

For soil P and K contents in all sampling grids, CVs were classified as high to very high (26.58 to 31.46%) (Pimentel-Gomez & Garcia, 2002). The high dispersion in the values of soil P and K contents is widely reported in the literature (Nanni et al., 2011, Rodrigues et al., 2012, Santi et al., 2012, Cherubin et al., 2014, 2015). High CV values are an indication of high spatial variability of attributes in the area (Oliveira et al., 2015), which, consequently, requires the use of sampling designs with a higher number of samples to faithfully reproduce the spatial variability of attributes at non-sampled sites (Siqueira et al., 2014).

The mean values of soil pH_{water} in all sampling design were close to 5.30, being slightly below the value used as the critical limit (5.50) for liming recommendations in areas under no-tillage system in Rio Grande do Sul and Santa Catarina states (CQFS-RS/SC, 2016). Even applying a high lime rate (5 Mg ha^{-1}) in 2008, the soil presented a moderate acidity, requiring a new liming in practically the entire field. The reacidification of agricultural areas is mainly associated with leaching and extraction of basic cations by grain harvesting, nitrification of ammoniacal fertilizers, and oxidation of soil organic matter (Souza et al., 2007). The dispersion of soil pH_{water} values was classified as low (CV <5%) for data from all sampling designs.

When data presented spatial dependence, the best data adjustment was provided by the Gaussian model, except for K data from grid of 0.5 ha (Table 2). Soil pH_{water} and soil P contents presented a defined spatial structure for dataset collected through grid sampling designs with cell sizes $\leq$ 2 ha, while soil K contents data, spatial structure was revealed only for grids with cell sizes $\leq$ 1 ha. Dataset from sampling grids with cells of 3 and 4.5 ha present pure nugget effect (PNE) (absence of spatial dependence), regardless of studied attributes. In practice, when a given variable presents PNE is impossible to use interpolation methods that consider the structure of spatial dependence to estimate attribute values in non-sampled sites, such as ordinary kriging (Vieira, 2002). Cherubin et al. (2015) also verified PNE for soil P and K contents data from sampling grids with cells higher than 2.25 ha. The authors associated this result with an increase in the distance between points and the consequent reduction in the number of samples, generating an insufficient number of pairs (observations) to accurately adjust the data to a theoretical model. According to Webster & Oliver (2007), recognizing the spatial distribution pattern of a given variable by means of well-structured semivariograms requires at least 50 observations (soil samples, for example), which in our study was obtained only for grid sampling designs with cell size of 0.5 ha (243 samples), 1 ha (119 samples) and 2 ha (60 samples).

Range values were for P, K and pH data, ranging from 198 to 339 m (Table 2). They represent the limit distance in which there is spatial dependence between samples (Webster & Oliver, 2007). Some authors such as Souza et al. (2014) and Oliveira et al. (2015) have indicated the use of half the range value as the maximum distance between points for subsequent samplings. In this sense, the results obtained in the present study indicated the possibility of using grid sampling designs with maximum cell sizes, ranging from 1 to 3 ha. However, Cherubin et al. (2015) alerted that depend on size of field, this recommendation may result in sampling designs with reduced number of samples, compromising the reliability of results.

TABLE 2. Geostatistical analysis of soil phosphorus (P) and potassium (K) contents, and soil pH_{water} values systematically sampled from grid sampling designs with different cell sizes.

Grid (ha)	N[1]	Nugget effect	Sill	Range (m)	Model	R^2	SDI[2] (%)	DSD[3]
Soil P content (mg dm^{-3})								
0.5	243	5.66	13.88	339	Gaussian	0.92	14	Moderate
1	119	2.68	13.43	229	Gaussian	0.80	12	Moderate
2	60	0.20	13.79	223	Gaussian	0.72	15	Moderate
3	42	PNE[4]	PNE	PNE	PNE	PNE	PNE	PNE
4.5	29	PNE	PNE	PNE	PNE	PNE	PNE	PNE
Soil K content (mg dm^{-3})								
0.5	243	859.42	2290.35	317	Exponential	0.62	8	Moderate
1	119	1042.06	2041.12	196	Gaussian	0.31	7	Weak
2	60	PNE	PNE	PNE	PNE	PNE	PNE	PNE
3	42	PNE	PNE	PNE	PNE	PNE	PNE	PNE
4.5	29	PNE	PNE	PNE	PNE	PNE	PNE	PNE
Soil pH_{water}								
0.5	243	0.03	0.05	245	Gaussian	0.91	7	Weak
1	119	0.01	0.04	198	Gaussian	0.73	10	Moderate
2	60	0.02	0.04	281	Gaussian	0.70	10	Moderate
3	42	PNE	PNE	PNE	PNE	PNE	PNE	PNE
4.5	29	PNE	PNE	PNE	PNE	PNE	PNE	PNE

[1]N: Number of observations (soil samples); [2]SDI: spatial dependence index; [3]DSD: degree of spatial dependence calculated and classified according to Seidel & Oliveira (2014) and Seidel & Oliveira (2016), respectively; [4]PNE: pure nugget effect.

The data indicated that an increase in the dimension of the sampling grid promoted a reduction in the coefficients of determination (R^2) of theoretical models, as reported by Bottega et al. (2014). The spatial dependence was classified as weak for grids with cell sizes of 0.5 and 1 ha for soil pH_{water} and soil K content, respectively. All other datasets with defined spatial structure presented spatial dependence classified as moderate (Seidel & Oliveira 2016). The stronger the spatial dependence is, the better the attribute prediction performed by kriging in non-sampled sites (Kravchenko, 2003) because there is less contribution of random components in the data variability.

The values of soil P and K contents, and pH_{water} predicted from the data obtained in the different sampling designs showed significant positive correlations ($p<0.01$) with the values of reference sampling (grid of 0.5 ha), except for the data of soil pH_{water} obtained by conventional sampling (Table 3). In general, there was a reduction of the correlation coefficient as the dimension of the grid cells increased, which is similar to the pattern observed by Cherubin et al. (2015). The data obtained through sampling grids presented correlation coefficients above 0.60, regardless of their dimensions.

TABLE 3. Pearson's linear correlation and coefficient of relative deviation of soil phosphorus (P) and potassium (K) contents and pH_{water} sampled using different sampling designs, such as systematic (grids), directed by management zones (MZ) delimited by grain yield (Yield) and field elevation data (Elevation), conventional (Conv), and simplified conventional (Simp Conv).

Soil	--------------Sampling grids (ha)------------------				---------------MZ------------		Conv	Simpl
attributes	1	2	3	4.5	Yield	Elevation		Conv
----------Pearson's linear correlation----------								
P	0.93 **	0.89 **	0.83 **	0.81 **	0.27 **	0.10 **	0.55 **	-
K	0.91 **	0.77 **	0.68 **	0.74 **	0.16 **	0.18 **	0.75 **	-
pH_{water}	0.79 **	0.65 **	0.74 **	0.64 **	0.20 **	0.44 **	-0.25 **	-
----------Coefficient of relative deviation (%)----------								
P	8.07	10.78	10.24	11.19	20.74	20.06	16.32	23.68
K	5.86	9.11	11.46	10.33	13.93	11.39	14.34	14.49
pH_{water}	1.25	1.33	1.51	1.59	1.68	1.70	1.72	2.16

**=$p<0.01$; n= 722 observations.

The correlation coefficients of soil P, K, and pH_{water}, obtained using directed samplings at MZ and the reference grid sampling design, were lower than 0.45 (Table 3). On the other hand, the correlation coefficients in the conventional sampling were high for soil P and K content, being 0.55 and 0.75, respectively. However, a negative correlation was observed for soil pH_{water}. This negative correlation between soil pH_{water} in conventional sampling and in reference grid sampling design is attributed to the lack of representativeness of plots in the conventional sampling. This result shows the importance of searching for the best possible representation of the plot from a higher number of subsamples when using conventional sampling design for soil fertility assessments.

The low correlation coefficient between directed and the reference (grid of 0.5 ha) sampling designs suggested that directed sampling designs were not efficient to reproduce the spatial variability of soil attributes (Siqueira et al., 2014). Possibly, the limitation of MZ based on elevation data is on the soft wavy relief of the area, with an elevation variation of only 42 m (518–560 m). This difference may have been insufficient to induce significant changes in the spatial distribution pattern of soil attributes. Similarly. the inefficiency of MZ based on crop grain yield may have occurred due to the high soil fertility of field, leading to a low or even no correlation between soil chemical attributes and crop yield (CQFS-RS/SC, 2016). In that case, other factor are limiting crop yield, such as soil physical restrictions and water availability to plants (Santi et al., 2012).

The dissimilarity analysis of maps performed using CDR showed that the smallest deviations occurred in maps generated from the systematically sampled data (grids), with values ranging from 8.07 to 11.19% for soil P content, from 5.86 to 13.93% for soil K contents, and from 1.25 to 1.68% for soil pH_{water} (Table 3). Cherubin et al. (2015) studying grid sampling designs with cell sizes ranging from 0.5 to 4 ha observed higher CRD values when compared to those obtained in this study, reaching 36.2 and 19.4% for the maps of soil P and K contents, respectively. Higher CRD values observed between maps by Cherubin et al. (2015), may be related to soil samples collected independently for each tested sampling grid instead of using the systematic point elimination technique to simulate different grid sampling designs, as we used in this study. The use of this technique has the advantage of preventing the confounding effects induced by inherent micro-variability soil expressed in short distances, and variations in laboratory results, as well as significantly reducing costs of the research.

Maps elaborated from conventional and directed sampling designs showed CRD similar to each other, but higher when compared to those obtained for sampling grids. The lowest CRD deviations were obtained for soil pH_{water} and the highest for soil P and K contents, while the inverse was observed in the correlation analysis. This occurred because soil pH_{water} had a lower variation among the values when compared to the other attributes, resulting in lower correlation coefficients. The limited number of sampling points in directed sampling designs reduced the amplitude of values, making the correlation analysis an inefficient strategy to evaluate maps elaborated from these soil sampling designs.

Figure 2 shows the thematic maps of the soil attributes P, K, and pH_{water}. In general, the three soil attributes presented similar pattern, confirming the results obtained through CRD and the linear correlation analysis. Increases in the cell sizes of grid sampling designs made the maps more generalists, causing loss of information on the spatial variability of attributes. A clear difference can be observed in the maps interpolated by ordinary kriging (data with defined spatial structure) (sampling grids ≤ 2 ha) and inverse-square distance, with the ordinary kriging providing a smoothing of isolines, which facilitates variable rate applications.

Maps from grids of 0.5, 1, and 2 ha are visually similar, while those from grids of 3 and 4.5 ha partially lost spatial variability information. In contrast, completely different patterns were observed in the maps from directed sampling designs, regardless of the criteria used to delimit MZ. Soil sampling efficiency directed by MZ is possibly dependent on the choice of the delimitation criteria for subareas, being more efficient when the spatial variability of soil attributes is conditioned primarily by intrinsic factors to soil and landscape (*e.g.* soil type and relief) (Mallarino & Wittry, 2004).

High soil P contents (*i.e.* above the critical content of 9 mg dm^{-3}) was consistently observed in the studied field (Figure 2). As a result, only 8.6% of the area (10.3 ha) had soil P contents classified as medium (6–9 mg dm^{-3}) and, therefore, required P fertilization (Table 4). Thus, regardless of the soil sampling design, the fertilizer recommendations were quite similar.

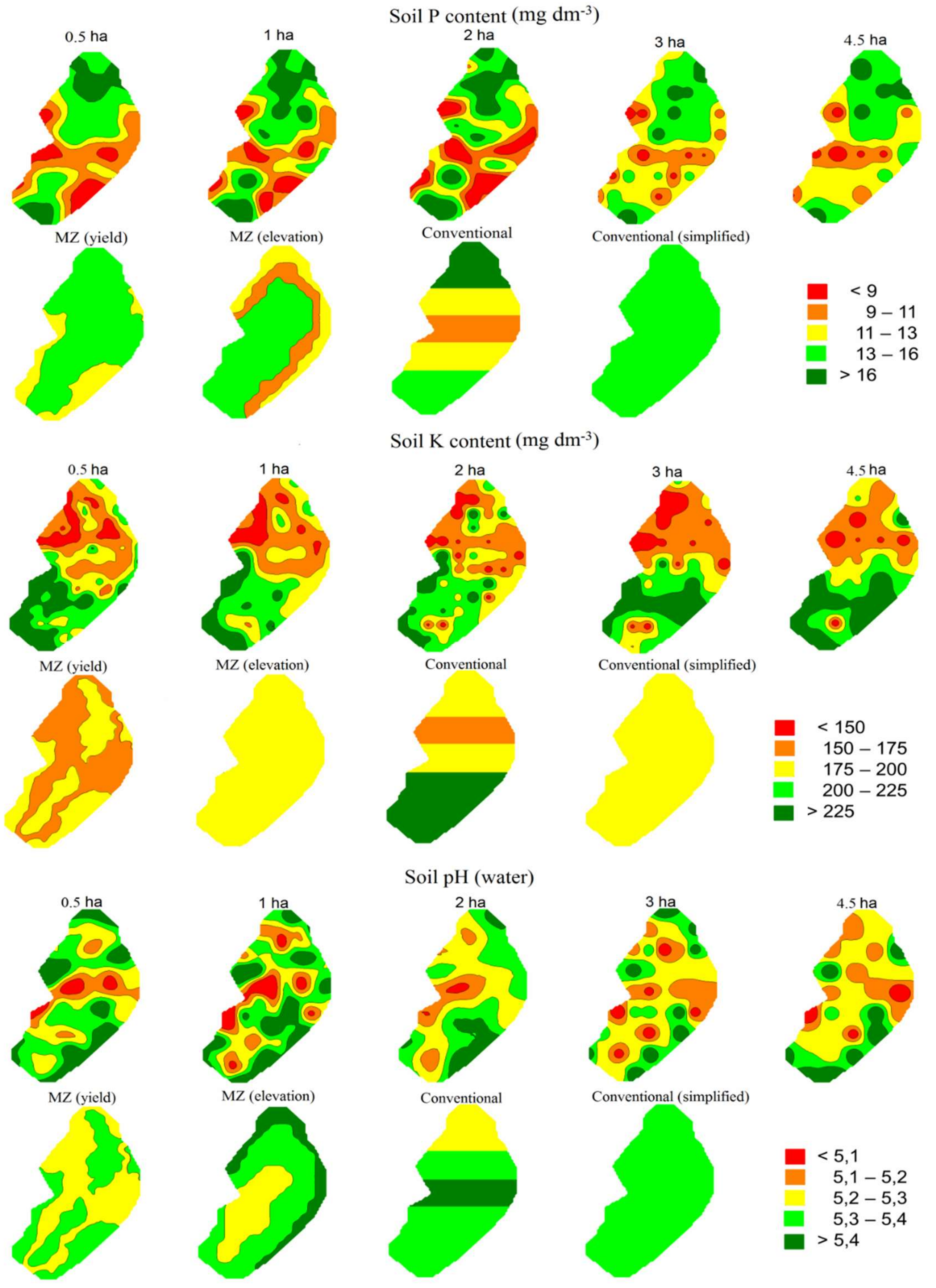

FIGURE 2. Thematic maps of soil phosphorus (P) and potassium (K) content (mg dm^{-3}) and soil pH_{water} sampled using different sampling designs, such as systematic (grids), directed by management zones (MZ) delimited by grain yield (yield) and field elevation data (elevation), conventional, and conventional (simplified).

Data from directed sampling designs suggested that P fertilization was no necessary in that field. It reveals that this alternative methodologies were inefficient in showing subareas of the field that had fertilizer application requirement, which can induce reductions of crop yield in these subareas (Bottega et al., 2014, Cherubin et al., 2015, CQFS-RS/SC, 2016). The cost of the triple superphosphate (TSP) incorrectly recommended (higher and lower doses than the reference) using systematic sampling with grid of 1 ha was R$ 1,238.00 (approximately R$ 10.00 per ha). For the other sampling designs, the deviations in the recommendations resulted in extra cost ranging from R$ 1,633.00 to 1,817.00 (approximately from R$ 14.00 to 15.00 per ha).

TABLE 4. Economic analysis of costs of sampling, inputs, and deviations of recommendations of triple superphosphate (TSP) and lime carried out from soil attributes systematically sampled from sampling grids and directed by management zones (MZ) delimited by grain yield (Yield) and field elevation data (Elevation), conventional (Conv), and simplified conventional (Simp Conv) in relation to the reference sample (sampling grid of 0.5 ha).

Parameter	-----------------Sampling grids (ha)-----------------					----------MZ---------		Conv	Simpl Conv
	0.5	1	2	3	4.5	Yield	Elevation		
N(1)	243	119	60	43	29	3	4	5	1
---Triple superphosphate---									
ARRBR(2) (%)	-	2.3	1.5	7.2	7.4	8.6	8.6	8.6	8.6
ARRAR(3) (%)	-	4.2	7.6	1.5	2.3	0.0	0.0	0.0	0.0
TARI(4) (kg)	1,002	1,212	1,713	339	404	0	0	0	0
ARIBR(5) (kg)	-	275	188	840	856	1,002	1,002	1,002	1,002
ARIAR(6) (kg)	-	485	889	178	259	0	0	0	0
TSP IR(7) (R$)	-	1,238	1,738	1,659	1,817	1,633	1,633	1,633	1,633
---Lime(8)---									
ARRBR (%)	-	20.2	18.8	19.4	15.6	41.6	39.5	47.8	36.7
ARRAR (%)	-	26.3	30.4	34.8	38.9	31.2	31.6	24.7	34.0
TARI (Mg)	191.3	192.9	196.1	197.4	200.6	188.7	188.5	185.7	191.3
ARIBR (Mg)	-	6.0	5.3	5.2	4.4	13.7	13.8	15.5	12.4
ARIAR (Mg)	-	7.6	10.1	11.2	13.7	11.0	11.0	9.8	12.3
Lime IR (R$)	-	1,681	1,907	2,033	2,242	3,054	3,065	3,127	3,053
---Costs of sampling, inputs, and deviations of recommendations---									
Total SFT (R$)	1,633	1,975	2,791	553	658	0	0	0	0
Total calcário (R$)	23,677	23,870	24,266	24,424	24,826	23,346	23,325	22,977	23,674
Calcário + SFT (R$)	25,310	25,845	27,058	24,977	25,484	23,346	23,325	22,977	23,674
Amostragem (R$)	17,010	9,520	5,400	4,085	2,900	600	600	750	200
Custo total (R$)	42,320	35,365	32,458	29,062	28,384	23,946	23,925	23,727	23,874
Saldo (R$)	0	-6,955	-9,862	-13,258	-13,936	-18,374	-18,395	-18,593	-18,446
TCIRI(9) (R$)	0	2,918	3,645	3,692	4,059	4,687	4,698	4,760	4,686
SSC(10) + TCIRI (R$)	17,010	12,438	9,045	7,777	6,959	5,287	5,298	5,510	4,886
Balance (R$)	0	-4,572	-7,965	-9,233	-10,051	-11,723	-11,712	-11,500	-12,124

(1)n: Number of observations (soil samples); (2)ARRBR= Area with recommended rates below the reference; (3)ARRAR= Area with recommended rates above the reference; (4)TARI= Total amount recommended inputs (fertilizer or lime); (5)ARIBR= Amount of recommended input below the reference; (6)ARIAR= Amount of recommended input above the reference; (7)IR= Incorrectly recommended; (8)Lime= Effective calcium carbonate equivalent =75%; (9)TCIRI= Total cost of incorrectly recommended inputs; (10) SSC= Soil sampling cost.

Increasing cell size of sampling grid from 0.5 to 4.5 ha and the use of directed sampling designs reduced the cost of soil sampling by 83 and 96%, respectively, compared with reference grid (Table 4).

The total cost of inputs recommended (lime and TSP) for the area showed little variation among the sampling designs, as observed by Bottega et al. (2014). However, the amount of inputs recommended from systematic samplings were slightly higher when compared to directed samplings. For the higher cost sampling scheme to be economically viable, it is necessary to reduce the amount of recommended inputs and/or increase crop yield due to a better soil fertility management (Mallarino & Wittry, 2004). In the present study, the use of systematic sampling resulted in higher expenditures on inputs because of the better detection of small subareas in the field with soil P deficiency. However, grain yield changes induced by contrasting recommendation from different soil sampling designs (CQFS-RS/SC, 2016) would not be expected, because of the high soil fertility (*i.e.* contents close to or above the critical level).

The sum of the costs of sampling and costs resulting from erroneous recommendations (*i.e.* above and below the reference) indicated that the use of directed samplings was more economically viable, generating a mean saving of R$ 11,765.00 (R$ 98.40 per ha). The largest sampling grid (4.5 ha) presented a saving of R$ 10,051.00 (R$ 84.07 per hectare) in relation to the sampling grid of 0.5 ha (reference), suggesting that grids with larger dimensions can be alternatively used when soil fertility is high and there is no available data or expertise to delimit MZ. These results are in accordance with those described by several authors, in which cost is the main limiting factor to the widespread use of systematic soil sampling designs that resulting in high number of samples (Souza et al., 2014, Oliveira et al., 2015).

In addition, although the soil nutrient contents are close or above the critical level, our results showed that the spatial variability of soil P and K contents remained high even in the area with a history of PA tools applied to soil fertility. Thus, systematic samplings using larger sampling grids (>2 ha) and directed and conventional samplings failed to capture this spatial variability efficiently, presenting a technical drawback in relation to more dense systematic sampling designs.

Therefore, when spatial variability of soil attributes is unknown, the use of a dense systematic sampling (≤ 1 ha) is suggested to better detecting and mapping the spatial distribution of attributes in the field. (Corá & Beraldo, 2006). These results are in line with recommendations of several studies previously conducted in Brazil (Corá & Beraldo, 2006, Nanni et al., 2011, Souza et al., 2014, Cherubin et al., 2014, 2015). For a subsequent soil sampling, farmers/consultants may decide between repeating a systematic sampling design or changing to a directed sampling design based on the existing spatial variability and the mean nutrient contents in the previous sampling. Our results showed that sampling grid with a larger dimension should be economically more attractive if the farmer/consultants choose to continue using systematic sampling.

When almost the entire area already has adequate fertility levels (contents above the critical level), periodic soil samplings for fertility monitoring purposes can be conducted in a directed manner or even from conventional sampling, thus saving time and financial resources. The use of a directed soil sampling at MZ, in addition to the lower cost, has as advantages the possibility of conducting a more complete exploratory investigation of soil attributes (chemical, physical, and biological) that may be limiting crop yield (Santi et al., 2012). Under these same soil fertility conditions, fertilizer recommendation can be based on thematic maps of nutrient removed by grains plus a percentage of losses to the environment (25–35% for the no-tillage system) (CQFS-RS/SC, 2016).

The results of the present study help to understand the findings of Walton et al. (2010) on cotton fields in the USA. From the application of a questionnaire, they found that 33% of the farmers who abandoned the use of systematic samplings adopted MZ for fertility management. The correct soil fertility management based on systematic samplings leads to an increase in nutrient contents above the critical levels and directed samplings become more economically viable from that moment. It is a virtuous circle, where proper soil sampling results in a precise detection of spatial variability of soil variable and consequently suitable fertilization management. Afterwards, soil fertility can be monitored by MZ or larger grid sampling designs in a more economically way without impair the technical efficiency of soil fertilization management.

CONCLUSIONS

In an area with a history of soil fertility management by using precision agriculture tools, the spatial variability of soil P and K contents remained high. Therefore, conventional soil samplings at MZ or systematic sampling designs with reduced number of samples were ineffective for mapping the spatial variability of soil P and K contents. However, the different sampling designs showed no significant influence on fertilizer and corrective recommendations, because nutrient contents were close to or above critical levels (high soil fertility). Therefore, when soil present high fertility, systematic sampling with large number of samples can be replaced by directed based on MZ or even by conventional sampling designs to reduce sampling costs without loss efficiency on soil fertilization management. Nevertheless, crop responses must be monitored to validate fertilization management based on these simplifications on soil sampling procedure.

REFERENCES

Baio FHR, Silva SP, Camolese HS, Neves DC (2017) Financial analysis of the investment in precision agriculture techniques on cotton crop. Engenharia Agrícola 37(4):838-847.

Bottega EL, Queiroz DM, Pinto FAC, Neto AMO, Vilar CC, Souza CMA (2014) Sampling grid density and lime recommendation in an Oxisol. Revista Brasileira de Engenharia Agrícola e Ambiental 18(11):1142-1148.

Cherubin MR, Santi AL, Eitelwein MT, Amado TJC, Simon DH, Damian JM (2015) Dimensão da malha amostral para caracterização da variabilidade espacial de fósforo e potássio em Latossolo Vermelho. Pesquisa Agropecuária Brasileira 50(2):168-177.

Cherubin MR, Santi AL, Eitelwein MT, Menegol DR, Ros CO, Pias OHC, Berghetti J (2014) Eficiência de malhas amostrais utilizadas na caracterização da variabilidade espacial de fósforo e potássio. Ciência Rural 44(3):425-432.

Cherubin MR, Santi A L, Pias OHC, Eitelwein MT, Basso CJ, Della Flora LP, Damian JM (2016) Amostragem de solo na agricultura de precisão. In: Santi AL, Giotto E, Sebem E, Amado TJC (eds). Agricultura de precisão no Rio Grande do Sul. CESPOL, p.79-98.

CQFS-RS/SC - Comissão de Química e Fertilidade do Solo do Rio Grande do Sul e Santa Catarina (2016) Manual de calagem e Adubação para os estados do Rio Grande do Sul e Santa Catarina. Sociedade Brasileira de Ciência do Solo, Núcleo Regional Sul, 11 ed. 376p.

CONAB - Companhia Nacional de Abastecimento (2016) Preço dos insumos Agropecuários 2016. CONAB. Available: http://consultaweb.conab.gov.br/consultas/consulta-Insumo.do?method=acaoCarregarConsulta. Accessed: Dec 23, 2016.

Corá JE, Beraldo JMG (2006) Variabilidade espacial do solo antes e após calagem e fosfatagem em doses variadas na cultura de cana-de-açúcar. Engenharia Agrícola 26(2):374-387.

Kravchenko AN (2003) Influence of spatial structure on accuracy of interpolation methods. Soil Science Society America Journal 67(5):1564-1571.

Mallarino AP, Wittry DJ (2004) Efficacy of grid and zone soil sampling approaches for site-specific assessment of phosphorus, potassium, pH, and organic matter. Precision Agriculture 5(2):131-44.

Molin JP, Amaral LR, Colaço AF (2015) Agricultura de precisão. Oficina de Textos, 238p.

Molin JP (2002) Definição de unidades de manejo a partir de mapas de produtividade. Engenharia Agrícola 22(1):83-92.

Nanni MR, Povh FP, Demattê JAM, Oliveira RB, Chicati ML, Cezar E (2011) Optimum size in grid soil sampling for variable rate application in site-specific management. Scientia Agrícola. 68(3):386-392.

Oliveira IA, Junior JM, Campos MCC, Aquino RE, Freitas L, Siqueira DS, Cunha JM (2015) Variabilidade espacial e densidade amostral da suscetibilidade magnética e dos atributos de Argissolos da Região de Manicoré, AM. Revista Brasileira de Ciência do Solo 39(3):668-81.

Pimentel-Gomes F, Garcia CH (2002) Estatística aplicada a experimentos agronômicos e florestais. Piracicaba, FEALQ, 309p.

Rodrigues MS, Corá JE, Fernandes C (2012) Soil sampling intensity and spatial distribution pattern of soils attributes and corn yield in no-tillage system. Engenharia Agrícola 32(5):852-65.

Santi AL, Amado TJC, Cherubin MR, Martin TN, Pires JL, Della Flora LP, Basso CJ (2012) Análise de componentes principais de atributos químicos e físicos do solo limitantes à produtividade de grãos. Pesquisa Agropecuária Brasileira 47(9):1346-1357.

Santos HG, Jacomine PKT, Anjos LHC, Oliveira VA, Lumbreras JF, Coelho MR,
Almeida JA, Cunha TJF, Oliveira JB (2013) Sistema Brasileiro de Classificação de Solos (3a ed.).
Brasília, DF: Embrapa Solos.

Schmidt JP, Taylor RK, Milliken GA (2002) Evaluating the potential for site-specific phosphorus applications without high-density soil sampling. Soil Science Society America Journal 66(1):276-283.

Seidel EJ, Oliveira MS (2014) Novo índice geoestatístico para a mensuração da dependência espacial. Revista Brasileira de Ciência do Solo 38:699-705.

Seidel EJ, Oliveira MS (2016) A Classification for a Geostatistical Index of Spatial Dependence. Revista Brasileira de Ciência do Solo 40:1-10.

Siqueira DSJ, Junior M, Pereira GT, Barbosa RS, Teixeira DB, Peluco RG (2014) Sampling density and proportion for the characterization of the variability of Oxisol attributes on different materials. Geoderma 232-234(1):172-182.

Soares Filho R, Cunha JPAR (2015) Agricultura de precisão: particularidades de sua adoção no sudoeste de Goiás – Brasil. Engenharia Agrícola 35(4):689-698.

Soil Survey Staff (2014) Keys to soil taxonomy (12th ed.). Washington, DC: USDA-Natural Resources Conservation Service.

Souza DMG, Miranda LN, Oliveira SA (2007) Acidez do solo e sua correção. In*:* Novais RF, Alvarez VH, Barros NF, Fontes RL, Cantarutti RB, Neves JCL (eds). Fertilidade do solo. Sociedade Brasileira de Ciência do Solo, p.206-274.

Souza ZM, Souza GS, Júnior JM, Pereira, GT (2014) Número de amostras na análise geoestatística e na krigagem de mapas de atributos do solo. Ciência Rural 44(2):261-268.

Suszek G, Souza EG, Uribe-Opazo MA, Nobrega LHP (2011) Determination of management zones from normalized and standardized equivalent productivity maps in the soybean culture. Engenharia Agrícola 31(5):895-905.

Vieira SR, Millete J, Topp GC, Reynolds WD (2002) Handbook for geostatistical analysis of variability in soil and climate data. In: Alvarez VVH, Schaefer CEGR, Barros NF, Mello JWV, Costa LM, (eds) Tópicos em ciência do solo. 2ª ed. Sociedade Brasileira de Ciência do Solo, 2 ed. p.1-45.

Walton JC, Roberts RK, Lambert DM, Larson JA, English BC, Larkin SL, Martin SW, Marra MC, Paxton KW, Reeves JM (2010) Grid soil sampling adoption and abandonment in cotton production. Precision Agriculture 11(2):135-147.

Webster R, Oliver MA (2007) Geostatistics for environmental scientists. Chichester, John Wiley, 2nd ed. 309p.