SOIL SAMPLE DENSITIES COMBINED WITH ADDITIONAL POINTS IN THE VARIABILITY OF SOIL CHEMICAL ATTRIBUTES

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ABSTRACT

Objective: To evaluate regular sampling meshes and the allocation of additional collection points based on the transition regions of the previous culture NDVI maps in determining spatial variability of chemical attributes such as phosphorus and potassium.

Theoretical benchmark: The spatial variability of the soil’s chemical attributes, such as K (potassium) and P (phosphorus) levels, are used in geo-referenced soil sampling technique guided by remote sensing products, such as the normalized difference vegetation index (NDVI), which is related to the productivity of corn crops. To allow to know the spatial distribution of these elements respecting the AP bases.

Method: The experiment was carried out in the 224 ha plot of a commercial farm located in the municipality of Maracaju - MS, Distroferric Red Latossolo (Lvdf). Sample arrangements were generated by a regular grid of one sample per hectare (1:1), with up to 50% additional points allocated by the NDVI map, thus composing 336 sample points and the other grids by removing 10% of the additional points up to 0% and as well as for the grid (1:4). The levels of P and K, descriptive statistics, geostatistics, ordinary kriging, evaluation of the maps by the relative deviation coefficients (CRD) and Kappa were evaluated.

Results and conclusion: For the P, there was no statistical improvement in the 1:4 grid with additional points and in the 1:1 grid with 30% of the additional points is achieved satisfactory. For K, as it showed high values in the whole area, however it was possible to obtain an ideal grid 1:1 + 40%

Implications of the research: It was not possible to obtain a less dense sample mesh with point allocation based on the NDVI of the corn crop for the 1:4 grades.

Originality/value: Conduct future research using other vegetation indices, soil classes as well as other interpolation methods.

Keywords: Geostatistics, Soil Fertility, Precision Agriculture, Fertilization.

DENSIDADES AMOSTRAIS DE SOLO COMBINADAS COM PONTOS ADICIONAIS NA VARIABILIDADE DE ATRIBUTOS QUÍMICOS DO SOLO

RESUMO

Objetivo: Avaliar malhas amostrais regulares e a alocação de pontos adicionais de coleta baseados nas regiões de transições dos mapas de NDVI da cultura anterior na determinação da variabilidade espacial de atributos químicos como o fósforo e o potássio.

Referencial teórico: A variabilidade espacial dos atributos químicos do solo, como teores de K (potássio) e P (fósforo) são utilizadas a técnica de amostragem georreferenciada de solo guiada por produtos do sensoriamento remoto, como o índice de vegetação por diferença normalizada (NDVI) que possui relação dependência com a

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Soil Sample Densities Combined with Additional Points in the Variability of Soil Chemical Attributes

produtividade das culturas do milho. Para permitir conhecer a distribuição espacial desses elementos respeitando as bases da AP.

Método: O experimento foi realizado no talhão de 224 ha de uma fazenda comercial localizada no município de Maracaju – MS, Latossolo Vermelho Distroférrico (Lvd). Os arranjos amostrais foram gerados por uma grade regular de uma amostra por hectare (1:1), com adição de até 50% de pontos adicionais alocados pelo mapa de NDVI, compondo assim 336 pontos amostrais e as demais grades pela retirada de 10% dos pontos adicionais até 0% e assim como para a grade (1:4). Foram avaliados os teores de P e K, estatística descritiva, geoestatística, krigagem ordinária, avaliação dos mapas pelos coeficientes de desvio relativo (CRD) e Kappa.

Resultados e conclusão: Para o P, não houve melhorias estatísticas na grade 1:4 com acréscimo de pontos adicionais e na grade 1:1 com 30% da pontos adicionais se atinge resultado satisfatório. Para o K, como apresentou valores elevados em toda área, porém foi possível obter uma grade ideal 1:1 + 40%

Implicações da pesquisa: Não foi possível obter uma malha amostral menos adensada com alocação de pontos baseada no NDVI da cultura do milho para as grades 1:4.

Originalidade/valor: Realizar futuras pesquisas com o uso de outros índices de vegetação, classes de solo bem como outros métodos de interpolação.

Palavras-chave: Geoestatística, Fertilidade do Solo, Agricultura de Precisão, Adubação.

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1 INTRODUCTION

The term precision agriculture (PA) has some definitions and concepts. Thus, it can be defined as a system of agricultural management based on spatial and temporal variation with the goal of economic return, sustainability, among others. This management is carried out with tools and AP technologies that in turn allow the rational use of agricultural inputs aiming at detecting, monitoring and managing the temporal and spatial variability of the farming systems (Map, 2017).

Within the scope of the AP cycle, information on soil chemical attributes may be obtained in some sampling methodologies. In this way, to detect the spatial variability of an attribute, the assertive characterization of the size and shape of the sample points is necessary. Second Guedes, Bastiane & Uribe-Opazo, (2015), the shape and size of the sample directly influence the prediction of this variability. For, they direct the theoretical models of interpolation of the non-sampling locations and successively the structure of the spatial dependence, the stage of the interpretation and analysis of data and finally in the construction of the thematic maps with the stage of intervention of the PA.

Remote sensing is one of the technologies used in AP. This tool can be defined as obtaining data from a target without requiring direct physical contact. Thus, this technology evolved into certain mathematical combinations among the reflectance data of the targets from different spectral bands that culminated in the formation of vegetation indices (IV) (Shiratsuchi et al., 2014).

Potassium (K), is one of the nutrients that plants need in great quantity. When it comes to scale, its requirement is second in scale, behind only nitrogen (N). The example in soybean cultivation (Glycine max), for every 1000 kg of grains produced 20 kg ha⁻¹ of K22 are exported (Cavalini, Seville, Cruz & Alberton, 2018).
Phosphorus (P) is one of the elements present in the soil. Its importance is due to its essentiality the mineral nutrition of plants, so that the levels of this element in the plant can vary from 0.5 to 3.0 g kg\(^{-1}\) of dry matter, but the balance range is 1.0 to 1.5 g kg\(^{-1}\). Its dynamics in the soil are somewhat complex in terms of its chemical forms and chemical interactions with the particles in the soil (Vinha, Carrara, Souza, Santos & Arantes, 2021).

Thus, the objective was to evaluate regular sampling meshes and the allocation of additional collection points based on the transition regions of the NDVI maps of the previous culture, in the determination of the spatial variability of the chemical attributes phosphorus and potassium.

2 THEORETICAL FRAME

Precision agriculture (PA) covers the study of the spatial and temporal variability of agricultural resources in order to optimize their use to integrate the foundations of sustainability.

2.1 Georeferenced Soil Sampling

One soil sampling strategy that can be carried out is the so-called cell sampling. This method consists of representing the area to be studied no longer at spatially known localized points, but rather the total area of the cell that would represent the average of this. This method represents an alternative to the producer when the traditional method results in a large number of samples, leading to a higher financial and operational expenditure (Molin, Amaral & Collaço, 2015).

Valente, Fontenelli, Brasco & Amaral (2018) studying grid sampling efficiency for soil potassium characterization studied 3 different sampling strategies. The first, being regular grid 1:1, that is, one sample per hectare, regular grid 1:4, that is, one sample every 4 hectares and the third was sampled per cell every 4 hectares. They concluded that small dense grids such as 1:4, the most appropriate would be to carry out sampling by cell.

Soil sampling by grid consists of one of the strategies. In this manner, this strategy defines itself, through sampling, the study of the spatial variability of the element to be studied (Lopes, Aguiar, Oliveira & Dantas, 2020). According to Cherubin et al. (2015), when one wishes to evaluate the quality of a study of the spatial distribution of soil attributes, one must define an appropriate sampling grid.

According to Grego, Oliveira & Vieira (2014) the unsampled locations are determined from the sampled points using the interpolation tool as occurs with the geostatistical interpolators. Among the interpolators used, the example is the ordinary Krigagem which consists of an interpolation method whose purpose is to estimate the locations not sampled based on the known points, using the spatial dependence between the samples, which are estimated by the validation of the variograms that correlates the variance among the known locations with the physical distance between them (Motomiya, Corá & Pereira, 2006).

According to Ferraz, Silva, Oliveira, Custódio & Ferraz (2017), the equation \( \gamma'(h) = 1 \cdot ([2 \cdot N(h)] \cdot [Z(x_i) - Z(x_i + h)]^2)^{-1} \) brings with it its definitions. The \( N(h) \) represents the number of experimental pairs of observations, represented by the symbol \( Z(x_i) \) of their pair \( Z(x_i + h) \), separated by the \( h \)-vector from the geo-referenced points \( (x_i) \), are the data itself of the variable analyzed and the \( y(h) \) represents the variance on the Y-axis while \( h \) represents the distance values on the x-axis. From these elements, the existing models are realized, contributing to the parameters: Nugget effect \( (C_0) \), Range \( (A) \) and Range \( (C_1) \). The parameters determined by the variogram are essential tools for sample planning. Thus, the peptide effect \( (C_0) \), represents through the theoretical model above, the point at which the model intersects the Y-axis.
represented by the variance $\gamma(h)$. This point indicates the unexplained variability, which is intrinsic to the variable that you want to determine (Ferraz et al., 2017).

While the range (A) represents the point at which the variability of the variable in question no longer correlates with the $h$-vector of another known point. Lemos Filho, Oliveira, Faria & Andrade (2008) describe how the distance from which there is no more spatial continuity and the data start to behave in a random manner. And also serve as an indicative parameter for the sampling intervals.

According to Molin et al. (2015), the range represents the degree of homogenization of a given variable under study. In this way, the minimum distance between samples shall be equal to or less than half the range. This condition is clearly present when one has the prior geostatistical analysis of the study site to then conduct a sample planning.

Thus, to carry out the propositional planning of a geo-referenced soil sampling, there are some strategies. The use of a regular grid is highlighted, in which the sample points are evenly evenly distributed as a function of a sampling density. Cherubin et al. (2015) They evaluated different sample meshes for characterizing spatial dependence and their accuracy parameters for phosphorus (P) and potassium (K) contents for Latosols, and concluded that sampling grids less than 100 m are efficient for modeling these soil chemical attributes.

Morato, Oliveira & Silva (2021) with research in one location as 3 different soil classes obtained different results. These authors developed the research with regular meshes of 200 m, that is, 1 sample every 4 hectares, and after cutting the outliers identified the K with a range of 1,207 m and the CTC with a range of 396.57 m.

Amado, Pes, Lemainski & Schenato (2009) evaluating soil chemical attributes, of class of Latossolos, in two experimental fields, in 1:1 grid obtained different results. In its results, the descriptive statistics highlight the parameter of the coefficient of variation, which was presented in the magnitude of 62.2% in the field, in the municipality of Trindade do Sul. As for the geostatistical parameters, in the field of South Trinity (TS), the range of P was 102 m and in the field of Palmeiras das Misções (PM), they obtained a range of 255 m. While the range for K in the TS was 416 m and in the PM field was 408 m.

### 2.2 NDVI as Tool in Soil Sampling

Thus, the known vegetation indices (IVs) of the remote sensing stand out for their use in the inference of behavior of the studied targets. Thus, as is the case of the normalized difference vegetation index (NDVI), which is composed by a ratio of the sum by the difference between data of two spectra of electromagnetic wave reflectance (Vian et al., 2018).

The NDVI results in a scale value of -1 to 1, being -1 for water, close to zero (0) for exposed soil, and close to +1 indicating the presence of vegetation (Fontgalland et al., 2023). These dimensionless values, to which the index results in the respective interim, represent the degree of vigor expressed by the vegetation. The higher NDVI values, are therefore the gradient between the reflectance of infrared and red, thus indicating a higher amount of chlorophyll and dry matter and thus higher the plant's productive potential (Rissini, Kawakawa & Genú, 2015).

This IV may be related to factors of production. Second Trindade, Carvalho, Noetzold, Andrade & Pozza (2019), evaluating the NDVI in soybean crop observed that the NDVI correlated with productivity when obtained at phenological stage R2. Just as Bolton & Friedl (2013) observed high correlation ($r^2 = 0.69$) of NDVI with productivity for growing corn ($Zea mays$).

Second Zanzarini, Pissarra, Brandão & Teixeira (2013)), there was spatial correlation involving NDVI and chemical attribute such as phosphorus and granulometric attribute such as clay. While Santos et al. (2021), showed a significantly positive correlation between base saturation V% and NDVI.
Molin et al. (2015) recommend as a sample planning strategy to allocate 30% additional points in the planned regular mesh. According to the authors, this recommendation, coupled with the randomized positioning of the sample points, can characterize an efficient strategy in determining the variability of the studied attribute.

2.3 Potassium

This element (K), unlike phosphorus, stands out in the soil relation because it is in electropositive ionic form. Thus, its exchangeable, monovalent (K+) form may interact with soil colloids in the form of adsorption. Potassium, as far as its transport in the soil is concerned, can be carried out both by mass flow, where movement occurs in favor of the gradient of water potential formed by the process of water absorption by plants. However, the majority process in K transport occurs by the diffusion process (Oliveira, Rosolem & Trigueiro, 2004).

Oliveira et al. (2004) evaluated the effect of K transport on the availability of nutrients for cotton growing (*Gossypium L*). The authors concluded that the diffusion mechanism was responsible for the range of 72 to 96%, in the absorption of K. They also concluded that water, when present in greater quantity in the soil solution, contributed to the favoring of the diffusion transport mechanism, while in drier regions there was a favoring of the mass flow mechanism.

In this manner, in the light of information on the main elements for growing plants, a search is being made to determine an efficient fertilizing program. Thus, as the classical methodology asserts in essence knowledge of the contents of those elements present in the soil, since if considered at a level lower than a given protocol it provides for correction fertilization for subsequent maintenance fertilization. Second Lange, Cavalli, Cavalli & Buchelt (2019), in the maize-soybean succession system, potassic fertilization in the soybean crop interferes with the export of nutrients from the maize crop.

2.4 Phosphorus

Soil may be a source and/or drain of phosphorus. This statement is explained by the fact that this element's chemical behavior in the soil is correct. In this way, the more weathered the soil becomes chemically more electropositive, leading to the tendency to occur processes called adsorption and subsequent fixation of phosphorus to the soil (Lima Matos, Neto, Uchôa, Nascimento & Pereira, 2017).

This process occurs mainly through the presence of iron and aluminum oxyhydroxides. This is due to the increased adsorption capacity of anions mainly due to the presence of weathered iron and aluminum minerals. In this scenario, it is largely perpetuated in the soil class of Latossolos, Novais & Smith (1999) cite that the Latosols located in the Brazilian cerrado biome can adsorb an amount of 2 mg g⁻¹ of P, equivalent in other units to 9,200 kg ha⁻¹ of P₂O₅ (Novais & Mello, 2019).

In this way, this element has high potential to become unavailable to plants. This factor is due to the fact that diffusion is one of the main transport mechanisms of this element in the soil. Although its movement in the soil is relatively slower when compared to other elements, it is explained by the high sorption of the soil with the colloids. Thus constituting a problem to be faced in fertilizing cultivated plants (Costa, Barros, Albuquerque, Moura-Filho & Santos, 2006).

Silva, Barros & Souza (2015) studied the influence of compaction on the diffusive flux of P and Zinc (Zn) in Latossolos. The authors concluded that under the effect of compaction there was an increase in diffusive flow of P, however, in soils with higher clay texture, there was a greater limitation of diffusion of P due to the adsorptive processes related to clay.
3 METHOD

The experiment was carried out on a 224-hectare plot located in the municipality of Maracaju in the central-western region of Brazil and the northern center of Mato Grosso do Sul. This region is located at latitude 21° 42' 59" from south and longitude 55° 31' 36" from west, with average altitude of 533 m, with values ranging from 509 to 545 m (Figure 1) and presenting average slope of 1.33%.

This plot, comes from a commercial farm called Fazenda Nossa Senhora Consoladora II, where there is since 1996 the system of production of succession of crops, which the soybean crop is cultivated in the period from October to February, while the corn crop is cultivated in the period from February to August.

The experiment was installed in a soil environment classified as dystroferric red latosol (LVdf) according to the classification of (Santos et al., 2011). It has an average clay content of 72%, with values ranging from 65 to 76%.

The allocation of the sampling points was based on the strategy guided by the NDVI vegetation index of the previous crop, corn. The images were taken from the Sentinel 2 satellite, and the L2A product was downloaded on April 13, 2021, with a spatial resolution of 10 m. This date was chosen because it was the immediately preceding product available in which there was no saturation by the maize crop. NDVI was calculated using the geoprocessing tools of SIG software, QGIS version 3.22.11 (QGIS, 2022). According to Aragão, Pereira & Silva (2022) there is still prejudice involving the choice of free software.

In the calculation of the NDVI, sensor values were used in Band 4 representing red reflectance \((P_v)\) at 664.6 nm wavelength and band 8 providing infrared reflectance data \((P_{iv})\) at 832.8 nm wavelength. NDVI calculated as Bezerra et al., (2018), \(\text{NDVI} = \frac{(P_{iv} - P_v)}{(P_{iv} + P_v)}\), where \(P_{iv}\) is the reflectance range in the near infrared region and \(P_v\) of the red region. The NDVI result can be seen in Figure 3.

Sample planning based on maize NDVI was carried out with a regular sample grid application with the highest sample density, 1:1, i.e. 1 sample for 1 hectare combined with 50%
additional points the highest percentage of additional points, thus ending in 336 geo-referenced soil samples. With 224 points coming from the regular grid and 112 coming from the additional grid (Figure 2). Other grids with additional point variations. Thus, Table 1 presents the quantitative of points in each grid studied.

**Figure 2.** Sample grid 1:1 plus 50% additional points.  
*Source: Prepared by the authors (2023)*

### Table 1. Quantitative points in sample grids.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Adjust + additions</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>50%</td>
<td>224 + 112</td>
<td>336</td>
</tr>
<tr>
<td>40%</td>
<td>224 + 89</td>
<td>313</td>
</tr>
<tr>
<td>30%</td>
<td>224 + 58</td>
<td>282</td>
</tr>
<tr>
<td>20%</td>
<td>224 + 23</td>
<td>268</td>
</tr>
<tr>
<td>10%</td>
<td>224</td>
<td>247</td>
</tr>
<tr>
<td>0</td>
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<td>224</td>
</tr>
<tr>
<td>1:4 Grid</td>
<td>56 + 28</td>
<td>86</td>
</tr>
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<td>62</td>
</tr>
<tr>
<td>20%</td>
<td>56</td>
<td>56</td>
</tr>
</tbody>
</table>

*Source: Prepared by the authors (2023)*

The geo-referenced soil sampling collection (21/08/2021 - 30/08/2021) was performed using a 1 inch 20 cm deep helical drill, with 8 sub-samples. A Global Navigation Satellite System (GNSS) receiver operating with Course Acquisition (C/A) code was used to navigate the samples in the field.

The available P (mg dm$^{-3}$) was analyzed by the Mehlich$^1$ method as well as the available K (locally cmolc dm$^{-3}$).

The data interpolation was performed in the QGIS with the Smart-map complement (Pereira et al., 2022) being selected the option “eliminate outliers” that makes an analysis of the variable under study and verifies the possibility of discrepant data. The outliers were removed according to the same criteria (Bottega, Queiroz, Pinto & Souza, 2013), first occurs the definition of the interquartile range (IQ), which results from the difference of the upper quartile (Q3) by the lower quartile (Q1). Thus the upper limit (LS) was defined as (Q3 + 1.5 x IQ), as
well as the lower limit defined as \((Q_1 - 1.5 \times IQ)\). When identified, these outliers are not used in the analysis of the semivariogram and kriging.

Semi-variogram models were selected based on the lowest sum of squares of residues (SQR) and highest coefficient of determination \((R^2)\) (Dalchiavon, Rodrigues, Lima, Lovera & Montonari, 2017). After the choice of the model this was tested by cross-validation, and the values of the angular coefficient \((a)\) of the line were observed which the closer to one (01) the better the validation of the model of the semivariogram.

The interpolator used was the ordinary, isotropic kriging, with a search radius equal to the range \((a)\) and neighborhood of 16 dice and was carried out in the resolution of 10 m, the same used for the vegetation indices.

The calculation of the degree of spatial dependence (GDE) was also performed. This parameter proposed by Cambardella et al. (1997) consists of the relation between the peptide effect \((C_0)\) and the plateau \((C)\). GDE \((\%) = \left(\frac{C_0}{C}\right) \times 100\)

Thus, the resulting layers were transformed into vector and extracted the information from the 10 m resolution grid, where de obtained for all attributes the same 22798 data, spatially allocated. Starting from this procedure, the construction of the thematic maps of the soil attributes was carried out according to the classification described by (Sousa & Lobato, 2004).

After the construction of the thematic maps, they were evaluated by means of the relative deviation coefficient \((\text{CDR.}, \%)\), which from a reference map (grid 1:1 plus 50% of additional points), is calculated the difference in modulus of the other maps, so the smaller the magnitude of the value, the greater the similarity between the maps compared (Cherubin et al., 2015). CDR. = \sum |(T_{ij} - T_{i\text{ref}})| \times T_{i\text{ref}} \times 100 Where \(T_{ij}\) is the value of attribute \(i\) \((K \text{ (Cmol.dm}^{-3}), P \text{ (mg.dm}^{-3})\) of the different sample grids \(j\) (1:1 and 1:4) from 0 to 50% of samples allocated. \(T_{i\text{ref}}\) represents the geographically placed values of the respective thematic reference map and \(n\) represents the total number of data (Coelho, Souza, Uribe-Opazo & Pinheiro-Neto, 2009).

The kappa coefficient \((K)\) corresponds to an error matrix calculation, confusion, of which its magnitude varies from 0 to 100, in which the closer to 0, the lower the agreement between the maps and the contrary is true, the closer to 100, the greater the agreement among the thematic maps (Alba et al., 2022). It was used as a reference map to grid 1:1 plus 50% additional points. \(K = (P_0 - P_c) \times (1 - P_c)\) Where \(P_0\) is the observed proportion of agreement of the objects evaluated and \(P_c\) is the proportion that agreement occurs at random. The standard deviation for performing the Z-test \((\text{ek})\) has also been calculated and is calculated as follows, \(\text{ek} = \frac{P_c.(\text{N}.(1 - P_c))}{\sqrt{\text{N}}}\), where \(N\) is the number of data. To finally calculate the significance test Z, \(Z = K \times \text{ek}^{-1}\).

4 RESULTS AND DISCUSSION

4.1 Phosphorus (P)

Soil P levels are high according to Souza and Lobato (2004), higher than 6.0 mg dm\(^{-3}\). The cause can be explained by the excess fertilizer located in the groove when planting crops (Cherubin et al., 2015). The authors also observed decreases in amplitude as the decrease in sample density explained, because the smaller the number of samples, the values tend to approach the average.

It is observed that high values of the coefficients of variation (CV) occur in all sampling arrangements for P (Table 2). According to Warrick & Nielsen (1980) the CV is low when it is less than 10% (high accuracy), medium when it is between 10% and 60% very high when greater than 60% (very low accuracy). Overall, CVs were above 70% in all grades analyzed.

Cherubin et al. (2015) obtained CV below in different sample meshes for P. The CVs obtained in red Latossolo, were in the range of 23 to 58% for P. Silva Carneiro et al. (2016) obtained a value of 46% CV for P in red latosolos studying regular meshes.
Table 2. Descriptive statistics of available P (mg dm$^{-3}$) in 1:1 and 1:4 grades.

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<td>50%</td>
<td>40%</td>
<td>30%</td>
<td>20%</td>
<td>10%</td>
</tr>
<tr>
<td>Medium</td>
<td>27.95</td>
<td>27.58</td>
<td>27.28</td>
<td>27.</td>
<td>26.33</td>
</tr>
<tr>
<td>PA¹</td>
<td>18.77</td>
<td>20.25</td>
<td>19.70</td>
<td>19.76</td>
<td>19.33</td>
</tr>
<tr>
<td>CV (%)²</td>
<td>78.16</td>
<td>81.26</td>
<td>79.82</td>
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<td>79.85</td>
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<td>40%</td>
<td>30%</td>
<td>20%</td>
<td>10%</td>
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<tr>
<td>Medium</td>
<td>27.65</td>
<td>26.52</td>
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<td>PA¹</td>
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<td>18.81</td>
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<tr>
<td>CV (%)²</td>
<td>78.88</td>
<td>82.45</td>
<td>81.31</td>
<td>81.14</td>
<td>80.88</td>
</tr>
</tbody>
</table>

(¹) SD: standard deviation; (²) CV (%): coefficient of variation.

Source: Prepared by the authors (2023)

Another parameter that indicates the proper fit of the models is the angular coefficient of the line (a), which was obtained by means of cross-validation. The values were close to 1.0 for all grids (Table 3). Values close to 1 indicate greater reliability and efficiency of the model presented (Garlic, Campos, Silva, Montovanelli & Souza, 2014).

Table 3. Geostatistical parameters, relative deviation coefficient and Kappa of P.

<table>
<thead>
<tr>
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<td>Gaussian</td>
<td>Spherical</td>
<td>Spherical</td>
<td>Gaussian</td>
</tr>
<tr>
<td>C₀</td>
<td>89.49</td>
<td>162.88</td>
<td>96.82</td>
<td>85.30</td>
<td>252.31</td>
</tr>
<tr>
<td>C₀ + C₁</td>
<td>513.163</td>
<td>565.290</td>
<td>496.90</td>
<td>494.272</td>
<td>805.55</td>
</tr>
<tr>
<td>A (m) to GDE (%)</td>
<td>1.03</td>
<td>1.04</td>
<td>1.04</td>
<td>1.05</td>
<td>1.04</td>
</tr>
<tr>
<td>CRD (%)</td>
<td>17.44</td>
<td>28.81</td>
<td>19.48</td>
<td>17.26</td>
<td>31.33</td>
</tr>
<tr>
<td>Kappa</td>
<td>100</td>
<td>76.59**</td>
<td>93.53**</td>
<td>71.51**</td>
<td>89.28**</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters</th>
<th>1:4 Grid</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Exponential</td>
<td>Spherical</td>
<td>Spherical</td>
<td>Spherical</td>
<td>Gaussian</td>
</tr>
<tr>
<td>C₀</td>
<td>89.95</td>
<td>51.97</td>
<td>133.76</td>
<td>136.57</td>
<td>38.06</td>
</tr>
<tr>
<td>C₀ + C₁</td>
<td>404.34</td>
<td>374.99</td>
<td>391.56</td>
<td>404.34</td>
<td>394.92</td>
</tr>
<tr>
<td>A (m) to GDE (%)</td>
<td>1.02</td>
<td>0.92</td>
<td>1.02</td>
<td>1.03</td>
<td>1.07</td>
</tr>
<tr>
<td>CRD (%)</td>
<td>19.50</td>
<td>13.86</td>
<td>34.16</td>
<td>33.78</td>
<td>46.27</td>
</tr>
<tr>
<td>Kappa</td>
<td>56.57**</td>
<td>47.48**</td>
<td>44.58**</td>
<td>47.18**</td>
<td>50.67**</td>
</tr>
</tbody>
</table>

(C₀) - Nugget effect; (C₀ + Cassumed14) - Range (m); (a) - Angular coefficient, cross-validation; (GDE) - Degree of Spatial Dependency; (GDE) - Relative deviation coefficient. *Significant by z-test at 1% significance level.

Source: Prepared by the authors (2023)

Based on the spatial dependency index (SDI) one can classify the degree of spatial dependency (SDI) as: strong, for FDI ≤ 25%; moderate, for FDI between 25 and 75%; and weak, for FDI > 75% (Cambardella et al., 1994). From the data it can be verified that (Table 3) in the 1:1 grids, only the 40 and 10% had moderate GDE and in the 1:4 grids only those with 50 and 40% additional points had strong GDE.

As for the values of the relative deviation coefficient and the kappa index (Table 3), it is verified that when the grids have smaller sample numbers, it is observed that there are greater differences between the maps. According to the Landis & Koch classification (1977), all the kappa coefficients of the sample arrangements for the 1:1 grids obtained substantial agreement, while the coefficients referring to the 1:4 grids obtained only moderate agreement. These results show the difficulty of knowing the spatial distribution of phosphorus in the soil in smaller grids.
Cherubin et al. (2015) achieved response behavior with respect to similar range. As the sample density had increased, and thus the sampling mesh decreased, there was a reduction in the data variation. This phenomenon occurred only when comparing 1:4 mesh data with no additional dots with all other fabrics (Table 3).

It is observed for the Kappa coefficient that the index values in the grid of 1:1 and others were with values ranging from 71 to 93%, while in the grid of 1:4 the values were from 40 to 56%. Demonstrating the importance of denser sample grids (Table 3).

For phosphorus the grid that most closely approximated the adopted standard (grid1:1 with 50%) was with 30% additional points. In the 1:4 grid it was with 50% additional points, emphasizing once again the question of quantitative sample points for analysis of variability.

Figures 3 and 4 show the spatial variability of phosphorus. As seen in Table 2, the mean indicated a high value, but from the maps one can see that there is a region to the northeast of the area that is not with high values. It presents values from low to adequate, according to Souza and Lobato (2004). Based on the 1:1 grid with 50% would be around 10.8 ha that would be in the low and middle classes and that would need correction.

Figure 3. P-phosphorus thematic maps (mg dm-3) in grid 1:1 and classified according to Sousa & Lobato (2004).
Source: Prepared by the authors (2023)
Soil Sample Densities Combined with Additional Points in the Variability of Soil Chemical Attributes

4.2 Potassium (K)

As for the results involving potassium (K), there was greater similarity among the sample grids (Table 4). For above 0.20 cmolc dm$^{-3}$ is already considered high value (Souza & Lobato, 2004) for soils with CTC above 4.0 cmolc dm$^{-3}$. The CV of all grades according to Warrick and Nielsen (1980), considered average.

The variation of K associated with the high levels of this element in the soil can be explained by its variation and magnitude. According to Cherubin et al (2015) also obtained average values of K and can be explained by the handling of fertilizer both in sowing line and in total area. As well as the high degree of weathering of primary minerals such as micas (muscovite of 70 to 110 g kg$^{-1}$ of K$_2$O) and biotite (60 to 110 g kg-14 of K 24) feldspatos and feldspatoids as well as secondary minerals such as ilite, vermiculite and interstratified minerals (Melo, Castilho & Pinto, 2019)

Table 4. Descriptive statistics of K available (cmolc dm$^{-3}$) in the 1:1 and 1:4 grades.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>1:1 Grid</th>
<th>1:4 Grid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50%</td>
<td>40%</td>
</tr>
<tr>
<td>Medium</td>
<td>0.63</td>
<td>0.63</td>
</tr>
<tr>
<td>PA$^1$</td>
<td>0.31</td>
<td>0.31</td>
</tr>
<tr>
<td>CV (%)$^2$</td>
<td>50.37</td>
<td>50.83</td>
</tr>
</tbody>
</table>

($^1$) SD: standard deviation; ($^2$) CV (%): coefficient of variation.

Source: Prepared by the authors (2023)
With regard to the geostatistical parameters (Table 5), the appropriate adjustment of the models can be verified by the angular coefficient of the straight line (a), which was obtained by means of cross-validation. Values were found to be greater than 0.8 for all grades (Table 5).

Table 5. Geostatistical parameters, relative deviation coefficient and Kappa of K.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>1:1 Grid</th>
<th>1:4 Grid</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50%</td>
<td>40%</td>
</tr>
<tr>
<td>Model</td>
<td>Gaussian</td>
<td>Gaussian</td>
</tr>
<tr>
<td>C0</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>C0 + C1</td>
<td>0.16</td>
<td>0.17</td>
</tr>
<tr>
<td>A</td>
<td>1308.06</td>
<td>1311.70</td>
</tr>
<tr>
<td>to</td>
<td>0.81</td>
<td>0.82</td>
</tr>
<tr>
<td>GDE</td>
<td>23.31</td>
<td>21.58</td>
</tr>
<tr>
<td>CRD</td>
<td>1.00</td>
<td>1.60</td>
</tr>
<tr>
<td>Kappa</td>
<td>100</td>
<td>99.57</td>
</tr>
</tbody>
</table>

(C0) - Nugget effect; (C0 + Cassumed14) - Range (m); (a) - Angular coefficient, cross-validation; (GDE) - Degree of Spatial Dependency; (CDR.) - Relative deviation coefficient. ** Significant by z-test at 1% significance level.

**Source:** Prepared by the authors (2023)

From the GDE data (Table 5) it can be verified that in the 1:1 grids, all had strong GDE and in the 1:4 grids only those with 10 additional points had strong GDE (Cambardella et al., 1994).

As for the values of the Kappa coefficient (Table 5), it was found that the grids had values close to 100, which indicates high agreement (Alba et al., 2022) with the default map that was the 1:1 grid with 50% additional points.

The thematic classification of the maps (Figure 5 and 6) that followed the technical criteria indicated the same class in almost the whole area of studies. This fact arises from the fact that due to intense fertilization in total area, fixed rate at the study site and there was an increase in K levels in the whole area to high and in a few points with adequate values (Souza & Lobato, 2004).

For recommendation purposes, potassium is found to be at a high level throughout the area in the 1:4 grid (Figure 5) and some points appear as appropriate in the 1:1 grid (Figure 6). However, for all intents and purposes, the recommendations for fertilizing with potassium are only when the areas show low and medium levels. This way, this area would have zero rate (0), and there is no need for the application of potassium, based on the levels available in the soil.
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Figure 5. Thematic maps of potassium K (cmolc dm$^{-3}$) in grid 1:1 and classified according to Sousa and Lobato (2004).
**Source:** Prepared by the authors (2023)

Figure 6. Thematic maps of potassium K (cmolc dm$^{-3}$) in grid 1:4 and classified according to Sousa & Lobato (2004).
**Source:** Prepared by the authors (2023)
Therefore, areas with high levels of potassium in the soil can be sampled with more spaced grids, such as 1:4, because the similarity agreement with high sample density maps was high.

Morato et al. (2021) studying spatial variability of soil chemical attributes yielded similar results. These authors directed their research in regions of 3 different soil classes, Cambisol Haplicum (HX), Latossolo Vermelho (LV) and Neossolo Regolitico (RR), in 1:4 meshes obtained the range of 1,207.34. This value is close to that obtained in all sample meshes (Table 5).

Souza, Souza, Marques Junior & Pereira, (2014) in their results indicate that sample densities that are efficient in characterizing the spatial variability of K and P can be used for full variable rate application. These statements support the reported results of P when other classes of element levels are present in the soil according to the objective criterion used.

5 FINAL CONSIDERATIONS

The 1:4 grids were not satisfactory for determining the variability of P and K.
The 1:1 grids are needed to determine the variability of P and K, with an emphasis on 1:1 + 30% for P and 1:1 + 40% for K.
The P even with values suitable for highs in the area allows to separate grids of different sample intensities, being the most dense grids suitable for evaluating the variability of this attribute.

It is verified that the grids with one sample per hectare have already achieved satisfactory results, but with 30% of additional points the best representation of variability occurs.

Further work is recommended in areas with lower P and K levels in order to better characterize the appropriate meshes for soil sampling.

ACKNOWLEDGEMENTS

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REFERENCES


Soil Sample Densities Combined with Additional Points in the Variability of Soil Chemical Attributes


QGIS.org. QGIS Geographic Information System. QGIS Association. Disponível em:


