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Scientific Article

Can sampling density affect the spatial variability mapping of soil properties?

Diferentes grades amostrais podem mudar o mapa de variabilidade espacial de atributos do solo?

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ABSTRACT - Precision agriculture uses tools and technologies to optimize the application of agricultural inputs. To characterize the spatial variability of soil chemical properties and texture, georeferenced soil sampling techniques are applied. This study aimed to evaluate different regular sampling grid sizes for determining the spatial variability of soil properties. The experiment was conducted on a 224-ha plot of a commercial farm in Maracaju, Mato Grosso do Sul, Brazil, on a Rhodic Dystric Haplustox soil. Sampling arrangements were based on a regular grid with one sample per hectare (1:1), with reduced densities in subsequent evaluations (1:2, 1:3, 1:4, 1:5, 1:7, and 1:10). Soil analyses included Ca, Mg, pH in $CaCl_2$, organic matter, sand, silt, and clay contents. Data were subjected to descriptive statistics, geostatistical analysis, ordinary kriging, and Kappa index evaluation. Results indicated that the soil in the study area was clayey. The 1:3 sampling grid was effective for assessing pH and calcium levels in $CaCl_2$. The 1:4 grid was suitable for evaluating organic matter, while magnesium was best assessed using the 1:7 grid.

Keywords: Soil Fertility. Particle-size Distribution. Precision Agriculture.

RESUMO - Para avaliar a variabilidade espacial dos atributos químicos e da granulometria do solo, são utilizadas técnicas de amostragem georreferenciada do solo. Assim, objetivou-se avaliar malhas amostrais regulares para a determinação de variabilidade espacial dos atributos do solo. O trabalho foi realizado em um talhão de 224 ha de uma fazenda comercial localizada no município de Maracaju – MS, Latossolo Vermelho Distroférrico argiloso. Os arranjos amostrais foram gerados por uma grade regular de uma amostra por hectare (1:1), reduzindo a densidade nas demais avaliações (1:2, 1:3, 1:4, 1:5, 1:7, 1:10). Foram avaliados os atributos: Ca, Mg, pH em $CaCl_2$, matéria orgânica, areia, silte e argila. Os resultados foram submetidos a estatística descritiva, geoestatística, krigagem ordinária e índice Kappa. De acordo com os resultados, o solo da área avaliada é argiloso. A grade amostral de 1:3 foi satisfatória para avaliar os teores de pH em $CaCl_2$ e Cálcio. As Grades 1:4 e 1:7 foram eficientes para avaliar a matéria orgânica e magnésio respectivamente.

Palavras-chave: Fertilidade do solo. Granulometria. Agricultura de precisão.

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INTRODUCTION

Agricultural management practices are typically preceded by a detailed crop assessment that collects information reflecting the crop's needs. Precision agriculture (PA) employs soil, crop, and climate data to improve production system management, recognizing that crop potential can vary substantially over short distances, sometimes within only a few meters (BRAMLEY, 2009).

Small-scale variability is detected through sampling, which captures both agronomic parameters and spatial variability, as sampling points are georeferenced using a global navigation satellite system (GNSS) (MOLIN; AMARAL; COLAÇO, 2015). When geographic coordinates are added to sampling locations, data analysis shifts from classical statistics to geostatistics, which accounts for the spatial position of each sample. In geostatistical analysis, the value at a given location is influenced by the values of neighboring points, with stronger influence from closer points (MOLIN; AMARAL; COLAÇO, 2015).

Selecting an appropriate sampling grid remains a topic of study, as results can vary due to site-specific conditions and interference factors. Sampling density affects both the choice of the theoretical spatial model and the construction of spatial variability maps (KESTRING et al., 2015). Higher-density grids generally produce more accurate maps (GUEDES et al., 2016). Bottega et al. (2014) reported that reducing the number of sampling points led to overestimates of 11% and underestimates of 8% in variable-rate maps compared with the densest grid. In general, grids with fewer points have lower reliability in modeling spatial variability, reducing map accuracy. While dense grids improve analytical precision, they also increase sampling costs. Consequently, the choice of sampling density directly affects the description of soil property spatial variability. According to Leandro Junior et al. (2020), less dense grids tend to underestimate soil property values, resulting in reduced reported concentrations of certain elements.

Comparin and Cortez (2023) demonstrated that the quality of spatial distribution studies for soil properties depends on a sampling grid that accurately represents the property distribution, while balancing operational costs and increasing point density in highly variable areas. They noted that unsampled locations are estimated through interpolation, such as kriging, which predicts values at unsampled points based on known locations. This method uses spatial dependence between samples, determined by validating variograms that correlate the variance between points with the physical distance separating them.

For soil property maps (particle-size distribution and fertility), increasing the sampling interval and reducing point density results in greater estimation error. Souza et al. (2014) found no significant differences between grids containing 105 points and those with 208 points; however, they cautioned that sparse grids in variable-rate application maps can lead to over- or under-application of inputs, undermining the benefits of PA. They emphasized that maps degrade progressively as sampling intervals increase and intensity decreases. Similar trends were observed for soil physical properties such as penetration resistance, where smaller grids were more suitable for generating correction maps (SPLIETHOFF et al., 2020).

Thus, studying the spatial variability of soil properties through sampling grids plays a critical role in guiding management decisions (FREIRE, 2023), as crop growth and development are influenced by soil chemical conditions. Maximizing yield potential is possible only when nutrient availability meets crop demand (THAPA et al., 2021).

Based on these considerations, this study aimed to evaluate regular sampling grids for determining the spatial variability of soil properties.

MATERIALS AND METHODS

Site

The study was conducted on a private farm within a 224-ha plot with a history of dryland farming, featuring a soybean corn succession (soybean during the main season and corn in the off-season) under no-tillage for more than 10 years. The site is located in Maracaju, southwestern Mato Grosso do Sul, Brazil (21°42′59″ S; 55°31′36″ W). The mean elevation is 533 m, based on a digital elevation model (DEM) derived from ALOS PALSAR satellite data (ALOS, 2024), with values ranging from 509 to 548 m (Figure 1). The average slope is 1.33%, classifying the area as flat relief (SANTOS et al., 2018).

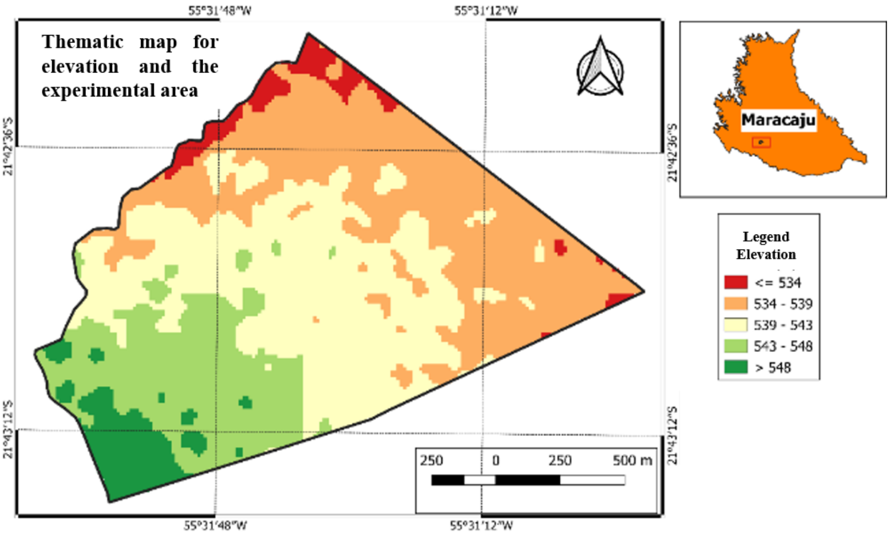

Figure 1. Location and elevation map of the study area.

According to the IBGE (2001) classification at a 1:500,000 scale, the soil in the experimental area is a dystroferric Red Latosol, with texture classes ranging from clayey to very clayey. Previous analyses indicate a mean clay content of 72%, ranging from 65% to 76%. Based on the Köppen climate classification, the region has a humid mesothermal climate with hot summers and dry winters (Cwa), and occasional frost events (FIETZ et al., 2017).

Sampling scheme

The sampling plan was based on a regular grid with the highest density of 1:1, corresponding to one sample per hectare, totaling 224 points (Figure 2). Additional grids with lower densities were generated at 1:2, 1:3, 1:4, 1:5, 1:7, and 1:10 ratios.

To derive the lower-density grids from the 1:1 arrangement, a regular grid was generated for each target density. Within each cell, points were evaluated and selectively removed to maintain both the target number of points and a homogeneous spatial distribution. The resulting grids can therefore be considered regular, with a random distribution of points within each cell. The final number of sampling points for each grid was as follows: 1:1 = 224; 1:2 = 112; 1:3 = 75; 1:4 = 56; 1:5 = 45; 1:7 = 32; and 1:10 = 22.

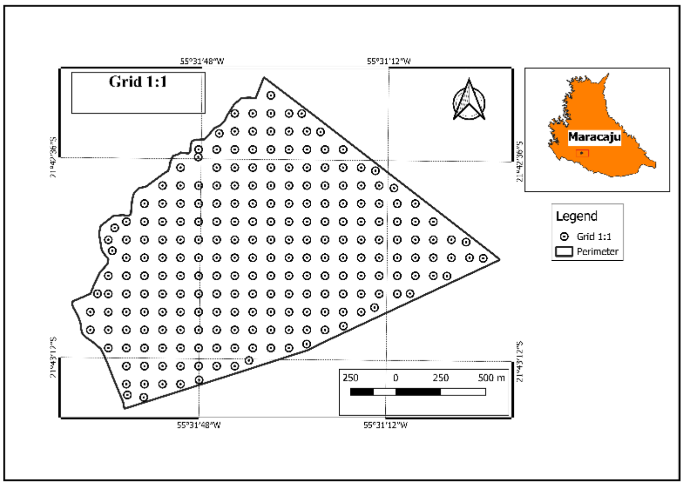

Figure 2. Location of sampling points in a 1:1 grid (one sample per hectare).

Equipment and supplies for soil analysis

Georeferenced soil sampling was conducted from August 21 to August 30, 2021, using a 1-inch (2.54 cm) twist drill with a 60 cm depth capacity, powered by a Buffalo 4.0® stationary engine (Solo Drill®). The drilling system was mounted on a Honda Fourtrax® 4×4 ATV (17.78 kW; 26.9 hp; 6,250 rpm). A GNSS (Global Navigation Satellite System) receiver operating with the C/A (Course Acquisition) code was used to navigate to the sampling points in the field.

Assessments

At each sampling point, soil samples were composed of eight subsamples and labeled with the corresponding point identification (ID). Analyses were performed in a commercial soil laboratory following the protocol of EMBRAPA's Fertility Laboratory Analysis Program (PAQLF). The chemical properties evaluated, and their results provided by the laboratory and used in this study, included pH in $CaCl_2$, organic matter, Ca, Mg, and particle-size distribution (sand, silt, and clay), according to Teixeira et al. (2017).

Data analysis

Data were first subjected to descriptive statistics to obtain the mean, standard deviation, and coefficient of variation. The QGIS Smart-Map add-on (PEREIRA et al., 2022) was used to generate spatial distribution maps of the evaluated properties, with the "eliminate outliers" option enabled to detect and remove possible outliers.

Semivariograms were obtained and subsequently cross -validated, followed by interpolation using ordinary isotropic kriging. The semivariogram model was selected based on the lowest sum of squared residuals (SQR) and the highest coefficient of determination (R^2) (DALCHIAVON et al., 2017). The selected model was then tested through cross-validation, with preference given to models whose slope parameter (a) was closest to 1, indicating stronger model validation. The interpolator settings included a search radius equal to the range (a) and a neighborhood of 16 data points. Maps were interpolated at a spatial resolution of 10 m (COMPARIN; CORTEZ, 2023).

The Kappa index, calculated according to Cohen (1960), was used to compare maps generated from different sampling grids. Values greater than 0.70 were considered to indicate excellent agreement, values between 0.40 and 0.70 reasonable agreement, and values below 0.40 low agreement.

RESULTS AND DISCUSSION

Sand, silt, and clay

Analysis of the mean sand, silt, and clay contents (Table 1) shows that the soil in the study area is classified as very clayey according to the textural triangle (SOUZA; LOBATO, 2004). This classification requires a clay content above 60%, as confirmed in Figure 3, regardless of the sampling grid. The greatest variation in the spatial distribution of particle-size fractions was observed for sand, with coefficients of variation ranging from 27.07% to 8.75%, followed by silt (8.61% to 3.96%) and clay (4.33% to 2.44%) (Table 1). According to Warrick and Nielsen (1980), the coefficient of variation (CV) is considered low when below 10%, medium between 10% and 60%, and very high above 60%, clay presents low variability, suggesting that even less dense grades (up to 1:7 or 1:10) may be sufficient for this particular attribute, unlike sand.

Table 1. Descriptive statistics of sand (%), silt (%), and clay (%) in sampling grids.

Parameter	Sampling grids						
	1:1	1:2	1:3	1:4	1:5	1:7	1:10
				Sand			
Mean	10.56	10.31	10.30	10.15	10.23	10.58	10.84
SD[1]	2.86	2.54	2.52	2.39	2.52	1.86	0.94
CV (%)[2]	27.07	24.61	24.49	23.56	24.62	17.60	8.75
				Silt			
Mean	18.00	17.72	17.81	17.76	18.13	18.17	17.88
SD[1]	1.09	0.79	0.70	0.90	0.89	0.99	1.54
CV (%)[2]	6.05	4.49	3.96	5.07	4.92	5.48	8.61
				Clay			
Mean	71.42	71.92	71.87	72.09	71.67	71.19	71.18
SD[1]	3.09	2.42	2.34	2.02	2.36	1.74	2.32
CV (%)[2]	4.33	3.36	3.26	2.80	3.29	2.44	3.27

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

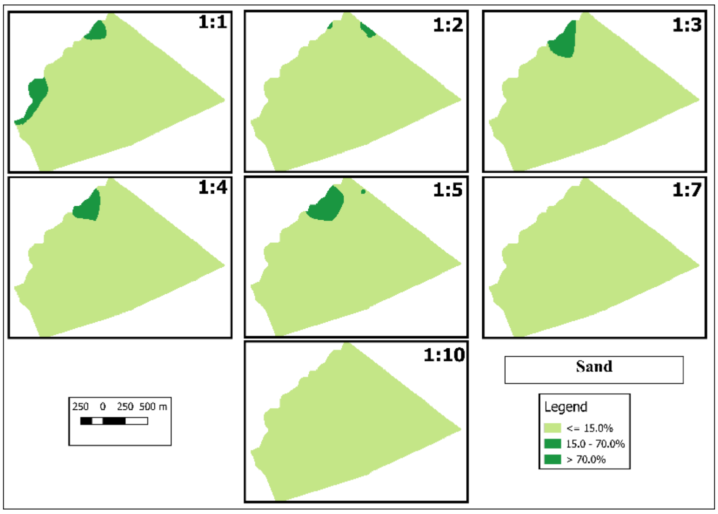

Figure 3. Spatialization of sand distribution (%) in the sampling grids.

For the sand fraction (Table 2), the spherical semivariogram model was fitted to all grids. The range varied from 1,144.95 m (1:10) to 1,304.34 m (1:4), with no major fluctuations, indicating that the spatial dependence structure remained relatively stable even at reduced sampling densities. One parameter indicating model fit is the slope of the regression line (a), obtained through cross-validation. Values close to 1 indicate higher efficiency in representing the phenomenon under study (ALHO et al., 2014). The "a" values revealed a decreasing trend in predictive accuracy as sampling density decreased, demonstrating that grids with fewer points are less capable of accurately reproducing observed values. Regarding the Kappa index, grids with ratios of 1:2 or higher showed a marked reduction, with values approaching zero, indicating low spatial agreement between interpolated and observed data.

Sand content in the study area (Figure 3) is generally low, with values below 15% across most of the area. In the denser grids (1:1 to 1:5), small zones with sand contents between 15% and 70% are present; however, these areas disappear entirely from the 1:7 grid onward, indicating a loss of capacity to detect small variations in marginal-value areas. For sand, the use of denser grids or hybrid grids with additional points is therefore recommended, as proposed by Comparin and Cortez (2023). This finding supports the observations of Souza et al. (2014), who reported that grids with fewer points result in a marked loss of spatial precision.

For silt (Table 3), content remained consistent across all sampling grids, with values below 40% throughout the area. All spatial distribution maps were identical, showing no changes as grid density decreased. This uniformity is likely due to the low silt content in the soil.

Table 2. Geostatistical parameters, Kappa index, and area estimates for sand in each sampling grid.

Parameter	Grid						
	1:1	1:2	1:3	1:4	1:5	1:7	1:10
Model	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical
A	1286.00	1296.92	1296.76	1304.34	1274.98	1196.59	1144.95
A	0.94	0.90	0.88	0.77	0.70	0.64	0.69
Kappa	1.0	0.03	0.25	0.20	0.26	0	0
%	100	94.63	93.96	94.10	93.48	95.15	95.15
Class	Area						
1 (<15%)	213.41	222.54	216.30	217.88	214.33	224	224
2 (15 a 70%)	10.86	1.73	7.97	6.39	9.94	0	0
3 (>70%)	0	0	0	0	0	0	0

(A) – Range (m); (a) - Angular coefficient, cross-validation.

Table 3. Geostatistical parameters and Kappa indices for silt in each sampling grid.

Parameter	Grid						
	1:1	1:2	1:3	1:4	1:5	1:7	1:10
Model	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical
A	1286.00	650.74	1296.76	1304.34	1274.98	1196.59	734.00
a	1.12	0.61	0.55	0.54	0.42	0.42	0.47
Kappa	1.0	-	-	-	-	-	-
%	100	100	100	100	100	100	100

(A) – Range (m); (a) – Angular coefficient, cross-validation.

In the geostatistical analysis of clay content, a reduction in sampling grid density corresponded to a decrease in angular coefficients (Table 4). Up to the 1:3 grid, angular coefficients remained close to 1, indicating high predictive accuracy. From the 1:4 grid onward, accuracy began to decline, and at the 1:10 grid it dropped markedly, with a = 0.67. The range, representing the extent of spatial dependence, remained high and stable up to the 1:7 grid but decreased sharply to 340.93 m at the 1:10 grid. Comparin and Cortez (2023) recommend caution when reducing sampling density excessively, particularly when the range shows substantial variation.

For the Kappa index, fewer sampling points resulted in lower values, reflecting greater differences between maps and a loss of data quality and informational value. Souza et al. (2014) and Kestring et al. (2015) emphasize that low-density grids can reduce spatial accuracy and negatively influence agronomic decision-making.

For clay content, the spatial distribution map (Figure 4) shows a small area of less clayey soil in the western portion of the study area, which disappears as sampling density decreases.

Table 4. Geostatistical parameters and Kappa indices for clay in each sampling grid.

Parameter	Grid						
	1:1	1:2	1:3	1:4	1:5	1:7	1:10
Model	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical
A	1286.00	1150.45	1169.34	1304.34	1274.98	1196.59	340.93
a	1.00	0.92	0.94	0.83	0.85	0.83	0.67
Kappa	1.0	0	0	0	0	0	0
%	100	99.64	99.64	99.64	99.64	99.64	99.64

(A) – Range (m); (a) – Angular coefficient, cross-validation.

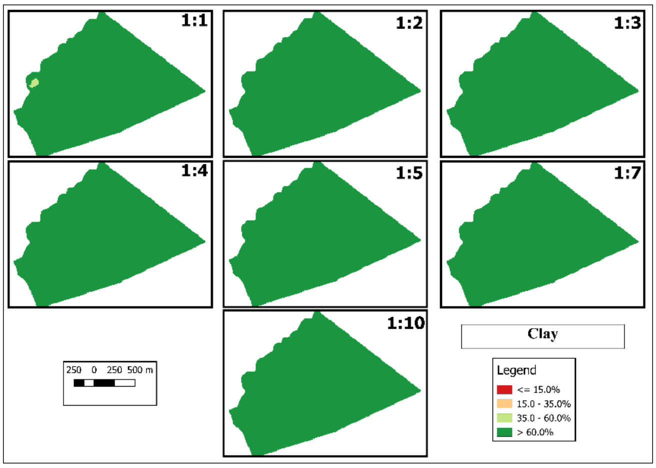

Figure 4. Spatialization of clay distribution (%) across sampling grids.

Soil chemical properties

The greatest variations in soil chemical properties (Table 5) were observed for calcium (Ca) and magnesium (Mg), although mean values across sampling grids remained stable, with coefficients of variation (CV) ranging from 48.93% to 39.80% for Ca and from 21.59% to 15.51% for Mg. Variation in organic matter (OM) ranged from 10.59% to 6.34%, while low pH in $CaCl_2$ ranged from 5.43% to 2.93% (Table 6). The high variability in Ca and Mg, along with the low variability in pH, may be related to the method of limestone application, corroborating the findings of Matias et al. (2019).

OM and pH in $CaCl_2$ showed low variation, remaining stable across different grid densities. According to Warrick and Nielsen's (1980) classification, a CV below 10% is considered low, between 10% and 60% medium, and above 60% high. By this criterion, Ca and Mg exhibited medium variability. The stability of pH and OM suggests that wider sampling grids do not necessarily improve data quality and may reduce sensitivity in detecting local variations. Caution is therefore advised when reducing sampling density in areas with differing management histories, as this may lead to underestimation of actual soil variability.

In general, CV values decreased as grid size increased, due to the reduced number of points and, consequently, fewer comparisons. While this suggests less variability between points, it may also indicate underestimation of true variability. Cherubin et al. (2014) emphasize the importance of using smaller grids, which decrease the distance between sampling points and increase sample numbers, enabling the extrapolation of a reliable model of soil property spatial variability.

Table 5. Descriptive statistics of pH in $CaCl_2$, organic matter, calcium, and magnesium.

Parameter	Grid						
	1:1	1:2	1:3	1:4	1:5	1:7	1:10
				pH em $CaCl_2$			
Mean	4.86	4.86	4.87	4.87	4.86	4.85	4.87
SD[1]	0.26	0.23	0.19	0.22	0.22	0.19	0.14
CV (%)[2]	5.43	4.78	3.92	4.53	4.71	4.05	2.93
				Organic matter (g dm^{-3})			
Mean	38.67	38.55	38.56	38.78	39.11	39.34	39.53
SD[1]	3.52	3.90	3.46	3.97	4.14	3.61	2.50
CV (%)[2]	9.10	10.13	8.97	10.25	10.59	9.04	6.34
				Calcium ($cmol_c$ dm^{-3})			
Mean	4.98	4.88	4.86	4.88	4.87	4.83	5.08
SD[1]	2.44	2.33	2.21	2.25	2.13	2.01	2.02
CV (%)[2]	48.93	47.71	45.44	46.21	43.80	41.67	39.80
				Magnesium ($cmol_c$ dm^{-3})			
Mean	1.59	1.60	1.57	1.58	1.57	1.61	1.66
SD[1]	0.34	0.32	0.30	0.27	0.29	0.25	0.25
CV (%)[2]	21.59	20.33	19.33	17.17	18.79	15.73	15.51

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

All evaluated properties, whose spatial distributions are shown in Figures 4, 5, 6, and 7, were classified into five categories (1, 2, 3, 4, and 5), which correspond to very low, low, medium, good, and excellent values, respectively, according to Souza and Lobato (2004). For pH in $CaCl_2$, fertility maps were best fitted using the spherical semivariogram model (Table 6), corroborating the findings of Santos (2017). Based on these results, pH in $CaCl_2$ can be reliably sampled at a density of one sample per 3 ha (1:3).

Analysis of maps of pH $CaCl_2$ (Figure 5) and the values in Table 6 shows a difference of 41.85 ha in class 2 when comparing the 1:1 grid with the 1:10 grid. In class 4, no values were detected in the 1:10 grid. Agreement according to Cohen's (1960) Kappa coefficient was observed only up to the 1:3 grid (Table 6), where the Kappa value exceeded 0.7. Overall, reducing sampling density decreased the range, angular coefficient, Kappa index, and percentage of hits, indicating a decline in interpolation quality and map accuracy.

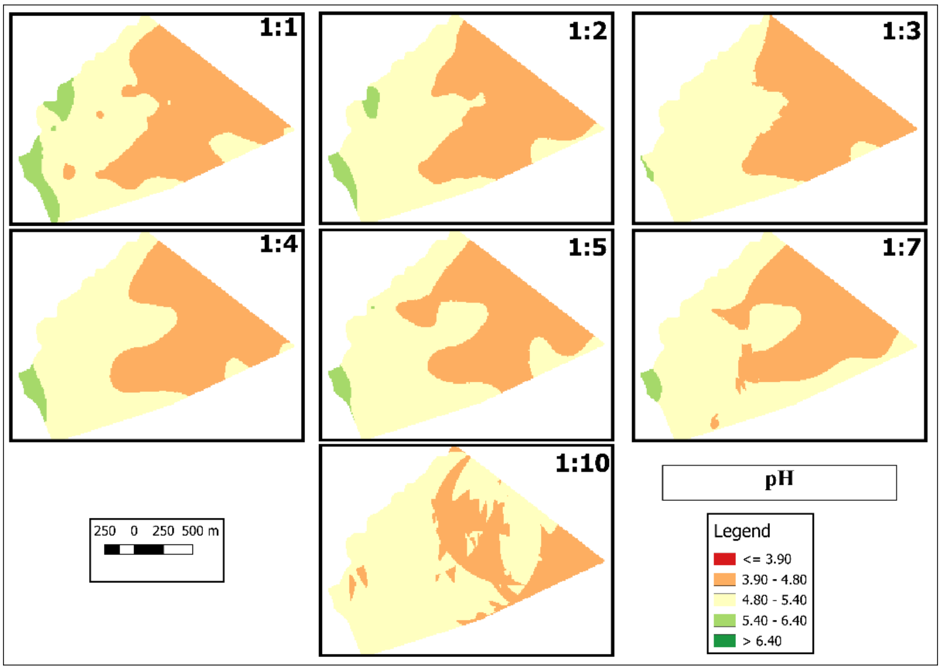

Figure 5. Spatial distribution of pH in $CaCl_2$ across sampling grids, with legend based on Souza and Lobato (2004).

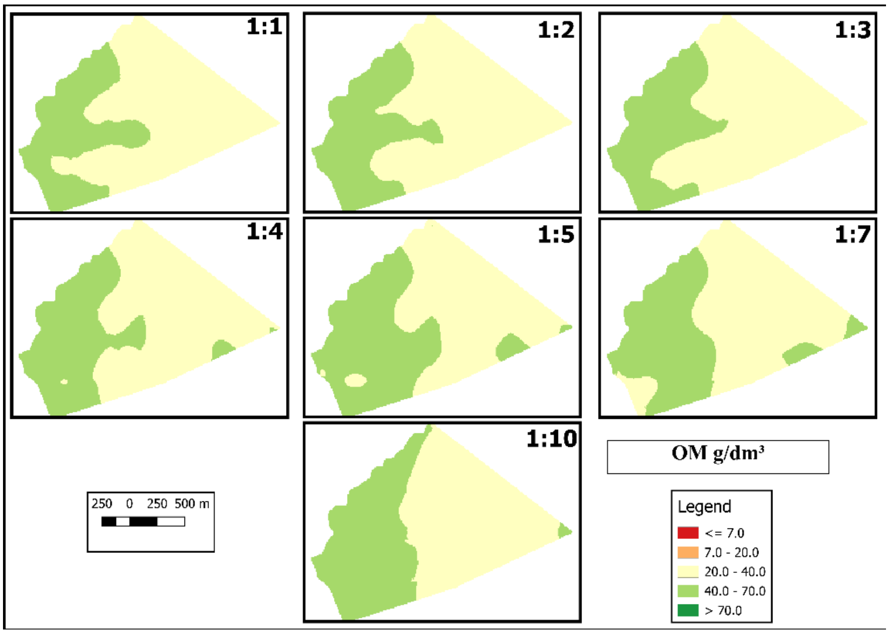

Figure 6. Spatial distribution of organic matter (OM - g dm^{-3}) across sampling grids, with legend based on Souza and Lobato (2004).

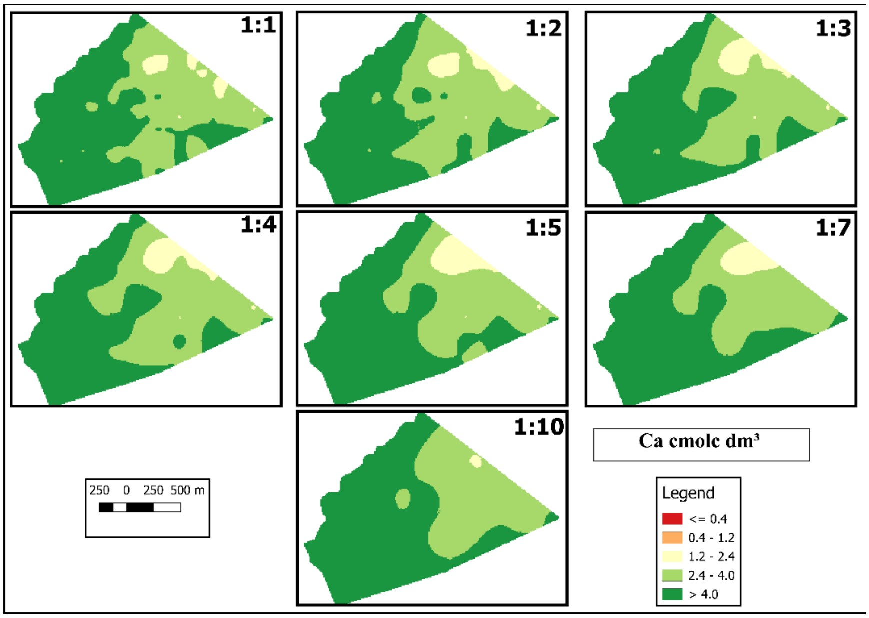

Figure 7. Spatial distribution of calcium (Ca - cmolc dm^{-3}) across sampling grids, with legend based on Souza and Lobato (2004).

Table 6. Geostatistical parameters, Kappa indices, and area distribution by class for pH in $CaCl_2$.

Parameter	Grid						
	1:1	1:2	1:3	1:4	1:5	1:7	1:10
Model	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical
A	1286.00	1296.92	1161.41	1304.34	127.98	1196.59	720.76
a	0.99	1.00	1.04	0.99	0.80	0.85	0.76
Kappa	1.00	0.80	0.71	0.69	0.61	0.53	0.26
% of hits	100	89.20	83.96	82.85	78.32	73.59	58.38
Class	Area (ha)						
2 (3.90 – 4.80)	107.07	102.08	103.09	100.46	95.28	90.42	65.22
3 (4.80 – 5.40)	99.01	109.91	115.26	113.01	121.50	121.27	150.53
4 (5.40 – 6.40)	13.76	6.68	0.24	4.82	3.67	2.89	0
5 (> 6.40)	4.43	5.6	5.92	11.9	3.82	9.69	8.52

(A) – Range (m); (a) – Angular coefficient, cross-validation.

Analysis of the pH maps in $CaCl_2$ (Figure 5) shows that the 1:1 grid clearly delineated the most acidic areas (<4.8) and identified regions with pH values above 6.4. The 1:2 and 1:3 grids produced results similar to the 1:1 grid, offering a more economical alternative with good accuracy. From the 1:4 grid onward, map generalization and smoothing became evident, with the lowest-density grid (1:10) posing a clear risk of agronomic errors due to reduced accuracy.

These findings contrast with those of Leandro Junior et al. (2020), who evaluated 1:3 and 1:5 grids and reported that reducing sampling density was viable, maintaining high precision, strong spatial dependence, and lower costs. In the present study, however, grids with densities above 1:3 already showed significant information loss.

For organic matter, the spherical semivariogram model provided the best fit for all grids (Table 7). The range remained high up to the 1:7 grid but dropped sharply at the 1:10 grid. The cross-validation angular coefficient declined markedly from the 1:4 grid onward, indicating a substantial loss in prediction accuracy as sampling density decreased. The Kappa index and percentage of correct classifications supported these findings, confirming that wider grid spacing (lower point density) compromises map reliability.

Analysis of the OM maps (Figure 6) shows that reducing sampling density visually affected class 3. Comparing the 1:1 and 1:5 grids revealed a 26.44 ha reduction in class 3, with this area being reclassified into class 4 (Table 7), which lowered the Kappa index to a medium level. Although the soil exhibited generally good OM levels, the model achieved strong agreement only up to the 1:4 grid, according to Cohen's (1960) classification. From the 1:5 grid onward, maps showed smoothing, with an increase in class 4 (40-70 g dm^{-3}) and a decrease in class 3 (20-40 g dm^{-3}). Lopes et al. (2020) reported that varying sampling densities (80, 100, and 121 points) produced maps with high similarity for attributes such as OM and Ca, reinforcing that in certain situations and locations, spatial interpolation can maintain high accuracy even with controlled sample reduction.

Table 7. Geostatistical parameters, Kappa indices, and area by class for organic matter (OM - g dm^{-3}).

Parameter	Grid						
	1:1	1:2	1:3	1:4	1:5	1:7	1:10
Model	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical
A	1286.00	1296.92	1296.76	1304.34	1240.98	1196.59	657.13
a	1.03	0.92	0.82	0.68	0.65	0.70	0.76
Kappa	1.00	0.87	0.83	0.80	0.68	0.58	0.66
% of hits	100	94.30	92.45	90.84	84.26	80.18	83.71
Classes	Area (ha)						
3 (20 – 40)	149.9	145.09	149.67	139.55	123.46	133.47	128.01
4 (40 – 70)	74.88	78.42	74.56	84.41	101.45	90.70	96.20

(A) – Range (m); (a) – Angular coefficient, cross-validation.

Calcium geostatistical analysis indicated that the spherical semivariogram model was fitted to all grids (Table 8). The range decreased markedly at the 1:10 grid, although the slope remained stable across all densities. From the 1:4 grid onward, both the Kappa index and the percentage of hits between maps declined as sampling density decreased.

Table 8. Geostatistical parameters, Kappa indices, and area by class for calcium (Ca - cmolc dm^{-3}).

Parameter	Grid						
	1:1	1:2	1:3	1:4	1:5	1:7	1:10
Model	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical
A	1286.00	1296.92	1296.76	1304.34	1274.98	1196.59	748.72
a	0.96	0.96	1.01	0.97	0.96	0.98	0.98
Kappa	1.00	0.81	0.74	0.69	0.66	0.64	0.66
% of hits	100	90.08	86.38	83.92	82.26	81.60	83.33
Class	Area (ha)						
2 (0.4 – 1.2)	0.58	0.43	0.53	0.51	0.33	0.17	0.13
3 (1.2 – 2.4)	6.99	9.97	11	11.39	12.65	10.73	0.96
4 (2.4 – 4)	87.77	94.63	87.16	92.11	79.89	76.38	79.9
5 (>4)	128.93	119.24	125.58	120.26	131.400	136.99	143.28

(A) – Range (m); (a) – Angular coefficient, cross-validation.

No calcium (Ca) values were recorded in class 1 (<0.4 cmolc dm^{-3}). In class 2 (0.4-1.2 cmolc dm^{-3}), Ca distribution was minimal, occurring only in areas between 0.58 ha (1:1 grid) and 0.13 ha (1:10 grid) (Table 8; Figure 7). Most of the area fell into class 5 (>4 cmolc dm^{-3}), representing the highest Ca values, which ranged from 128.93 ha (1:1 grid) to 143.28 ha (1:10 grid).

Freitas (2021), in a study of three sampling arrangements, found that the regular grid performed best for Ca. Although the regular grid is the most common approach in precision agriculture, Freitas (2021) and others highlight that, when combined with the use of covariates, alternative methods can improve soil property mapping. For Ca and Mg, these authors recommend denser grids when the objective is to detect small-scale variability.

In Ca class 3 (1.2–2.4 cmolc dm^{-3}), there was a marked reduction in area at the 1:10 grid (Table 8; Figure 6), decreasing from 6.99 ha in the 1:1 grid to 0.96 ha in the 1:10 grid. The Kappa index indicated good agreement only up to the 1:3 grid (Table 8), according to Cohen's (1960) classification. Thus, reducing sampling density led to an overestimation of the highest Ca class (>2.4 cmolc dm^{-3}) and a reduction in the areas of classes 2 and 3. Such distortions from using less dense grids can result in inaccurate agronomic recommendations.

For Mg, the spherical semivariogram model was fitted to all grids (Table 9). The range decreased at the 1:10 grid, along with the slope from cross-validation. The Kappa index showed good agreement, according to Cohen (1960), up to the 1:7 grid. Among all properties evaluated in this study, Mg exhibited the greatest stability and consistency between grids based on Kappa values, maintaining agreement up to the 1:7 grid. Notably, one way to improve estimates is by incorporating targeted sampling points in areas of macro- and microvariability, which can offset the limitations of sparse grids and enhance map accuracy even with fewer samples (MELO, 2024).

Table 9. Geostatistical parameters, Kappa indices, and area (ha) by class for magnesium (Mg - cmolc dm⁻³).

Parameter	Grid						
	1:1	1:2	1:3	1:4	1:5	1:7	1:10
Model	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical
A	1286.00	1296.92	1296.76	1304.34	923.95	1161.33	396.17
a	1.04	0.94	0.86	0.84	0.95	0.84	0.68
Kappa	1.00	0.80	0.77	0.79	0.78	0.75	0.68
% of hits	100	90.60	89.20	89.95	89.72	88.25	85.19
Classes	Area (ha)						
4 (0.9-1.5)	91.34	83.79	84.3	82.84	81.39	74.99	73.88
5 (>1.5)	132.61	140.58	140.35	141.79	142.88	149.55	150.32

(A) – Range (m); (a) – Angular coefficient, cross-validation.

The Mg distribution maps showed the presence of classes 4 (0.9–1.5 cmolc dm⁻³) and 5 (>1.5 cmolc dm⁻³) (Table 9; Figure 8), which correspond to good and very good concentrations, respectively (SOUZA; LOBATO, 2004). A noticeable change occurred in the spatial distribution of class 4 (Figure 8), while class 5 increasingly dominated the mapped area as sampling density decreased, indicating spatial generalization. The variation in mapped area for these classes between the 1:1 and 1:10 grids was 17.46 ha and 17.71 ha, respectively.

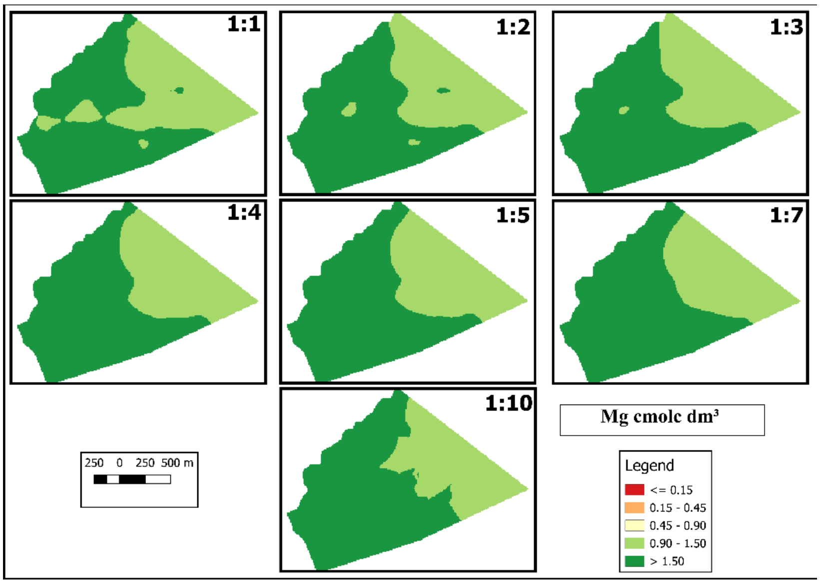

Figure 8. Spatial distribution of magnesium (Mg - cmolc dm-³) across sampling grids, with legend based on Souza and Lobato (2004).

Contrary to the findings of Lopes et al. (2020), whose maps remained stable between grids of 80 and 121 points, the results of this study indicate a marked loss of accuracy from the 1:5 grid onward, particularly for attributes such as pH and Mg. These findings suggest that reducing sampling density can compromise spatial interpretation.

The sampling density required for reliable estimates varies among soil properties, being higher for phosphorus, potassium, and base saturation, and lower for pH, organic matter, and clay (GELAIN et al., 2021). These findings corroborate the results of the present study, in which the spatial variability of chemical properties required denser sampling grids for accurate representation, whereas particle-size fractions could be reliably characterized with less dense grids.

Speranza, Grego and Gebler (2021) further demonstrated that in smaller production areas, spatial variability can be identified with reduced sampling density. Thus, determining the optimal sampling grid should consider both crop type and field size to maximize efficiency and minimize costs. Ultimately, sampling design should be guided by the spatial variability and spatial dependence of each soil property (MELO, 2024).

CONCLUSIONS

For clay and silt, which exhibit lower variability, less dense grids up to 1:7 (one sample per hectare) can be used without compromising accuracy, optimizing both time and cost. In contrast, denser grids are necessary to better capture the variability of sand. Generally, in predominantly clayey areas, less dense grids are suitable, whereas in sandier soils, denser grids are recommended.

A sampling density of up to 1:3 (one sample per hectare) can be applied for most soil properties, as the spatial structure of the data remains well preserved. From the 1:4 grid onward, map smoothing and generalization become evident. Overall, for more stable properties, such as particle-size distribution, lower-density grids can be used, while for chemical properties, denser grids are required to ensure adequate accuracy.

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