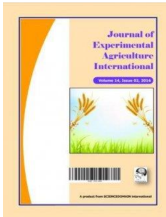

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# Adjustment of Sampling Grids for Soil Penetration Resistance, Bulk Density, and Soil Moisture Mapping

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***Authors' contributions***

*This work was carried out in collaboration between all authors. Authors RNM, ARO and LTSM did the data acquisition, data analysis, writing and editing. Authors FFLS and JASS were involved in data analysis and English language review. Author WCS did the coordination, design of methodology, conceptualization, critical review and conclusions. All authors read and approved the final manuscript.*

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## ABSTRACT

There is still a lack of information in the literature regarding the sampling grid size and its effect on the accuracy of soil attributes spatial variability mapping. Thus, the present study aimed to evaluate the influence of different sampling grid sizes regarding accuracy for soil penetration resistance (SPR), soil bulk density (SBD) and soil moisture (SM) spatial variability characterization, as well as the correlation between these attributes. The study was conducted in a 5.7 ha Red Yellow Latosol area in Januária, Minas Gerais state, Brazil. Soil samples were taken at the 0.00–0.20 m layer, using a regular sampling grid of 20x20 m. (145 points). Other two grids (41 and 21 points) were derived by deleting lines or lines and points from the initial grid. SPR, SBD, and SM data were

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subjected to descriptive statistics and geostatistical analyses. Furthermore, the similarity of the thematic maps and correlation among these attributes were analyzed through the relative deviation coefficient (RDC), and Pearson's correlation matrix. The reduction of the grid density (number of points) increased the estimation error for SPR, SBD, and SM, especially when using only 21 points (grid C), whereas, denser grids (Grid A and B) showed maps with greater similarity (accuracy). The SPR levels are directly related to SBD levels, in other words, the highest SPR levels in the area occurred due to higher SBD levels, as well as the lowest values, whereas SM levels were inversely proportional to SPR values since wetter areas presented lower SPR levels. Also, denser areas are directly correlated with higher levels of SM in the study area. In essence, only the grid with 25 points per hectare (20x20 m) is recommended for mapping these attributes spatial variability.

*Keywords: Precision agriculture; spatial variability; soil compaction; penetrometer.*

## 1. INTRODUCTION

Precision agriculture (PA) is referred as a technological advancement for management of the soil-plant-atmosphere system, which is based on principles of spatial variability and information management that encompasses factors of soil attributes and crop production [1,2]. Among the PA tools, georeferenced soil sampling using regular grids, to characterize the variability of soil attributes, is one of the most important and traditionally used in agriculture. However, georeferenced soil sampling, even when used on a large scale, still lacks methodological definitions, especially regarding the sampling grid size [3,4].

The efficiency of a soil sampling plan is dependent on prior knowledge of the spatiotemporal variability structure that the investigated attributes present in the soil [2,5,6]. Thus, the knowledge of soil attributes and crop property variability, in space and time, is considered a fundamental principle for the precise management of agricultural areas, independent of their scale [7,8]. However, the spatiotemporal variability of soil attributes, resulting from soil formation and anthropogenic interventions, varies at different spatial and temporal scales [2,9].

Based on that, different scales of soil attributes levels make it complicated to develop a sampling plan that uses a single-spaced sample grid when several soil attributes are involved [1,2,10]. This justifies investigations that aim to define the ideal size of the sampling grid for specific soil attributes, such as soil penetration resistance (SPR), soil bulk density (SBD) and soil moisture (SM). SPR is used to quantify the mechanical impedance of the soil for plant root growth [11]. In this sense, SPR has been considered one of the main parameters for diagnosis of soil compaction and determination of restrictive soil layers for plant development [12,13].

Additionally, the SPR levels vary with temporally and spatially highly dynamic soil properties such as SBD and SM. Experiments conducted with various soils revealed that SPR is directly correlated to SBD and it exhibits an inverse relationship to SM [14]. As a consequence, high coefficients of variation (CV) were usually observed in different studies [15,16]. Therefore, to correctly determine the spatial variability of the SPR, it is crucial to establish an adequate density of sampling points per area that best represents each sampling point.

The sampling density is an important factor in the management of soil attributes spatial variability. About 80–85% of the total error in the application of agricultural inputs, as fertilizers and corrective materials, is attributed to poorly planned soil sampling [17]. Due to this issue, the optimization of sampling grids should consider the allocation of sampling points, which plays a key role in the economic feasibility of PA. Researchers have demonstrated that ideal sampling grids are approximately 50 × 50 m (*i.e.*, four samples per ha) [18] or 30 × 30 m (*i.e.*, more than ten samples per ha) [19].

Thus, the primary purpose for performing this study is to show that a single size of a grid sampling cannot be used in all areas. Moreover, the sampling grid must meet two main requirements. First, the number and spatial distribution of the sampled points should ensure a minimum precision for estimating in unsampled locations. Secondly, the optimization technique must be numerically practicable [20].

In essence, the optimal sampling grid density is one that, with a minimal amount of points, can characterize the spatial variability of soil attributes, guaranteeing the reliability of an estimate. Among the difficulties in providing this kind of information, the level of detail required [21], and implementation costs [22,23] must be considered. Thus, the objective of this study was to evaluate the influence of different sampling grid densities regarding accuracy for SPR, SBD and SM spatial variability characterization, as well as to evaluate the correlation between these attributes.

## 2. MATERIALS AND METHODS

The study was conducted in the Federal Institute of Northern Minas Gerais – Campus Januária, located between the geographical coordinates of 15° 28' 55'' S and 44° 22' 41'' W. The average altitude is 474 m. The relief of the area is classified as smoothly undulating, and the soil is classified as Red Yellow Latosol according to the Brazilian System of Soil Classification [24]. The experimental site has a total area of 5.7 ha, where sorghum (*Sorghum bicolor* (L.) Moench) and maize (*Zea mays*) were cultivated in crop rotation using conventional tillage system for at least 20 years.

In order to map the soil attributes, the agricultural area was georeferenced and divided into a regular sampling grid of 20 x 20 m density consisting of 145 points. Soil sampling was performed at the 0 – 20 cm layer depth due to the highest volume of the root system of annual crops, and the greatest physical and chemical changes in soils under conventional tillage system take place at this depth. The SPR was determined using a portable digital penetrometer (PenetroLOG). The SM at the moment of SPR evaluation was determined through the gravimetric method using a Dutch type soil auger for soil sampling. The SBD was determined through the volumetric ring method using a soil auger for undisturbed samples [25]. Four subsamples were collected within a radius of 5 m from the georeferenced point. Then, all subsamples were identified and sent to the lab for the proposed analyses.

In order to evaluate the effects of using different sampling grids densities for mapping the spatial variability of SPR, SBD, and SM, other two grids were created from the sampling grid density of 145 points (A). The grids were composed of 41 (B) and 21 sampling points (C). The sampling grid (B) was originated by eliminating one interspersed line from grid A. On the other hand, the sampling grid (C) emerged eliminating one interspersed line from (B) (Fig. 1).

The datasets from each soil attribute were organized into a spreadsheet and subjected to outlier analysis. Any values outside the range of two standard deviations from the mean were considered outliers. The SPR, SBD, and SM data considering all sampling grids were subjected to descriptive statistical analysis to obtain the positional means (mean, median, minimum and maximum) and dispersion (coefficients of variation – CV, and standard deviation - SD) skewness and kurtosis. The CV values were used to classify the data variability into low (CV < 12%), medium (12 % <CV< 62 %) and high (CV > 62 %) as proposed in the literature [26].

The spatial dependence of the soil attributes using the three sampling grids densities was evaluated by adjusting semivariograms, assuming the hypothesis of intrinsic stationarity, defined by Equation 1.

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \quad (1)$$

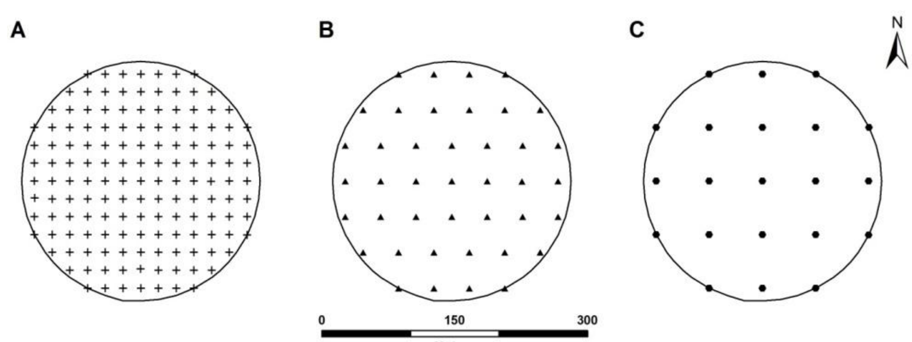


**Fig. 1. Sampling grids evaluated: (a) 145 points, (B) 41 points, and (C) 21 points**

Where:

$\gamma$ (h): is the semivariance for interval class h.
N(h): is the number of pairs separated by a lag distance (separation distance between sample positions), Z(xi): is a measured variable at spatial location i,
$Z(x_i + h)$: is a measured variable at spatial location i +h.

The model that best represented the relationship between experimental semivariance and distance h was adjusted based on the highest coefficient of determination ($R^2$), the smallest residual sum of squares (RSS), and was confirmed by the cross-validation technique as proposed by [2]. Then, parameters, such as nugget effect ($C_0$), sill ($C_0 + C_1$) and range (A) were determined. The spatial dependence index (SDI) was determined and classified according to [27], by using the relation $C_1$ / ($C_0$+$C_1$) and assuming the following intervals: low spatial dependence for SDI < 25%, moderate for 25% < SDI < 75% and strong for SDI > 75%.

Maps interpolation was performed using ordinary kriging and inverse distance weighting (IDW), in case of absence of spatial dependence. Regardless of the sampling grid density used, the maps were generated with the same spatial resolution (pixel size). Thus, it was guaranteed that all maps possess the same number and location of points.

Two parameters were used to evaluate the effect of grids A, B, and C on the accuracy of thematic maps and the correlation between the soil attributes. The relative deviation coefficient (RDC) and Pearson's linear correlation coefficient ($p$ < 0.05). The RDC index expresses the mean difference as an absolute value, which shows the dissimilarity between two maps as demonstrated by the differences between the interpolated points of each map. The lower the percentage found, the higher is the similarity between maps [2,28].

In this study, the sampling grid A (145 points) was considered as a reference (standard) for comparison with the other two sampling grids (41 and 21 points). The RDC was determined using Equation 2, which was adapted from [2,28].

$$RDC = \Sigma\left|\frac{Tij - Tiref}{Tiref}\right| x\frac{100}{n} \qquad (2)$$

Where:

Tiref: is the soil attribute value at point i (reference value) using the sampling grid A;
Tij: is the soil attribute value at point i determined using the sampling grids B and C;
n: is the number of sampling points in the reference grid (145).

## 3. RESULTS AND DISCUSSION

A descriptive statistical summary of all the studied attributes is presented in Table 1. A low variability on the mean and median values of all attributes can be observed among the different sampling grids. Moreover, as the sampling point density increased, there was a reduction in amplitude among the minimum, and maximum values obtained, tending towards an approximation to the mean values. Thus, the increase in the number of samples (n) provided by denser sampling grids, made it possible to characterize with greater detail the SPR spatial variability map. Differently, less dense grids tended to soften the map by approaching to the mean values, which would not be a correct representation of this attribute's spatial variability. Moreover, these high levels of SPR should be taken into as it can induce the occurrence of restriction zones to root development of crops.

Additionally, the CV values for these attributes were classified as low (CV < 12 %) for SBD in all sampling grids and medium (12 % < CV < 62 %) for SPR and SM grids. This higher variation in SPR values may be related to the system and management practices adopted in the area. As the area is managed under conventional planting system, the major structural modification occurs in this layer (0 to 20 cm), which could happen due to mechanical action from plant roots, edaphic fauna, and machinery/equipment traffic.

According to [29], the observation of higher CV values is an indication of higher spatial variability of these attributes (SPR and SM) in the area. These results reinforce the use of sampling grids with a larger number of samples to precisely reproduce the spatial variability of SPR, SBD and SM values. Even though we did not investigate the effect of using a different number of subsamples per sampling point in this study, the results obtained by [13] indicated that using a higher number of subsamples per sampling point could be an SPR mapping alternative to use less dense sampling grids.

**Table 1. Descriptive statistics of soil penetration resistance (SPR, MPa), soil bulk density (SBD, g/cm³) and soil moisture (SM, %) using different sampling grids in Januária, Northern Minas Gerais**

| Soil attributes | Statistical parameters | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Median | Min | Max | SD | CV | Ck | Sk |
| | | | 20 x 20 meters | | | | | |
| SPR | 2.06 | 1.93 | 0.90 | 3.66 | 0.61 | 29.71 | -0.54 | 0.30 |
| SBD | 1.69 | 1.73 | 1.41 | 1.90 | 0.11 | 6.78 | -1.07 | -0.20 |
| SM | 5.14 | 5.21 | 3.23 | 7.18 | 0.98 | 19.11 | -0.85 | 0.09 |
| | | | 40 x 40 meters | | | | | |
| SPR | 2.23 | 2.28 | 1.24 | 3.66 | 0.66 | 29.50 | -0.89 | 0.00 |
| SBD | 1.67 | 1.65 | 1.41 | 1.85 | 0.11 | 6.81 | -1.07 | -0.23 |
| SM | 5.25 | 5.29 | 3.36 | 7.18 | 1.06 | 20.27 | -0.87 | -0.06 |
| | | | 60 x 60 meters | | | | | |
| SPR | 1.96 | 1.93 | 1.24 | 2.97 | 0.54 | 27.73 | -1.21 | 0.15 |
| SBD | 1.70 | 1.74 | 1.51 | 1.87 | 0.11 | 6.48 | -1.21 | -0.36 |
| SM | 4.74 | 4.46 | 3.38 | 6.75 | 0.97 | 20.52 | -0.66 | 0.61 |

*MIN: Minimum; MAX: Maximum; SD: Standard deviation; CV: Coefficient of variation; Ck: Coefficient of Kurtosis; Sk: Skewness; SPR: Soil penetration resistance; SBD: Soil bulk density; and SM: Soil Moisture*

Results of the geostatistical analysis (Table 2) showed that all variables presented spatial dependence, except to SBD at the 60x60 m grid density, which showed a random behaviour expressed as a pure nugget effect. Model selection for semivariograms was done by the higher coefficient of determination ($R^2$), visual fitting, and cross-validation parameters ($R^2$ and Standard error). The spherical, Gaussian and exponential models were fitted to the attributes that presented spatial dependence.

The spatial dependence was classified according to the SDI intervals mentioned before [27]. All studied variables showed a strong correlation (SDI > 75%), which confirms that the data distribution is not random. Moreover, the random behaviour (pure nugget effect) of the SBD, obtained in grid C (60x60 m), is related to the increase in the distance between the sampling points, associated with the reduction of sampled points. According to [30,31], reducing the dataset increases the confidence interval, which reduces the accuracy of fitted models until they become random.

The range is another important parameter in the study of semivariogram as it sets the limit distance (lag) to which sampling points influences each other, in other words, the maximum spatial correlation distance among variables [32]. It was observed that every range value was higher than the smallest distance between points for all sampling grids (exception to SPR in grid A). According to [33], the range of an attribute ensures that all points within a circle with a radius of equal value are so similar that can be used to estimate values for any point within this distance. [20] affirms that points located in an area where the radius is equal to the range value show greater similarity when compared to those separated by greater distances. Furthermore, range values can still be used as a standard to choose the minimum distance between sampled points [7].

Regarding the residual sum of squares (RSS) it was observed that with the decrease in the number of sampled points, the RSS value increased for some attributes, affecting the $R^2$ result which decreased. These results indicate that as the pairs of point's number decreased, the model accuracy for estimating unsampled locations decreased as well. Similar behaviour was found by other authors [2,20,34] when analyzing different grids densities.

As expected, when reducing the grid density, the minimum distance increased and the minimum pairs of point's number decreased. Reducing the minimum pairs of point's number affected directly the precision of the theoretical models to represent the spatial variability of all attributes studied. Thus, to ensure the reliability of the theoretical model set, it is of utmost importance that the semivariogram contains at least 30 pairs of points [35]. Although spatial dependence of SPR and SM was observed in grid C, the modelling of spatial dependence using only 21 sampling points would be unreliable, and the interpolation process may cause errors in attribute estimation of unsampled areas.

From this result, the decision of choosing a denser or less dense grid sampling should take into account some factors, such as land use history and soil management practices, area size, cost of sampling and lab analysis, technification level of the user, precision level and the equipment available for analysis.

The maps of attributes which presented spatial dependence were interpolated through ordinary kriging, whereas the inverse distance weighting (IDW: power = 2) method was used for mapping the SBD at the 60x60 m grid that presented pure nugget effect. Moreover, the similarity between grids A, B and C was evaluated through de RDC index. On the other hand, Pearson's linear correlation coefficient ($p \leq 0.05$) was used to verify the correlation between all attributes using 145 points extracted from all maps. The spatial distribution maps of SPR, SBD, and SM levels are shown (Fig. 2,3 and 4).

Looking at the thematic maps it is possible to observe that the SPR levels are directly related to SBD levels, in other words, the highest SPR levels in the area correlated to higher SBD levels, and possibly to the same soil management practices for many years and uncontrolled machinery traffic. Regarding SM levels, the relation was the opposite, since wetter areas presented lower SPR levels. Also, denser areas presented the highest levels of SM in the study area. Similar spatial distribution SPR, SBD, and SM levels were observed by several authors [14,36].

**Table 2. Parameters of the theoretical models fitted to empirical semivariance values of soil penetration resistance (SPR), soil bulk density (SBD) and soil moisture (SM) using different sampling grids in Januária, Northern Minas Gerais**

| Soil attributes | Statistical parameters | | | | | | |
|---|---|---|---|---|---|---|---|
| | Model | Range | Sill | Nugget effect | SDI | RSS | R² |
| | | | 20 x 20 meters | | | | |
| SPR | Gaussian | 19.2 | 0.352 | 0.004 | 92.15 | 0.009 | 0.771 |
| SBD | Spherical | 69.3 | 0.013 | 0.003 | 76.95 | 0.000 | 0.824 |
| SM | Exponential | 23.5 | 1.007 | 0.079 | 98.86 | 0.001 | 0.928 |
| | | | 40 x 40 meters | | | | |
| SPR | Spherical | 69.2 | 0.439 | 0.016 | 97.28 | 0.003 | 0.638 |
| SBD | Gaussian | 32.6 | 0.013 | 0.001 | 88.41 | 0.000 | 0.465 |
| SM | Spherical | 83.2 | 1.14 | 0.031 | 96.35 | 0.014 | 0.878 |
| | | | 60 x 60 meters | | | | |
| SPR | Spherical | 124.1 | 0.308 | 0.015 | 92.71 | 0.001 | 0.732 |
| SBD | | | | Pure Nugget Effect | | | |
| SM | Spherical | 129.9 | 0.989 | 0.072 | 94.91 | 0.014 | 0.722 |

*SDI: Spatial dependence index; RSS: Residual sum of squares; R²: Coefficient of determination*

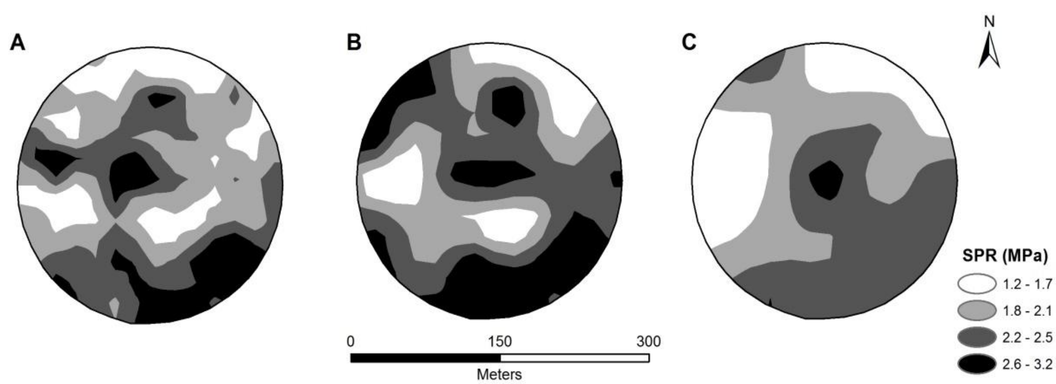


**Fig 2. Thematic maps of soil penetration resistance (SPR) obtained by different sampling grids in Januária, Northern Minas Gerais. (A) 145 points, (B) 41 points, and (C) 21 points**

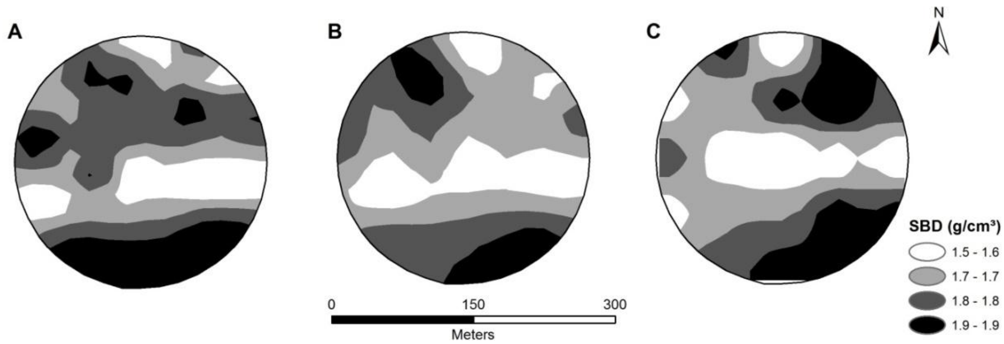


**Fig. 3. Thematic maps of soil bulk density (SBD) obtained by different sampling grids in Januária, Northern Minas Gerais. (A) 145 points, (B) 41 points, and (C) 21 points**

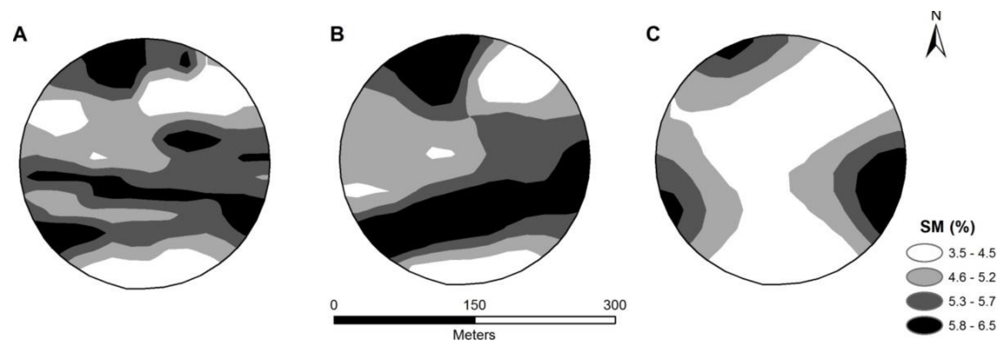


**Fig. 4. Thematic maps of soil moisture (SM) obtained by different sampling grids in Januária, Northern Minas Gerais. (A) 145 points, (B) 41 points, and (C) 21 points**

After analyzing the RDC results, it was verified that, as the sampling grid size increased, and consequently, the distance between the sampling points, there was an increase in the dissimilarity (accuracy) among maps when compared to the reference map (grid A). The SPR maps showed the highest dissimilarity among each other, with RDC ranging from 22.85% to 24.71%, whereas for SBD and SM maps the RDC values ranged from 3.86% to 4.54% and from 12.44% to 13.32%, respectively. Thus, it is possible to observe that the kriging method was more influenced by the use of less sampled points due to its robustness and complexity for unsampled point's estimation. On the other hand, the IDW method which was used for the SBD data interpolation in grid C was less influenced by this scenario.

As the RDC value was calculated from the mean difference in modulus of the interpolated values in relation to the reference map, there is no RDC value considered as optimum, and the choice of an acceptable RDC percentage value depends on the degree of accuracy desired by the user. Based on that, an RDC of 15% was considered a suitable value for guiding the interpretation of the results. Thus, the values obtained for SPR using grids B and C would not be recommended to represent the spatial variability of this attribute. Therefore, the utilization of an insufficient number of subsamples results in an erroneous representation of its variability and can indicate a necessity for denser sampling grids, which increases the sampling and lab analysis cost. However, the use of grids with less sampled points would still be useful for cokriging analysis if attributes present correlation among each other, which would reduce the sampling costs.

These results indicate that the RDC was an efficient parameter to evaluate the similarity among maps from different grid densities (A, B, and C), which confirms its potential for use in precision agriculture studies. Similar results were previously reported by several authors when analyzing spatial variability of SPR [13], K and P [2], and grain yield [28,37,38].

In order to perform the linear correlation between the SPR, SBD and SM maps, 145 points were extracted from all raster's using grid A as a

**Table 3. Correlation between soil penetration resistance (SPR), soil bulk density (SBD) and soil moisture (SM) using 145 sampled points in Januária, Northern Minas Gerais**

| | Grid Sampling | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **SPR (A)** | **SPR (B)** | **SPR (C)** | **SBD (A)** | **SBD (B)** | **SBD (C)** | **SM (A)** | **SM (B)** | **SM (C)** |
| SPR (A) | | | | | | | | | |
| SPR (B) | - | | | | | | | | |
| SPR (C) | - | - | | | | | | | |
| SBD (A) | 0.36* | 0.27* | 0.11 ns | | | | | | |
| SBD (B) | 0.26* | 0.48* | 0.21* | - | | | | | |
| SBD (C) | 0.13ns | 0.04ns | 0.09 ns | - | - | | | | |
| SM (A) | -0.17* | -0.19* | 0.05 ns | -0.08ns | -0.18* | -0.25* | | | |
| SM (B) | -0.10ns | -0.05ns | 0.27* | -0.02ns | 0.06 ns | -0.18* | - | | |
| SM (C) | -0.12ns | 0.07 ns | 0.09 ns | -0.29* | -0.22* | -0.21* | - | - | - |

** and ns: significant and non-significant Pearson's correlation coefficients (p < 0.05), respectively. A: 20x20 m; B: 40X40 m; and C: 60x60 m*

reference. Thus, it was found that significant correlation between SPR, SBD, and SM ranged from -0.17 to 0.48 as shown in Table 3. These results show that SM levels are inversely proportional to SPR values as mentioned before. However, the SBD values presented the highest correlation coefficient with SPR (0.48), which confirms the results of [39] that high SBD values and machinery traffic could speed up SPR and consequently reduce crop's yield.

Regarding the spatial distribution of SPR, SBD and SM levels on the soil, it was possible to detect zones with uniform patterns, which would allow the adoption of adequate management practices for each level of these attributes in the area, which would be impossible from an analysis by descriptive methods. In relation to SPR levels, average values ranged from 1.96 MPa to 2.23 MPa (Grids A, B, and C) which are within the interval (2 MPa to 2.5 MPa) considered as the critical limit for root development as suggested by [40]. However, divergent opinions exist regarding the SPR value that should be considered as the crucial limit in plant development. Other studies have shown that higher SPR values are tolerable (up to 3 MPa) in soils with no-tillage systems [12,41,42], which are probably due to better soil structure [13,43].

Independent of the critical limit considered for SPR, the maps showed that the study area presented restrictive values for root growth using all three grids. However, grids with 6.25 and 2.78 samples per hectare (B and C) are not recommended for representation of SPR, SBD and SM spatial variability mapping since the RDC values were above the maximum value proposed (15%). Thus, only the grid with 25 points per hectare (grid A) is recommended for mapping these attributes. Furthermore, one way to reduce the number of necessary samples is to divide the field into specific management zones and then use a stratified sampling or a less dense sampling grid with at least four samples per hectare (50 x 50 m) as recommended by [18]. In sum, this study could be used as an assistant tool for decision making, when regarding the sampling grid density that should be used for these attributes evaluation.

## 4. CONCLUSION

Reduction of the grid density (number of points) increased the estimation error for SPR, SBD, and SM, especially when using only 21 points (grid C), whereas, denser grids (Grid A and B) showed maps with greater similarity (accuracy).

Regarding the spatial distribution of these attributes, the SPR levels are directly related to SBD levels, in other words, the highest SPR levels in the area occurred due to higher SBD levels and vice versa, whereas SM levels presented inverse correlation with SPR values since wetter areas presented lower SPR levels. Furthermore, denser areas are directly correlated with higher levels of SM in the study area.

Grids with 6.25 and 2.78 samples per hectare (B and C) are not recommended for representation of SPR, SBD and SM spatial variability mapping since the RDC values were above the maximum value proposed (15%). Thus, only the grid with 25 points per hectare (grid A) is recommended for mapping these attributes.

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## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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