Title
Accuracy Assessments of Stochastic and Deterministic Interpolation Methods in Estimating Soil Attributes Spatial Variability

Journal
Communications in Soil Science and Plant Analysis, 50(20)

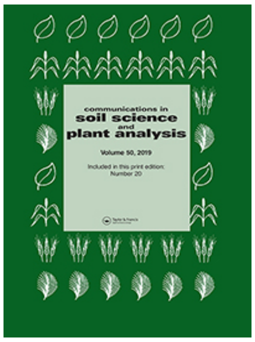
ISSN
0010-3624

Authors
Martins, Rodrigo Nogueira
Dos Santos, Fernando Ferreira Lima
De Moura Araújo, Guilherme
et al.

Publication Date
2019-11-13

DOI
10.1080/00103624.2019.1670836

Peer reviewed



Communications in Soil Science and Plant Analysis

ISSN: 0010-3624 (Print) 1532-2416 (Online) Journal homepage: https://www.tandfonline.com/loi/lcss20

Accuracy Assessments of Stochastic and Deterministic Interpolation Methods in Estimating Soil Attributes Spatial Variability

Rodrigo Nogueira Martins, Fernando Ferreira Lima Dos Santos, Guilherme De Moura Araújo, Lucas De Arruda Viana & Jorge Tadeu Fim Rosas

To cite this article: Rodrigo Nogueira Martins, Fernando Ferreira Lima Dos Santos, Guilherme De Moura Araújo, Lucas De Arruda Viana & Jorge Tadeu Fim Rosas (2019) Accuracy Assessments of Stochastic and Deterministic Interpolation Methods in Estimating Soil Attributes Spatial Variability, Communications in Soil Science and Plant Analysis, 50:20, 2570-2578, DOI: 10.1080/00103624.2019.1670836

To link to this article: https://doi.org/10.1080/00103624.2019.1670836

Published online: 26 Sep 2019.

COMMUNICATIONS IN SOIL SCIENCE AND PLANT ANALYSIS
2019, VOL. 50, NO. 20, 2570–2578
https://doi.org/10.1080/00103624.2019.1670836

Taylor & Francis
Taylor & Francis Group

Check for updates

Accuracy Assessments of Stochastic and Deterministic Interpolation Methods in Estimating Soil Attributes Spatial Variability

Rodrigo Nogueira Martins [a], Fernando Ferreira Lima Dos Santos [a], Guilherme De Moura Araújo [b], Lucas De Arruda Viana [a], and Jorge Tadeu Fim Rosas [a]

[a]Agricultural Engineering Department, Federal University of Viçosa, Viçosa, Brazil; [b]Biological and Biosystems Engineering Department, University of California Davis, Davis, CA, USA

ABSTRACT

Spatial interpolation methods are frequently used to characterize soil attributes' spatial variability. However, inconclusive results, about the comparative performance of these methods, have been reported in the literature. Therefore, the present study aimed to analyze the efficiency of ordinary kriging (OK) and inverse distance weighting (IDW) methods in estimating the soil penetration resistance (SPR), soil bulk density (SBD), and soil moisture content (SM) using two distinct sampling grids. The soil sampling was performed on a 5.7 ha area in Southeast Brazil. For data collection, a regular grid with 145 points (20 x 20 m) was created. Soil samples were taken at a 0.20 m layer depth. In order to compare the accuracy of OK and IDW, another grid was created from the initial grid (A), by eliminating one interspersed line, which resulted in a grid with 41 sampled points (40 x 40 m). Results showed that sampling grid A presented less errors than B, proving that the more sampling points, the lower the errors that are associated with both methods will be. Overall, the OK was less biased than IDW only for SBD (A) and SM (B) maps, whereas IDW outperformed OK for the other attributes for both sampling grids.

ARTICLE HISTORY
Received 1 July 2019
Accepted 11 September 2019

KEYWORDS
Ordinary kriging; inverse distance weighting; geostatistics; precision agriculture

Introduction

Several factors can interfere in the spatial variability of soil attributes. Some of them are inherent in nature due to geologic and pedologic soil-forming factors, but others are induced by tillage and some management practices (Iqbal et al. 2005). Soil attributes, such as soil penetration resistance (SPR), soil bulk density (SBD) and soil moisture content (SM) have proven to interact with each other across spatial and temporal scales and are dependent on an ideal sampling grid size for Spatio-temporal analysis (Beutler et al. 2007; Silveira et al. 2010).

Therefore, there is a need of adequate information about the spatial variability of these soil attributes, since uniform field management is not the most effective management approach (Moral, Terrón, and Da Silva 2010; Peralta et al. 2013). However, soil sampling and analysis are expensive and time-consuming. Consequently, the number of soil samples in a given area is often relatively sparse and does not represent the actual spatial variability. Thus, to provide a sufficiently detailed representation of the real spatial variability of soil properties for a Site-specific Management System, an appropriate sampling strategy with a spatial prediction method is needed for better planning and management. Moreover, depending on the soil attribute, the sampling grid density is dictated by convenience and the trade-off between resolution and cost (Whelan, Mcbratney, and Viscarra Rossel 1996).

CONTACT Rodrigo Nogueira Martins Rodrigonmartins@hotmail.com Agricultural Engineering Department, Federal University of Viçosa, Viçosa, Brazil.

There are several studies on the influence of sampling densities regarding soil attributes and related errors in sampling management (Liu et al. 2013; Nanni et al. 2011; Siqueira et al. 2014). However, there have been inconclusive results in the literature about the comparative performance of interpolation methods, especially about two of the most common methods: ordinary kriging (OK) and inverse distance weighting (IDW).

The OK method is a stochastic (also called geostatistical) interpolator that provides an estimate at an unobserved location of a specific variable, based on the weighted average of adjacent observed sites within a given area. The modeling of the correlation among neighboring values depends on the geographic distance between the points across the study area, defined by a variogram. On the other side, IDW is a deterministic method that does not provide any assessment of the error made on the interpolated value. This procedure has been used primarily because it is simple and quicker, while kriging has been used because it provides the best linear unbiased estimates (Miller, Franklin, and Aspinall 2007).

Several researchers have compared IDW and kriging methods. In some works, the performance of kriging was generally better than IDW. Adhikary and Dash (2017) concluded that kriging presented better accuracy than IDW when predicting spatial variation on groundwater depth. In addition, Shahbeik et al. (2014) compared both interpolation methods on the estimation of mineral reserves and concluded that estimation errors from OK were smaller than IDW.

On the other hand, some studies presented mixed results. Maroufi, Toranjeyan, and Zare (2009) and Costa and Bofana (2017) evaluated the performance of OK and IDW methods in estimating pH and soil electrical conductivity values. While the first concluded that IDW was the best interpolator, the second ones stated that OK was more accurate and less biased than the other method. Therefore, the present study aimed to, comparatively, analyze the efficiency of OK and IDW methods in estimating SPR, SBD, and SM attribute levels using two distinct sampling grids.

Material and methods

The study was conducted on a farm located in the city of Januária-MG, Brazil (15° 28′ 55″ S and 44° 22′ 41″ W). The climate of the region is classified as tropical wet (Aw) with dry winter and rainy summers, according to Köppen classification. The annual rainfall average is 900 mm with a mean relative humidity of 60% and a mean annual temperature of 27ºC. The soil of the experimental area is classified as Quartzarenic Neosol (Empresa Brasileira de Pesquisa Agropecuária (Embrapa) 2013). Also, the area is characterized by the presence of flat relief.

Prior to the study, soil sampling was performed on a 5.7 ha area, previously cultivated by sorghum (*Sorghum bicolor* (L.) Moench) and maize (*Zea mays*) in a crop rotation system. For the data collection, a regular grid of 20 × 20 m with 145 points was implemented. Soil samples were then collected at a 0–20 cm layer depth. Each sampling point was composed by four sub-samples, collected within a 5 m radius from the georeferenced point.

After that, the samples were sent to the Soil Laboratory of the Federal Institute of Northern Minas Gerais for SM and SBD analysis. The thermogravimetric method was used for determining the SM content. Moreover, soil samples for SBD analysis were collected using a soil auger, for undisturbed soil samples, and determined through the volumetric ring method (Empresa Brasileira de Pesquisa Agropecuária (Embrapa) 1997). The SPR levels were determined in situ using a portable digital penetrometer (PenetroLOG, Falker).

In order to compare the accuracy of OK and IDW methods in estimating SPR, SBD and SM attributes, another grid was created from the initial grid (A). The new grid (B) was composed by 41 sampled points (40 x 40 m). The grid B was originated by eliminating one interspersed line from grid A using the QGIS software, version 2.8 (QGIS Development Team 2018) as shown in Figure 1.

Results of SPR, SBD, and SM analysis were submitted to descriptive statistical analysis and then to spatial dependence analysis. Spatial dependence of all soil attributes using grids A and

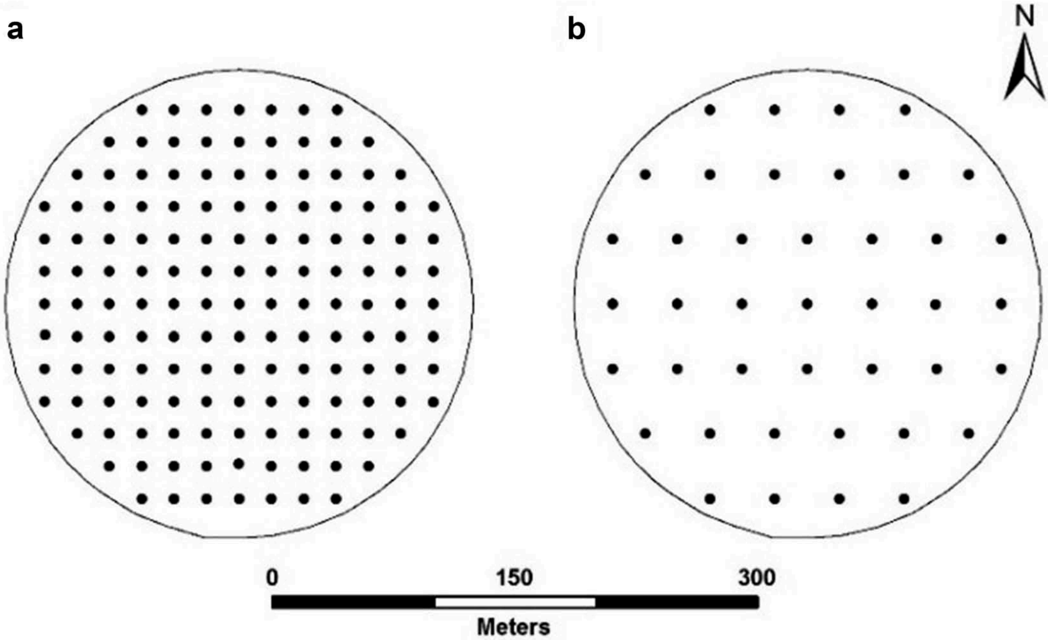


Figure 1. Sampling grids evaluated: (A) 145 points and (B) 41 points.

B was evaluated using the GS+ software, version 7 (Gamma Design Software 2004) by adjusting variograms, where the stationarity of the intrinsic hypothesis was assumed, as defined in Equation (1).

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

where

$\widehat{\gamma}$(h) = Semivariance as a function of the distance (h) between pairs of points; h = Distance between pairs of points, m; N (h) = Number of pairs of observations Z (x_i) and Z (x_{i+h}) separated by a distance h.

The model that best fit the theoretical variogram was chosen based on the highest coefficient of determination (R^2) and the smallest residual sum of squares (RSS). Then, parameters, such as nugget effect (C0), sill (C0 + C1) and range (A), were determined in the analysis. Moreover, the spatial dependence index (SDI) was determined according to Zimback (2001) using the relation C1/(C0+ C1) and then classified in the following intervals: low spatial dependence for SDI < 25%; moderate for 25% < SDI < 75%; and strong for SDI > 75%.

In order to compare OK and IDW accuracies, the difference between the known and predicted data by each method and grids (A and B) was accessed using three cross-validation parameters: mean absolute error (MAE), mean squared error (MSE) and root mean squared error (RMSE). The accuracy of spatial interpolation methods is higher when the values of those parameters are lower. Moreover, the MAE provides an absolute measure of the size of the error, while MSE and RMSE give a measure of prediction accuracy and a measure of the error size that is sensitive to outliers. The parameters were calculated by Equations (2), (3), and (4) using the R software, version 3.4.4, and the caret package (Kuhn 2008; R Core Team 2018).

$$\mathrm{MAE} = \frac{1}{n}\sum^{[Z(x_i) - Z^*(x_i)]} \tag{2}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}[Z(x_i) - Z^*(x_i)]^2 \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum[Z(x_i) - Z^*(x_i)]^2} \tag{4}$$

here $Z\ (x_i)$ the observed (known) value at location x_i; $Z\ ^*\ (x_i)$ is the predicted value at location x_i; and; N is the sample size.

Results and discussion

The summary statistics of soil penetration resistance (SPR), soil bulk density (SBD), and soil moisture content (SM) data from sampling grids A and B are shown in Table 1. It can be observed that all attributes presented low variation on mean, minimum, maximum, standard deviation (SD), and CV values. It indicates that the sampling grid approach did not have a significant impact when determining the soil attributes' descriptive statistics. In addition, it was observed that sampling grid A presented high range of attributes' values, which was expected as this grid evaluated a greater number of points compared to grid B.

SBD coefficient of variation was classified as low (0% < CV < 12%), while SPR and SM presented CV values were classified as medium for both sampling grids (12% < CV < 62%), which is an indicator of high spatial variability (Webster and Oliver 2007). Higher variation in SPR values might be related to management practices previously adopted in the area. As the area occupational record showed that it was previously used mainly for crop cultivation, under conventional planting system, the major soil structural modification was more likely to occur in the 0–20 cm layer, due to the mechanical action of plant roots and machinery/equipment traffic.

The coefficient of kurtosis (Ck) measures the peakedness of a distribution. High values, such as those observed for SM (grid A), indicate that there are several observations around the mean (distribution is peaked). On the other hand, negative values such as for SPR, SBD, and SM (grid B) indicate a greater dispersion of the data in relation to the normal distribution. Along with the Ck, the skewness (Sk) of a distribution is a measure of its asymmetry.

For both sampling grids, soil attributes' Sk values were close to zero, indicating that values were mostly well spread around its mean. Even though it was not evaluated, the existence of normal distribution is not a requirement for using OK. However, it is convenient that the distribution does not have very elongated tails, which could compromise the analyses (Isaaks and Srivastava 1989).

Table 1. Descriptive statistics of SPR (MPa), SBD (g/cm^3) and SM (%) using sampling grids A and B in Januária, Northern Minas Gerais, Brazil.

	Sampling grid					
	20 x 20 m			40 x 40 m		
Statistical parameters	SPR	SBD	SM	SPR	SBD	SM
n	145	145	145	41	41	41
Mean	2.07	1.65	5.20	2.45	1.63	5.27
Minimum	0.90	1.41	3.23	1.24	1.41	3.36
Maximum	3.66	1.90	7.18	3.66	1.85	7.18
SD	0.61	0.11	0.98	0.64	0.11	1.03
CV (%)	29.68	6.72	19.12	28.77	6.72	19.79
Sk	0.30	0.18	0.09	−0.01	−0.19	−0.05
Ck	−0.52	−1.08	0.83	−0.79	−1.07	−0.77

SD: standard deviation; CV: coefficient of variation; Ck: coefficient of kurtosis; Sk: skewness; SPR: soil penetration resistance; SBD: soil bulk density; SM: soil moisture.

Table 2. Parameters of the theoretical models fitted to empirical semivariance values of SPR (MPa), SBD (g/cm^3) and SM (%) using sampling grids A and B in Januária, Northern Minas Gerais, Brazil.

	Sampling grid					
	20 x 20 m			40 x 40 m		
Statistical parameters	SPR	SBD	SM	SPR	SBD	SM
Model	Gaussian	Spherical	Exponential	Spherical	Gaussian	Spherical
Range (m)	19.20	69.30	23.50	69.20	32.60	83.20
Sill (C_o + C)	0.352	0.013	1.007	0.439	0.013	1.140
Nugget (C_o)	0.004	0.003	0.079	0.016	0.001	0.031
SDI	92.15	76.95	98.86	97.28	88.41	96.35

SDI: spatial dependence index.

Results of the geostatistical analysis are shown in Table 2. The Spherical, Gaussian, and Exponential models were fitted to the soil attributes. All soil attributes presented SDI greater than 75% for both sampling grids, which proved that the studied attributes were strongly spatial dependent, i.e. data distribution across the area was not random. Nugget values for all attributes were generally low, indicating low sampling errors. Among the soil attributes, SM presented the higher spatial dependence, as it was the attribute with higher values of SDI for both sampling grids.

The range is the semivariogram parameter that sets the limit distance (lag) to which sampling points influence each other, i.e. the maximum spatial correlation among variables (Machado et al. 2007). It was observed that, except for SPR (grid A) and SBD (grid B), every range value was higher than the smallest distance between points for both sampling strategies, which ensured that the collected data could be used to estimate the values of any point within a circle with radius equals to the range value. Moreover, the range value is of great use to be considered as standard distance when setting sampling grid sizes (Corá et al. 2004).

In order to evaluate which interpolation method performed better, cross-validation analysis was run on data using MAE, MSE, and RMSE parameters, as shown in Table 3. According to Li and Heap (2011), OK usually outperforms IDW with better interpolation results, at least in theory. However, in this study, OK was outperformed by IDW in most of the studied attributes. Regarding grid A, except for SBD levels, OK was outperformed by IDW for SPR and SM, which resulted in smaller errors. Moreover, all attributes presented errors close to 0 (especially SBD), which indicates that all of them are relatively unbiased.

Interpolation methods proved to be a key factor when analyzing a greater number of points, as observed in grid A. However, when sampling grid B was used, results of MAE, MSE and RMSE for OK and IDW did not present significant differences between them. Although IDW outperformed

Table 3. Results of cross-validation parameters for SPR (MPa), SBD (g/cm^3) and SM (%) using sampling grids A and B in Januária, Northern Minas Gerais, Brazil.

	Sampling grid					
	20 x 20 m			40 x 40 m		
	OK					
Statistical parameters	SPR	SBD	SM	SPR	SBD	SM
MAE	0.4572	0.0656	0.6457	0.5580	0.1009	0.6974
MSE	0.3059	0.0072	0.6115	0.4403	0.0146	0.7660
RMSE	0.5531	0.0849	0.7819	0.6636	0.1208	0.8752
	IDW					
	SPR	SBD	SM	SPR	SBD	SM
MAE	0.1059	0.0720	0.2225	0.5508	0.0947	0.7697
MSE	0.0587	0.0079	0.2312	0.4329	0.0126	0.9313
RMSE	0.2424	0.0890	0.4808	0.6580	0.1124	0.9650

OK: ordinary kriging; IDW: inverse distance weighting; MAE: mean absolute error; MSE: mean squared error; RMSE: root mean squared error.

OK for SPR and SM as observed in grid A. Similar findings were reported by Liu et al. (2016), who found that OK performed similarly or was outperformed by IDW when a secondary attribute was used for mapping potassium levels.

Silva et al. (2008) observed that OK was less biased than IDW. However, the resulting errors of both methods were quite similar. Differently, Reza et al. (2010) reported smaller errors for OK over IDW when studying soil properties in Dhalai district of Tripma, India. As the semivariogram adjustments by OK is more sensitive and requires a larger number of sampling points, IDW presented higher accuracy for spatial prediction of soil attributes.

Overall, errors were small for all cross-validation parameters, independently of sampling strategy and interpolation method utilized. Nevertheless, sampling grid A, presented lower errors than B, proving that the more sampling points, the lower the errors that are associated with both methods will be.

The spatial interpolation maps generated by OK and IDW for grids A and B are shown in Figures 2 and 3, respectively. Regarding grid A (Figure 2), both methods were able to capture similar major spatial patterns and trends of SPR, SBD, and SM, respectively. In addition, the results from OK were smooth for all attributes, while the predictions of IDW displayed "bull's eyes" patterns at high and low attribute values. These results are in accordance with other studies where "bull's eyes" patterns and smoothening effects were reported for both methods after mapping pH, potassium, and soil pollution levels (Shi et al. 2009; Liu et al. 2013; Qiao et al. 2018).

Results from grid B (Figure 3) show that the spatial distribution patterns of SPR, SBD, and SM levels presented changes of great magnitude from those observed in Figure 2. Furthermore, the SPR spatial distribution was the most influenced by the lack of sampling points. It can be observed that

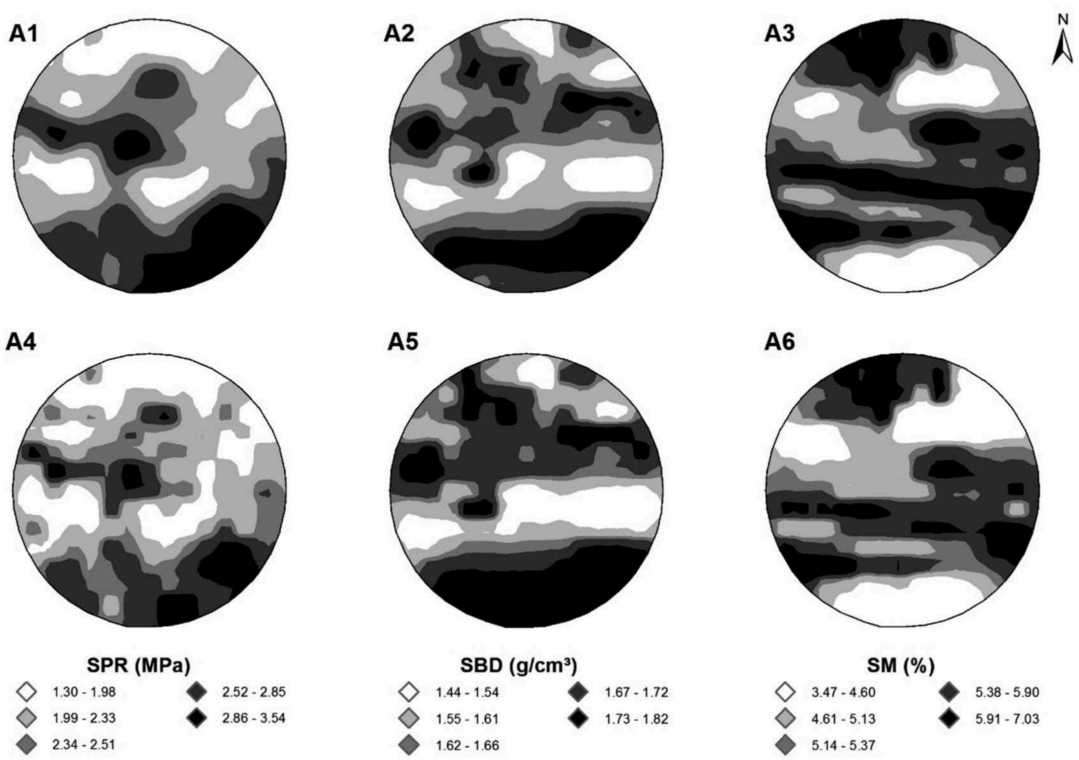


Figure 2. Thematic maps of SPR, SBD, and SM obtained by OK (A1, A2, A3) and IDW (A4, A5 and A6) using sampling grid A in Northern Minas Gerais, Brazil.

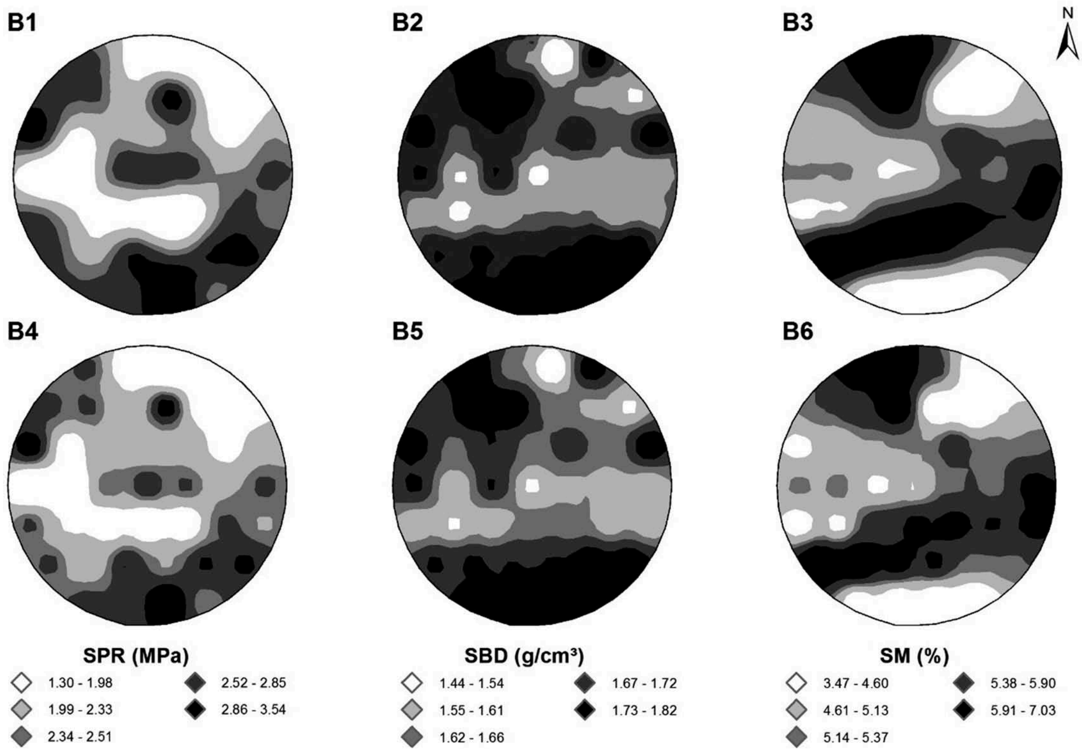


Figure 3. Thematic maps of SPR, SBD, and SM obtained by OK (B1, B2, B3) and IDW (B4, B5, and B6) using sampling grid B in Northern Minas Gerais, Brazil.

using a less dense grid increased the smoothing effect between classes and reduced the spatial variability of these attributes in the field. Thus, as the number of points decreased, the accuracy of the OK and IDW maps for estimating unsampled locations decreased as well. Silva et al. (2014) and Cherubin et al. (2015), observed the same behavior after mapping soil chemical attributes using different sampling approaches.

Also, it is essential to point out that in areas where there was less data (*e.g.*, number of neighbors), especially in grid B, interpolation results moved toward the overall mean, which increased the smoothing effect on the map. According to other authors, this is not only controlled by the number of neighbors, but also by the methods and their parameters (*e.g.*, semivariogram parameters in kriging) (Costa and Bofana 2017; Falivene et al. 2010). Overall, the results originated from the comparison between the two applied interpolation methods indicated that OK was less biased than IDW only for SBD (grid A) and SM (grid B) mapping, whereas IDW outperformed OK for the other attributes for both sampling grids.

Conclusion

The studied soil attributes presented strong spatial dependence (SDI > 75%) for both sampling grids, indicating that estimates based on mean values would fail to represent the spatial distribution in the field.

All cross-validation parameters showed low errors, independently of the sampling grid and the interpolation method used. Nevertheless, sampling grid A, presented smaller errors than B, proving that the more sampling points, the lower the errors that are associated with both methods will be.

Overall, the results indicated that OK was less biased than IDW only for SBD (grid A) and SM (grid B) maps, whereas IDW outperformed OK for the other attributes for both sampling grids.

Funding

This work was supported by the Federal Institute of Northern Minas Gerais.

ORCID

Rodrigo Nogueira Martins http://orcid.org/0000-0002-0265-0889
Fernando Ferreira Lima Dos Santos http://orcid.org/0000-0002-0946-6005
Guilherme De Moura Araújo http://orcid.org/0000-0002-3846-9387
Lucas De Arruda Viana http://orcid.org/0000-0001-5861-6949
Jorge Tadeu Fim Rosas http://orcid.org/0000-0002-3244-4816

References

Adhikary, P. P., and C. J. Dash. 2017. Comparison of deterministic and stochastic methods to predict spatial variation of groundwater depth. *Applied Water Science* 7 (1):339–48. doi:10.1007/s13201-014-0249-8.

Beutler, A. N., J. F. Centurion, M. A. P. D. C. Centurion, C. L. Leonel, A. D. C. G. São João, and O. D. S. Freddi. 2007. Intervalo hídrico ótimo no monitoramento da compactação e da qualidade física de um Latossolo Vermelho cultivado com soja. *Revista Brasileira De Ciência Do Solo* 31:1223–32. doi:10.1590/S0100-06832007000600001.

Cherubin, M. R., A. L. Santi, M. T. Eitelwein, T. J. C. Amado, D. H. Simon, and J. M. Damian. 2015. Dimensão da malha amostral para caracterização da variabilidade espacial de fósforo e potássio em Latossolo Vermelho. *Pesquisa Agropecuária Brasileira* 50 (2):168–77. doi:10.1590/S0100-204X2015000200009.

Corá, J. E., A. V. Araújo, G. T. Pereira, and J. M. G. Beraldo. 2004. Variabilidade espacial de atributos do solo para adoção do sistema de agricultura de precisão na cultura de cana-de-açúcar. *Revista Brasileira De Ciência Do Solo* 28 (6):1013–21. doi:10.1590/S0100-06832004000600010.

Costa, A. C., and J. D. R. Bofana. 2017. Comparison of spatial interpolators for variability analysis of soil chemical properties in Cuamba (Mozambique). *African Journal of Agricultural Research* 12 (25):2153–62. doi:10.5897/AJAR2016.12415.

Empresa Brasileira de Pesquisa Agropecuária (Embrapa). 1997. *Manual de métodos de análise de solo*. 2nd ed. Rio de Janeiro: Embrapa.

Empresa Brasileira de Pesquisa Agropecuária (Embrapa). 2013. *Sistema brasileiro de classificação de solos*. 3rd ed. Brasília: Embrapa.

Falivene, O., L. Cabrera, R. Tolosana-Delgado, and A. Sáez. 2010. Interpolation algorithm ranking using cross-validation and the role of smoothing effect. A coal zone example. *Computers & Geosciences* 36 (4):512–19. doi:10.1016/j.cageo.2009.09.015.

Gamma Design Software, 2004. GS+ Version 7. geostatistics for the environmental sciences. User's guide. Gamma Design Software, LLC (160 pp.).

Iqbal, J., J. A. Thomasson, J. N. Jenkins, P. R. Owens, and F. D. Whisler. 2005. Spatial variability analysis of soil physical properties of alluvial soils. *Soil Science Society of America Journal* 69 (4):1338–50. doi:10.2136/sssaj2004.0154.

Isaaks, E. H., and R. M. Srivastava. 1989. *An introduction to applied geostatistics*, 561. New York: Oxford University.

Kuhn, M. 2008. Building predictive models in R using the caret package. *Journal of Statistical Software* 28 (5):1–26. doi:10.18637/jss.v028.i07.

Li, J., and A. D. Heap. 2011. A review of comparative studies of spatial interpolation methods in environmental sciences: Performance and impact factors. *Ecological Informatics* 6:228–41. doi:10.1016/j.ecoinf.2010.12.003.

Liu, W., P. Du, Z. Zhao, and L. Zhang. 2016. An adaptive weighting algorithm for interpolating the soil potassium content. *Scientific Reports* 6:1–11. doi:10.1038/srep23889.

Liu, Y., J. Lv, B. Zhang, and J. Bi. 2013. Spatial multi-scale variability of soil nutrients in relation to environmental factors in a typical agricultural region, Eastern China. *Science of the Total Environment* 450:108–19. doi:10.1016/j.scitotenv.2013.01.083.

Machado, L. O., Â. M. Q. Lana, R. M. Q. Lana, E. C. Guimarães, and C. V. Ferreira. 2007. Variabilidade espacial de atributos químicos do solo em áreas sob sistema plantio convencional. *Revista Brasileira De Ciência Do Solo* 31 (3):591–99. doi:10.1590/s0100-06832007000300019.

Maroufi, S., A. Toranjeyan, and A. H. Zare. 2009. Evaluation of geostatistical methods for estimating electrical conductivity and pH of stream drained water in Hamedan-Bahar Plain. *Journal of Water and Soil Conservation* 16 (2):169–86.

Miller, J., J. Franklin, and R. Aspinall. 2007. Incorporating spatial dependence in predictive vegetation models. *Ecological Modelling* 202:225–42. doi:10.1016/j.ecolmodel.2006.12.012.

Moral, F. J., J. M. Terrón, and J. M. Da Silva. 2010. Delineation of management zones using mobile measurements of soil apparent electrical conductivity and multivariate geostatistical techniques. *Soil and Tillage Research* 106 (2):335–43. doi:10.1016/j.still.2009.12.002.

Nanni, M. R., F. P. Povh, J. A. M. Demattê, R. B. D. Oliveira, M. L. Chicati, and E. Cezar. 2011. Optimum size in grid soil sampling for variable rate application in site-specific management. *Scientia Agrícola* 68 (3):386–92. doi:10.1590/s0103-90162011000300017.

Peralta, N. R., J. L. Costa, M. Balzarini, and H. Angelini. 2013. Delineation of management zones with measurements of soil apparent electrical conductivity in the southeastern pampas. *Canadian Journal of Soil Science* 93 (2):205–18. doi:10.4141/cjss2012-022.

QGIS Development Team. 2018. QGIS geographic information system. Open Source Geospatial Foundation Project. http://qgis.osgeo.org

Qiao, P., M. Lei, S. Yang, J. Yang, G. Guo, and X. Zhou. 2018. Comparing ordinary kriging and inverse distance weighting for soil as pollution in Beijing. *Environmental Science and Pollution Research* 1–12. doi:10.1007/s11356-018-1552-y.

R Core Team (2018). R: A language and environment for statistical computing. Vienna: R foundation for statistical computing. Available: http://www.R-project.org/.

Reza, S. K., D. Sarkar, U. Baruah, and T. H. Das. 2010. Evaluation and comparison of ordinary kriging and inverse distance weighting methods for prediction of spatial variability of some chemical parameters of Dhalai district, Tripura. *Agropedology* 20 (1):38–48.

Shahbeik, S., P. Afzal, P. Moarefvand, and M. Qumarsy. 2014. Comparison between ordinary kriging (OK) and inverse distance weighted (IDW) based on estimation error. Case study: Dardevey iron ore deposit, NE Iran. *Arabian Journal of Geosciences* 7 (9):3693–704. 10.1007/s12517-013-0978-2.

Shi, W., J. Liu, Z. Du, Y. Song, C. Chen, and T. Yue. 2009. Surface modelling of soil pH. *Geoderma* 150 (1–2):113–19. doi:10.1016/j.geoderma.2009.01.020.

Silva, A. A., M. R. Nanni, C. A. Da Silva Junior, F. Romagnoli, M. L. Chicati, and A. De Carvalho Gasparotto. 2014. Diferentes grades de amostragem para avaliação de atributos químicos do solo na distribuição espacial em áreas de cana-de-açúcar. *Agrarian Academy* 1 (1):159–71. doi:10.18677/Agrarian_Academy.

Silva, S. D. A., J. S. D. Souza Lima, G. S. D. Souza, and R. B. D. Oliveira. 2008. Avaliação de interpoladores estatísticos e determinísticos na estimativa de atributos do solo em agricultura de precisão. *Idesia (Arica)* 26 (2):75–81. doi:10.4067/S0718-34292008000200010.

Silveira, D. C., J. F. Melo Filho, J. Sacramento, and E. C. P. Silveira. 2010. Relação umidade versus resistência do solo à penetração para um Argissolo Amarelo distrocoeso no Recôncavo da Bahia. *Revista Brasileira Ciência Do Solo* 659–67. doi:10.1590/S0100-06832010000300007.

Siqueira, D. S., J. Marques Jr, G. T. Pereira, R. S. Barbosa, D. B. Teixeira, and R. G. Peluco. 2014. Sampling density and proportion for the characterization of the variability of Oxisol attributes on different materials. *Geoderma* 232:172–82. doi:10.1016/j.geoderma.2014.04.037.

Webster, R., and M. A. Oliver. 2007. *Geostatistics for environmental scientists*. 2nd ed. Chichester: J. Wiley.

Whelan, B. M., A. B. Mcbratney, and R. A. Viscarra Rossel 1996. Spatial prediction for precision agriculture. In: Proc III International Conference on Precision Agriculture. Minneapolis, MN, USA, June. p. 23–26.

Zimback, C. R. L. 2001. Análise espacial de atributos químicos de solos para fins de mapeamento da fertilidade do solo. PhD Research Thesis. Botucatu: UNESP.