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Relationship between some geostatistical-based measures for agricultural attributes

Relacionamento entre algumas medidas baseadas em geoestatística para atributos agrícolas

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RESUMO

O objetivo do artigo foi avaliar o comportamento e o relacionamento de algumas medidas de variabilidade espacial empregadas no contexto agrícola. Foram avaliados o Grau de Dependência Espacial (SPD), o Índice de Dependência Espacial (SDI) e a Medida de Dependência Espacial (SDM). Obteve-se a correlação de Spearman entre Tamanho de amostra por hectare (n.ha^{-1}), Coeficiente de Variação [CV (%)], SDI (%), SDM (%), Alcance (m) e SPD (%), em cada modelo de semivariograma. Foram comparados os comportamentos de SDI, SDM e SPD, em função dos distintos modelos de semivariograma. Ocorre maior variabilidade espacial no semivariograma exponencial. O SDI e o SDM correlacionam-se com o CV somente no semivariograma esférico. O SPD se correlaciona com o CV nos semivariogramas exponencial e esférico. O SPD tende a gerar menos classificações fracas da variabilidade espacial, de modo que sugere-se considerar uma variabilidade espacial moderada a partir de valores de SPD de, pelo menos, 45%.

PALAVRAS-CHAVE: variabilidade dentro do campo; autocorrelação espacial; fatores de campo; agricultura de precisão.

ABSTRACT

The aim of the article was to evaluate the behavior and relationship of some spatial variability measures used in the agricultural context. The Degree of Spatial Dependence (SPD), the Spatial Dependence Index (SDI) and the Spatial Dependence Measure (SDM) were evaluated. The Spearman correlation was obtained between Sample size per hectare (n.ha^{-1}), Coefficient of Variation [CV (%)], SDI (%), SDM (%), Range (m) and SPD (%), in each semivariogram model. The behaviors of SDI, SDM and SPD were compared, depending on the different semivariogram models. Exponential semivariogram generated higher spatial variability. The SDI and SDM measurements correlated with the CV only in the spherical semivariogram. The SPD correlated with the CV in the exponential and spherical semivariograms. SPD tends to generate fewer weak classifications of spatial variability, so it is suggested to consider moderate spatial variability from SPD values of at least 45%.

KEYWORDS: within-field variability; spatial autocorrelation; field factors; precision agriculture.

Field observations are extensively collected to understand factors affecting agricultural productivity (LEROUX & TISSEYRE 2019), such as soil conditions, hydrology, climate, pests, management practices, and others. The variability of these factors in the field can be assessed through spatial or spatiotemporal methods, such as Geostatistics.

Geostatistics is a methodology widely used in Agriculture, as the knowledge of variability within the field is well related to profitability (ZHAO et al. 2023), so that the interaction between Precision Agriculture and Geostatistics is increasingly relevant (LEROUX & TISSEYRE 2019, RODRIGUES et al. 2020a, ZHAO et al. 2023). In geostatistical approaches, assessing the degree of spatial variability is a crucial step, typically conducted through metrics derived from semivariogram parameter estimates. Among the parameters of the semivariogram, the Range describes the spatial variability in the horizontal direction of the graph, while the Nugget Effect, the Contribution and the Threshold describe the spatial variability in the vertical direction of the semivariogram (SANTOS et al. 2018).

Soil and agriculture attributes present variations in space and time, and metrics based on Geostatistics may also present different behaviors due to field factors (SANTOS et al. 2018), and evaluations and discussions regarding such measures of spatial dependence have been carried out in recent years (SANTOS et al. 2018, AMARAL & DELLA JUSTINA 2019, LEROUX & TISSEYRE 2019, PINTO et al. 2019). Therefore, this study aims to evaluate the behavior and relationship among different spatial variability measures used in agricultural settings.

In the present study, the following measures of spatial variability were evaluated: Degree of Spatial Dependence (SPD) (BIONDI et al. 1994); Spatial Dependency Index (SDI) (SEIDEL & OLIVEIRA 2014, APPEL NETO et al. 2018); and Spatial Dependence Measure (SDM) (APPEL NETO et al. 2020). It was decided to present the SPD rather than the Relative Nugget Effect (RNE) (CAMBARDELLA et al. 1994), because SPD=100%-RNE, and the SPD has a geometric justification for its use (SEIDEL & OLIVEIRA 2015).

Therefore, scientific articles using SDI or SDM published between 2018 and 2022 and indexed in Web of Science and SCOPUS databases were analyzed. In total, 10 articles were selected in the Web of Science and 13 articles in SCOPUS. Finally, after considering only exponential, Gaussian, and spherical semivariogram adjustments in soil and agricultural attributes from research conducted in Brazil, 11 articles remained [FIGUEIREDO et al. 2018, MENDONÇA et al. 2018, COSTA et al. 2019, PIAS et al. 2019, RODRIGUES et al. 2019, SOARES et al. 2019, GUEDES et al. 2020, RODRIGUES et al. 2020b, BRITO et al. 2021, CURSI et al. 2021, TAGLIARI-BALESTRIN et al. 2021] from which information was collected to form the database: Sample size per hectare (n.ha^{-1}); Coefficient of variation [CV (%)]; Semivariogram model [exponential model, Gaussian model, spherical model]; SDI (%); SDM (%); Range (m); SPD (%). The database was made up of 193 observations. Of these observations, 88 were fitted with exponential semivariograms, 20 with Gaussian models, and 85 with spherical functions.

First, descriptive statistics were calculated, including minimum and maximum values, first and third quartiles, mean, median, standard deviation, and skewness coefficient. The Shapiro-Wilk normality test was performed to assess spatial variability measurements. Subsequently, Spearman's correlation was calculated between sample size per hectare (n.ha$^{-1),}$ CV, SDI, SDM, Range, and SPD for each semivariogram model. Finally, nonparametric tests were performed to compare SDI, SDM, and SPD behaviors according to different semivariogram models. The significance level was set at 5% ($P < 0.05$). Statistical analyses were performed using the R software (R CORE TEAM 2021).

Table 1 shows the descriptive statistics of spatial variability measurements. The SDI values ranged from 0.80% to 31.70% for the exponential model, 6.00% to 27.44% for the Gaussian model, and 0.09% to 20.00% for the spherical model. The SDI showed the highest mean in the exponential model (15.39%), followed by the Gaussian model (13.29%), with the spherical model exhibiting the lowest mean (8.89%).

The SDI values, in terms of median, for the exponential, Gaussian and spherical models are 13.67%, 11.50% and 8.15%, respectively. The median values for both exponential and Gaussian models are statistically equivalent. However, they differ from the spherical model, which shows the lowest median value. These median values align with those reported by SEIDEL & OLIVEIRA (2016), who found 10.40%, 11.70%, and 11.00% for the exponential, Gaussian, and spherical models, respectively. According to Seidel and Oliveira (2016), the maximum SDI values are 31.70%, 50.40%, and 37.50% for the exponential, Gaussian, and spherical models, respectively. However, in this study, the Gaussian and spherical models showed maximum values of 27.44% and 20.00%, respectively, indicating lower-than-expected maximum spatial dependence in this sampling.

The SDM, in the exponential model, varies from 1.33% to 42.20%; in the Gaussian model, from 9.42%

to 37.67%; and in the spherical model, it varies from 1.52% to 30.97%. The SDM shows the highest mean in the exponential model (22.11%), followed by the Gaussian model (19.48%), with the lowest mean observed in the spherical model (14.55%). The median values of the SDM are statistically equal for the exponential and Gaussian models (18.76% and 18.12%, respectively). In addition, they differ from the spherical model, which has the lowest median value (13.82%). The maximum values for the SDM, in theory, are 42.20%, 56.30% and 44.70%, for the exponential, Gaussian and spherical models, respectively (APPEL NETO et al. 2020). However, in this study, the Gaussian and spherical models showed maximum values of 37.67% and 30.97%, respectively, indicating lower-than-expected maximum spatial dependence in this sampling.

Table 1. Descriptive measures and multiple comparisons between medians of spatial variability measurements for exponential (Exp), Gaussian (Gaus) and spherical (Sph) semivariograms.

Semivariogram	Min	Q1	Media	Median*	Q3	Max	S	CA	Normality
SDI (%)									
Exp [n=88]	0,80	7,76	15,39	13.67a	23,77	31,70	9,83	0,37	No
Gaus [n=20]	6,00	8,07	13,29	11.50a	15,85	27,44	6,24	0,67	Yes
Sph [n=85]	0,09	5,07	8,89	8.15b	12,00	20,00	5,12	0,32	No
SDM (%)									
Exp [n=88]	1,33	10,80	22,11	18.76a	33,93	42,20	13,04	0,28	No
Gaus [n=20]	9,42	13,38	19,48	18.12a	22,18	37,67	7,91	0,87	Yes
Sph [n=85]	1,52	10,32	14,55	13.82b	18,14	30,97	6,45	0,37	Yes
SPD (%)									
Exp [n=88]	19,41	63,54	81,64	94.25a	100,00	100,00	23,11	-0,97	No
Gaus [n=20]	15,93	43,58	60,46	57.93b	79,54	100,00	25,41	0,06	Yes
Sph [n=85]	0,50	33,33	52,04	47.83b	70,55	100,00	29,52	0,20	No

Min=Minimum. Max=Max. Q1=First quartile. Q3=Third quartile. S=Standard deviation. CA=Asymmetry coefficient. Normality: Shapiro-Wilk test ($p<0.05$). *Models with equal letters do not differ according to Dunn's test at 5% probability.

The SPD, in the exponential model, varies from 19.41% to 100.00%; in the Gaussian model, from 15.93% to 100.00%; and in the spherical model, it varies from 0.50% to 100.00%. The SPD showed the highest average in the exponential model (81.64%), followed by the Gaussian model (60.46%), with the lowest average observed in the spherical model (52.04%). The exponential model showed significantly higher spatial dependence (94.25%) compared to the Gaussian (57.93%) and spherical (47.83%) models. To SANTOS et al. (2018), the median values of SPD 69.00%, 76.00% and 62.00% are observed for the exponential, Gaussian and spherical models, respectively.

The SPD, in theory, varies from 0.00% to 100.00%. However, in this study, the minimum values for the exponential and Gaussian models were 19.41% and 15.93%, respectively, indicating that the minimum spatial dependence in this sampling was higher than expected. SANTOS et al. (2018) also observed higher minimum values for SPD, with values of 34.00%, 21.00%, and 20.00% for the exponential, Gaussian, and spherical models, respectively. Also, according to SANTOS et al. (2018), SPD (or RNE) tends to generate greater degrees of spatial dependence than would occur in theory, i.e. with a degree of spatial dependence tending to be stronger.

Table 2 shows the correlations between the measures of spatial variability. For the exponential model, sample size per hectare ($n.ha^{-1}$) shows no significant positive correlations with spatial variability measures. VC has a negative and significant correlation only with NT ($r=-0.514$). The range is positively and significantly correlated with SDI ($r=0.609$) and SDM ($r=0.666$). SDI, SDM, and SPD correlate positively and significantly ($r>0.383$).

For the Gaussian model, stems ha^{-1} showed no significant positive correlations with spatial variability measures. The range does not have positive and significant correlations with the measures of spatial variability. VC does not present negative and significant correlations with measures of spatial variability. SDI correlates positively and significantly with SDM ($r=0.821$) and SPD ($r=0.500$), but SDM and SPD do not correlate.

For the spherical model, the $n.ha^{-1}$ has a positive and significant correlation only with SPD ($r=0.404$). The range does not present positive and significant correlations with the measures of spatial variability. VC presents negative and significant correlations with SDI ($r=-0.369$), SDM ($r=-0.319$) and SPD ($r=-0.340$). SDI, SDM, and SPD correlate positively and significantly (r>0.440).

Table 2. Spearman correlations between spatial variability measurements, range, sample size per hectare ($n.ha^{-1}$) and CV (%) in exponential, Gaussian and spherical semivariograms.

	SDI (%)	SDM (%)	SPD (%)
		Exponential [n=88]	
$n.ha^{-1}$	-0,253*	-0,285*	$-0,148^{ns}$
Alcance (m)	0,609*	0,666*	$0,052^{ns}$
CV (%) [n=31]	$0,083^{ns}$	$0,162^{ns}$	-0,514*
SDI (%)		0,986*	0,498*
SDM (%)			0,383*
		Gaussian [n=20]	
$n.ha^{-1}$	$-0,036^{ns}$	$0,001^{ns}$	$-0,230^{ns}$
Alcance (m)	$-0,070^{ns}$	$0,186^{ns}$	$-0,189^{ns}$
CV (%) [n=19]	0,460*	0,484*	$0,284^{ns}$
SDI (%)		0,821*	0,500*
SDM (%)			$0,008^{ns}$
		Spherical [n=85]	
$n.ha^{-1}$	$0,182^{ns}$	$0,021^{ns}$	0,404*
Alcance (m)	$-0,206^{ns}$	$0,062^{ns}$	-0,516*
CV (%) [n=80]	-0,369*	-0,319*	-0,340*
SDI (%)		0,894*	0,763*
SDM (%)			0,440*

*Significant Spearman correlation at 5% probability. ^{ns} Spearman's correlation not significant.

In theory, the correlation between sample size per hectare ($n.ha^{-1}$) and spatial variability measures is expected to be positive and significant. However, this occurs only with SPD for the spherical model, showing a moderate correlation.

In addition, theoretically, the correlation between VC and measures of spatial variability is expected to be negative and significant. Negative correlations between CV and spatial variability metrics support that stronger spatial structure is linked to higher sampling precision, as lower CV values (indicating greater precision) correspond to higher spatial variability measurements. In their study, FU et al. (2011) do not observe a correlation between VC and RNE (or between VC and SPD).

Overall, SDI, SDM, and SPD showed significant positive correlations with each other, except for the Gaussian model, where no significant correlation was found between SDM and SPD. SANTOS et al. (2018) observed that both exponential and spherical models showed significant positive correlation between SDI and SPD. In addition, SANTOS et al. (2018) for all three semivariogram models, the range shows a significant positive correlation with SDI but not with SPD. Range is a key geostatistical parameter that can be used to determine sample size requirements (OLIVEIRA et al. 2014).

Table 3 shows the frequency distribution of spatial variability classes for SDI, SDM, and SPD across different semivariogram models. It is observed that in the exponential semivariogram there are more strong classifications for all measurements. In the Gaussian and spherical semivariograms, moderate classifications are more frequent according to SDI and SPD measures, while weak classifications are more common based on SDM. According to SEIDEL & OLIVEIRA (2016), who employed SDI and SPD indices, moderate classifications were more prevalent in exponential and spherical semivariograms, while Gaussian semivariograms showed predominantly weak classifications for SDI and strong classifications for SPD.

Table 3. Classifications of SDI, SDM and SPD measures for the exponential (EXP), Gaussian (GAUS) and spherical (SPH) semivariograms.

Model	SDI*			Total
	Weak	Moderate	Strong	
EXP	19 (21,59%)	24 (27,27%)	45 (51,14%)	88 (100,00%)
GAUS	6 (30,00%)	10 (50,00%)	4 (20,00%)	20 (100,00%)
SPH	34 (40,00%)	43 (50,59%)	8 (09,41%)	85 (100,00%)
Model	SDM$			Total
	Weak	Moderate	Strong	
EXP	32 (36,36%)	19 (21,59%)	37 (42,05%)	88 (100,00%)
GAUS	10 (50,00%)	7 (35,00%)	3 (15,00%)	20 (100,00%)
SPH	44 (51,76%)	35 (41,18%)	6 (07,06%)	85 (100,00%)
Model	SPD#			Total
	Weak	Moderate	Strong	
EXP	1 (01,14%)	27 (30,68%)	60 (68,18%)	88 (100,00%)
GAUS	2 (10,00%)	10 (50,00%)	8 (40,00%)	20 (100,00%)
SPH	18 (21,18%)	48 (56,47%)	19 (22,35%)	85 (100,00%)

*Classification by SEIDEL & OLIVEIRA (2016). $Classification of APPEL NETO et al. (2020). #Classification adapted from CAMBARDELLA et al. (1994).

Overall, the SDI classified 30.57% of attributes as having weak spatial variability, 39.90% as moderate, and 29.53% as strong. The SDM classifies 44.56% as having weak spatial variability, 31.61% as moderate and 23.83% as having strong spatial variability. Finally, SPD classified 10.88% of the attributes with weak spatial variability, 44.04% with moderate, and 45.08% with strong variability. According to SEIDEL & OLIVEIRA (2016), in the SDI, 23%, 46%, and 31% of soil attributes showed weak, moderate, and strong spatial variability, respectively. In the SPD, these values were 1%, 61%, and 38%, respectively.

The SPD tends to generate more classifications of spatial variability from moderate to strong. Therefore, SPD should only be considered to generate moderate spatial variability classification when its value reaches at least 45% (1st quartile of overall SPD = 44.78%). This criterion aligns with DALCHIAVON & CARVALHO (2012), who established a spatial dependence classification system where values up to 40% indicate weak spatial dependence. In addition, it is suggested to maintain a strong SPD rating of at least 75% (median SPD overall = 68.57% is relatively close to 75%). The use of the 1st quartile and the median to suggest the cutoffs in the classification since the sample distribution of the SPD has a negative asymmetry behavior (Asymmetry Coefficient in general = -0.35). This idea is based on the studies of SEIDEL & OLIVEIRA (2016), APPEL NETO et al. (2018) and APPEL NETO et al. (2020) showing the cutoff points for SDI and SDM classifications based on the median and third quartile, as both measures displayed positive skewed distributions.

It is concluded that there is greater spatial variability in the exponential semivariogram. O SDI e o SDM correlacionam-se com o CV somente no semivariograma esférico. O SPD se correlaciona com o CV nos semivariogramas exponencial e esférico. It is suggested to consider a moderate spatial variability from SPD values of at least 45%.

REFERENCES

AMARAL LR & DELLA JUSTINA DD. 2019. Spatial dependence degree and sampling neighborhood influence on interpolation process for fertilizer prescription maps. Engenharia Agrícola 39: 85-95.

APPEL NETO E et al. 2018. Spatial dependence index for cubic, pentaspherical and wave semivariogram models. Boletim de Ciências Geodésicas 24: 142-151.

APPEL NETO E et al. 2020. Geostatistical-based index for spatial variability in soil properties. Revista Brasileira de Ciência do Solo 44: e0200086.

BIONDI F et al. 1994. Geostatistically modeling stem size and incremente in an old-growth forest. Canadian Journal of Forest Research 24: 1354-1368.

BRITO WBM et al. 2021. Pedotransfer functions to estimate some soil properties in Indian Black Earth, south of Amazonas State. Anais da Academia Brasileira de Ciências 93: e20190543.

CAMBARDELLA CA et al. 1994. Field-scale variability of soil properties in central Iowa soils. Soil Science Society of America Journal 58: 1501-1511.

COSTA BRS et al. 2019. Temporal variation and spatial distribution of relative indices of leaf chlorophyll in grapevine cv. chardonnat. Engenharia Agrícola 39: 74–84.

CURSI DE et al. 2021. Novel tools for adjusting spatial variability in the early sugarcane breeding stage. Frontiers in Plant Science 12: 749533.

DALCHIAVON FC & CARVALHO MP. 2012. Correlação linear e espacial dos componentes de produção e produtividade da soja. Semina: Ciências Agrárias 33: 541- 552.

FIGUEIREDO VC et al. 2018. Development of a methodology to determine the best grid sampling in precision coffee growing. Coffee Science 13: 312–323.

FU W et al. 2011. Using Moran's I and geostatistics to identify spatial patterns of soil nutrients in two different long-term phosphorus-application plots. Journal of Plant Nutrition and Soil Science 174: 785-798.

GUEDES LPC et al. 2020. Nugget effect influence on spatial variability of agricultural data. Engenharia Agrícola 40: 96-104.

LEROUX C & TISSEYRE B. 2019. How to measure and report within-field variability: a review of common indicators and their sensitivity. Precision Agriculture 20: 562-590.

MENDONÇA PG et al. 2018. Temporal and spatial uncertainty of erosion soil loss from an argisol under sugarcane management scenarios. Revista Brasileira de Ciência do Solo 42: e0170182.

OLIVEIRA IA et al. 2014. Spacial variability and sampling density of chemical attributes in archaeological black Earth and native forest soil in Manicoré, AM. Floresta 44: 735-746.

PIAS OHC et al. 2019. Transition from systematic to directed soil sampling designs in an area managed with precision agriculture. Engenharia Agrícola 39: 400–409.

PINTO LOR et al. 2019. Avaliação de índices de dependência espacial de modelos geoestatísticos sobre a krigagem. Enciclopédia Biosfera 16: 339-352.

R CORE TEAM. 2021. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

RODRIGUES MS et al. 2019. Soil mapping quality for site-specific management in fruit fields in the semiarid region of Brazil. Ciencia del suelo 37: 328-337.

RODRIGUES MS et al. 2020a. Geostatistics and its potential in Agriculture 4.0. Revista Ciência Agronômica 51: e20207691.

RODRIGUES AF et al. 2020b. Soil water content and net precipitation spatial variability in an Atlantic forest remnant. Acta Scientiarum: Agronomy 42: e43518.

SANTOS ELE et al. 2018. Some aspects about the spatial dependence index for variability of soil attributes. Ciencia Rural 48: e20170710.

SEIDEL EJ & OLIVEIRA MS. 2014. Novo índice geoestatístico para a mensuração da dependência espacial. Revista Brasileira de Ciência do Solo 38: 699-705.

SEIDEL EJ & OLIVEIRA MS. 2015. Medidas de dependência espacial baseadas em duas perspectivas do semivariograma paramétrico. Ciência e Natura 37: 20-27.

SEIDEL EJ & OLIVEIRA MS. 2016. A classification for a geostatistical index of spatial dependence. Revista Brasileira de Ciência do Solo 40: e0160007.

SOARES CM et al. 2019. Diagnóstico de perdas na colheita mecanizada de duas cultivares de tomate industrial. Revista Brasileira de Ciências Agrárias 14: 1-10.

TAGLIARI-BALESTRIN J et al. 2021. Variabilidade espacial da palha de soja distribuída na colheita e sua relação com o estande final de aveia preta. Revista Tecnología en Marcha 34: 28-37.

ZHAO M et al. 2023. Within-field spatial variability and potential for profitability of variable rate applications. Precision Agriculture 24: 2248-2263.