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EFFECTS OF SIZE AND SAMPLING GRID ON THE QUALITY OF APPARENT SOIL ELECTRICAL CONDUCTIVITY MAPS

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KEYWORDS

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ABSTRACT

The apparent soil electrical conductivity (ECa) is an attribute commonly used for the characterization of the spatial variability of soil, but its determination by handheld sensors consumes considerable time and labor. The reduction in the number of sampling points allows minimize them but can result in increased uncertainty of interpolated maps. Thus, the goal of this study was to identify the best spacing and number of ECa measurements, to guarantee the quality of maps generated in three vineyards. The ECa values were obtained using a handheld sensor in different sampling grids. The data were submitted to descriptive statistical and geostatistical analyses. The relative deviation and Kappa coefficient of agreement were used to assess the similarity of generated maps. The reduction in the number of points and increase in the size of the sampling grid reduced the quality of maps and this reduction was greater when the spacing increased in the direction of the terrain slope. A minimum limit of 100 sampling points should be considered for the sampling planning to generate ECa spatial distribution maps, with a more conservative approach when regarding the increase in spacing in the direction of the terrain slope.

INTRODUCTION

Precision agriculture (PA) encompasses the use of equipment for direct collection of information representing soil variability. In this context, the measurement of apparent soil electrical conductivity (ECa) is important because it can be correlated with several soil attributes (Fortes et al., 2015; Stadler et al., 2015; Uribeetxebarria et al., 2018); thus, it allows the prior knowledge of soil variability. This can assist in sampling of other properties (Fortes et al., 2015; Sanches et al., 2018) and in the demarcation of areas for various types of site-specific management, such as productivity (Bottega et al., 2017), quality of production (Urretavizcaya et al., 2017), irrigation (Haghverdi et al., 2015), and nutritional management (Peralta et al., 2015).

One type of equipment for the measurement of ECa can be towed by a vehicle (e.g., tractor or off-road vehicle), enabling a large number of measurements (Farahani & Flynn, 2007). On the contrary, handheld equipment can be used to measure ECa (Rabello et al., 2010; 2011) and this is not necessarily conducted continuously or in swaths. Handheld equipment is used for areas that are difficult to access or which, because of the type of crop, such as dense vegetation, tussocks (Rabello et al., 2011), and vineyards with crops on trellises with reduced spacing between rows, hinders the entry of towed equipment (Rabello et al., 2010). Nevertheless, manually operated equipment presents disadvantages because of the demand for labor and time, which can increase the costs of PA adoption.

One alternative to reduce costs and ECa sampling time is to reduce the distance between swaths for towed equipment (Farahani & Flynn, 2007; Andrenelli et al., 2013) and the number of points sampled by the handheld equipment (Nascimento et al., 2014). However, these alternatives can result in increased uncertainty in spatial distribution in the generated ECa maps and may lead to errors regarding specific management decisions for the area (Farahani & Flynn, 2007).

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In a 52 ha area with sandy soil irrigated by a central pivot, Farahani & Flynn (2007) observed a smaller and higher reduction in the quality of the ECa maps with an increase in distances up to 50 and 80 m between the measured swaths, respectively, using Veris 3100 equipment (Veris Technologies, Salina, KS). Andrenelli et al. (2013), using an ARP© (Automatic Resistivity Profiling) apparatus in a 3.5 ha vineyard with medium texture soil, verified that spacing between 12 and 24 m swaths resulted, respectively, in electrical resistivity maps (1/ECa) with substantial and moderate agreement with the map provided by 6 m between swaths. Regarding manually transported equipment, Nascimento et al. (2014) observed that the reduction from 820 to 90 sampling points guaranteed the generation of reliable ECa maps in a 1.6 ha table grape vineyard with sandy textured soil with low slope in the Brazilian semi-arid region.

However, the effects of the reduction in the number of sampling points on the quality of ECa maps with punctual measures using a handheld equipment have not been sufficiently studied. Nascimento et al. (2014) evaluated only the reduction in the number of sampling points, without considering the gradual reduction in spacing between them. Moreover, the results may not be valid for finer texture soils or steeper slopes. Thus, the goal of this study was to identify the optimal number of ECa measurements, as well as the best spacing between measurements, as acquired by handheld equipment, to ensure the quality of spatial distribution maps in irrigated vineyards.

MATERIAL AND METHODS

The study was conducted in three commercial vineyards denoted A, B, and C (Table 1), located in the municipality of Espírito Santo do Pinhal, state of São Paulo, Brazil. The vines were cultivated in trellises and irrigated by a drip system, with a lateral line per row of plants and two emitters per plant, with the flow of each emitter ranging between 1.83 L h^{-1} (vineyard C) and 1.60 L h^{-1} (vineyards A and B). The soil was classified predominantly as eutrophic Tb Haplic Cambisol (Santos et al., 2018). The classification of topographic relief of the predominant slope in vineyards A and C was wavy (8 - 20%), whereas that of vineyard B was strong wavy (20 - 45%) (Embrapa, 1979).

TABLE 1. General characteristics of the vineyards under study.

Vineyard	Cultivar	Rootstock	Area (ha)	Geographic coordinates	Altitude (m)	Sr × Sp[a] (m)	Soil Texture
A	Cabernet Franc	Paulsen 1103	1.5	22º10'41.1"S 46º42'11.8"W	1,183	3.0 × 1.0	Clay
B	Cabernet Sauvignon	Paulsen 1103	0.9	22º10'26.5"S 46º42'2.3"W	1,174	2.5 × 1.0	Clay
C	Chardonnay	Paulsen 1103	0.6	22º10'49.1"S 46º44'28.4"W	875	2.5 × 1.0	Clay

[a] Sr: spacing between rows; Sp: spacing between plants.

ECa measurements were conducted on December 20 and 21, 2017 (vineyards A and B, in this order) and February 7, 2018 (vineyard C), during the morning, using a handheld ECa meter (Rabello et al., 2010; 2011) (Figure 1). The meter was composed of metallic rods used as electrodes for the induction of electric current and it measured the potential difference in a given layer of soil. It had a PIC18F258 microprocessor, which was used as the central processor and a battery for power.

During field measurements, the equipment was coupled to a HiPer GGD (TOPCON, Pleasanton, CA, USA) GNSS (Global Navigation Satellite System) receiver with signal corrected by the RTK (Real Time Kinematic) system for the georeferencing of the points measured. The ECa measurements were obtained along interspersed rows and after every 5 plants within the rows, in the continuous wetted band resulting from the irrigation system. The metallic rods were spaced horizontally for the ECa readings to be representative of the soil layer from 0.0 to 0.4 m in depth. Thus, a sampling grid of 6 × 5 m was obtained for vineyard A and another of 5 × 5 m for vineyards B and C.

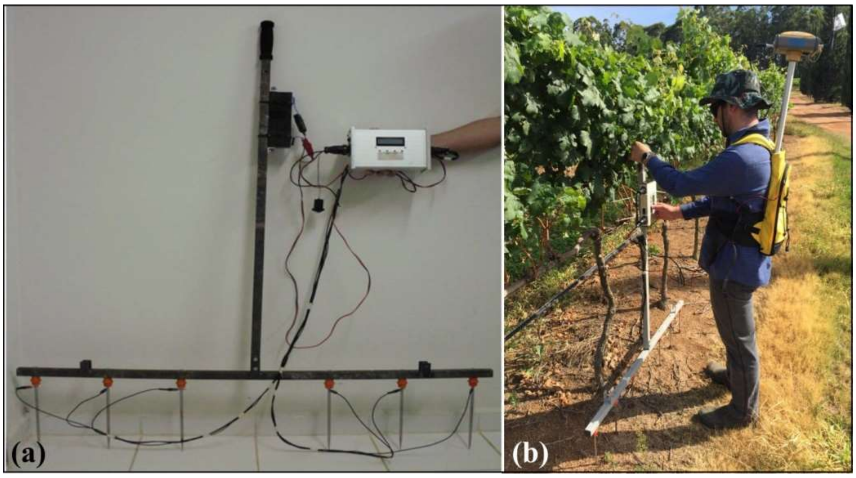

FIGURE 1. Handheld meter for apparent soil electrical conductivity (ECa) (a); and measurement of ECa in the vine rows, using the handheld meter coupled to the GNSS receiver (*rover*) (b).

To identify the best sample size in different grids to guarantee the quality of interpolated ECa maps, the number of points was reduced based on the initial grid size for each vineyard (6 × 5 m for vineyard A and 5 × 5 m for vineyards B and C), used as reference for the construction of an additional 15, 14, and 9 different grids for vineyards A, B, and C, respectively (Table 2). The number of grids evaluated varied according to the size of each vineyard; consequently, it also varied with the respective minimum number of practicable points to demarcate homogeneous zones.

TABLE 2. Sampling grid (SG) used for measurement of apparent soil electrical conductivity and number of points measured (n) in vineyards A, B, and C.

- - - - Vineyard A - - - -		- - - - Vineyard B - - - -		- - - - Vineyard C - - - -	
SG (m)	n	SG (m)	n	SG (m)	n
6 × 5 (reference)	511	5 × 5 (reference)	321	5 × 5 (reference)	221
12 × 5	263	10 × 5	163	10 × 5	115
12 × 10	132	10 × 10	85	10 × 10	59
18 × 5	190	15 × 5	110	15 × 5	75
18 × 10	95	15 × 10	57	15 × 10	38
18 × 15	71	15 × 15	39	15 × 15	29
24 × 5	143	20 × 5	86	20 × 5	59
24 × 10	72	20 × 10	45	20 × 10	30
24 × 15	53	20 × 15	31	20 × 15	22
24 × 20	42	20 × 20	26	20 × 20	18
30 × 5	119	25 × 5	66	-	-
30 × 10	60	25 × 10	33	-	-
30 × 15	44	25 × 15	24	-	-
30 × 20	35	25 × 20	20	-	-
30 × 25	30	25 × 25	17	-	-
30 × 30	25	-	-	-	-

A descriptive statistical analysis was conducted for the ECa dataset from all sampling grids used after removal of outliers (three times beyond the interquartile range) from the full dataset (removal of three values, required for vineyard B only). The Kolmogorov-Smirnov (K-S) non-parametric normality test was also applied with a 5% significance level for the dataset from each sampling grid to determine the need for data transformation because lack of normality could affect the reliability of semivariograms (Oliver & Webster, 2014). The descriptive statistical analysis and normality test were performed using the R 3.3.3 software (R Core Team, 2017).

Thereafter, a geostatistical analysis was applied to each dataset to characterize and evaluate the presence of spatial dependence in the data measured in different sampling grids. For this, experimental semivariograms were calculated using the Matheron's (1965) estimator, considering 50% of the maximum distance between sampling points as suggested by Landim (2006). The existence and type of anisotropy was verified to determine the need for correction based on a method described by Oliver & Webster (2014). According to Yamamoto & Landim (2013), the objective of the anisotropy correction, when present, is to obtain an isotropic semivariogram, allowing for the fittingof a single spatial correlation model.

Spherical, exponential, and gaussian models were fitted to the isotropic experimental semivariograms and selected on the basis of the lowest value of the root mean square error (RMSE) of the cross-validation. Then, the parameters (nugget effect: C_0, sill: $C_0 + C$, and the spatial dependence range: A) of the selected semivarigram model were obtained. The degree of spatial dependence (DSD, %) (Equation 1) was determined according to Cambardella et al. (1994) and classified as strong (DSD < 25%), moderate (25 % ≤ DSD < 75 %), and weak spatial dependence (DSD ≥ 75 %).

$$DSD = (C_0/(C_0 + C)) \times 100 \quad (1)$$

The data that presented spatial dependence, i.e., did not present a pure nugget effect (PNE) in the semivariogram analysis, were interpolated by ordinary kriging. Then, spatial distribution ECa maps were generated with three classes of values (high, moderate, and low) determined by the Jenks optimization method, which minimizes the differences between intraclass values and maximizes the differences between classes (Fraile et al., 2016). The calculation of the experimental semivariograms, the fittingof the respective theoretical models, cross-validation, and the interpolation of the data were performed using the GS^+ 7.0 software and the RMSE calculation was conducted with the R 3.3.3 software (R Core Team, 2017).

To assess the quality of ECa maps generated by the sampling grids, the Kappa coefficient of agreement (Cohen, 1960) was calculated in relation to the reference maps adopted for each vineyard. The higher the calculated value of this coefficient, determined using a confusion matrix, the greater the agreement between the compared map and the reference map. The degree of agreement, according to the Kappa coefficient, was classified according to the method of Landis & Koch (1977) (Table 3). The relative deviation coefficient (RDC) (Coelho et al., 2009) was also used for the comparison between maps to rank them from the best to the worst sampling grid, with smaller values being better. This coefficient reflects the difference between a thematic map and a map assumed as a reference by calculating the modulus of the mean difference for the interpolated values of both maps (Coelho et al., 2009). This differs from the comparison by the Kappa coefficient of agreement, which requires classes of values (categories) delimited in each of the maps. According to Cherubin et al. (2015), the RDC efficiently evaluates the similarity of soil attribute maps. The Kappa and RDC coefficients were calculated using a Microsoft Excel® spreadsheet.

TABLE 3. Classification of the strength of agreement according to the Kappa coefficient of agreement.

Kappa coefficient of agreement	Strength of agreement
<0.00	Poor
0.00-0.20	Slight
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Substantial
0.81-1.00	Almost Perfect

Source: Modified from Landis & Koch (1977).

Regression analyses were performed to verify the relationship between the number of sampling points and the values of the coefficients (Kappa and RDC), and the best model was chosen based on its coefficient of determination.

RESULTS AND DISCUSSION

Non-normality was verified only for the ECa data measured in the grid with a higher number of points of the vineyards A and B (grid size of 6 × 5 m and 5 × 5 m, respectively), according to the K-S test at 5% significance (Table 4). In some cases, this would require the transformation of the dataset for subsequent geostatistical analysis. However, it was not necessary to transform these data, because the corresponding values of the skewness coefficient were barely pronounced (<1), indicating a symmetry in the data, which is actually required for the use of the semivariograms estimated by kriging (Landim, 2006).

The presence of geometric anisotropy was observed (Yamamoto & Landim, 2013; Oliver & Webster, 2014), i.e., a variation only in the extent of spatial dependence with the change of direction of the terrain for the ECa data measured in vineyard A in the 6 × 5 m, 12 × 5 m, 12 × 10 m, 18 × 5 m, 30 × 15 m, and 30 × 20 m sampling grids. The anisotropic phenomenon observed was characterized by having higher spatial dependence in the direction of the plant rows (45°), suggesting a greater continuity in this direction, except for the grid size of 30 × 20 m, which presented greater continuity at 90°. As the plant rows were, in general, placed in a direction perpendicular to the slope of the vineyard, the anisotropy could be attributed to the intrinsic factors of the soil conditioned by the land topography. Valerian & Prado (2001) verified the existence of anisotropy with greater continuity of the clay attribute in the opposite direction to that of the toposequence. In other words, factors related to soil formation and the transport of particles may have contributed to the greater variability of soil attributes, such as the granulometric fraction and organic matter in the direction of the slope of the vineyard, and consequently, the ECa.

TABLE 4. Descriptive statistics and normality test of the apparent soil electrical conductivity (ECa, mS m^{-1}) data measured in different sampling grids (SG) in three vineyards.

Vineyard	SG (m)	n[(a)]	Statistical parameters[(b)]								D_{K-S}[(c)]
			Mean	Med	Min	Max	s	CV (%)	Kur	Ske	
A	6 × 5	511	5.2	5.2	2.8	8.8	0.93	18.0	0.17	0.07	0.06^{NN}
	12 × 5	263	5.3	5.3	3.0	8.8	0.93	17.6	0.27	0.00	0.06^{N}
	12 × 10	132	5.2	5.3	3.2	7.4	0.93	17.9	-0.47	-0.05	0.07^{N}
	18 × 5	190	5.3	5.4	3.1	8.8	0.96	18.1	0.25	0.05	0.09^{N}
	18 × 10	95	5.3	5.3	3.2	7.3	0.96	18.3	-0.43	-0.10	0.09^{N}
	18 × 15	71	5.4	5.4	3.2	8.8	1.09	20.2	0.22	0.10	0.12^{N}
	24 × 5	143	5.3	5.3	3.1	7.4	0.97	18.4	-0.50	-0.18	0.07^{N}
	24 × 10	72	5.2	5.3	3.2	7.4	1.01	19.3	-0.73	-0.15	0.10^{N}
	24 × 15	53	5.3	5.4	3.2	7.2	1.07	20.1	-0.62	-0.29	0.08^{N}
	24 × 20	42	5.2	5.3	3.2	7.1	1.07	20.6	-0.82	-0.11	0.10^{N}
	30 × 5	119	5.2	5.3	3.2	7.2	0.86	16.5	-0.29	-0.31	0.10^{N}
	30 × 10	60	5.2	5.4	3.2	7.2	0.93	17.7	-0.41	-0.40	0.12^{N}
	30 × 15	44	5.2	5.3	3.2	7.2	0.96	18.5	-0.16	-0.20	0.14^{N}
	30 × 20	35	5.1	5.4	3.2	7.1	0.97	19.2	-0.68	-0.29	0.14^{N}
	30 × 25	30	5.1	5.4	3.2	7.1	1.03	20.2	-0.74	-0.31	0.14^{N}
	30 × 30	25	5.2	5.2	3.2	7.2	1.13	21.9	-0.73	0.03	0.09^{N}
B	5 × 5	321	4.5	4.4	1.5	9.1	1.30	28.8	0.89	0.72	0.09^{NN}
	10 × 5	163	4.5	4.4	1.5	8.9	1.27	28.2	0.75	0.59	0.08^{N}
	10 × 10	85	4.4	4.5	1.5	8.9	1.27	28.6	1.15	0.50	0.07^{N}
	15 × 5	110	4.7	4.5	1.8	8.3	1.27	27.2	-0.13	0.56	0.12^{N}
	15 × 10	57	4.6	4.5	1.8	7.4	1.27	27.4	-0.06	0.43	0.10^{N}
	15 × 15	39	4.7	4.5	2.8	7.4	1.28	27.2	-0.53	0.57	0.12^{N}
	20 × 5	86	4.4	4.5	1.5	7.6	1.32	30.0	-0.13	0.27	0.06^{N}
	20 × 10	45	4.3	4.4	1.5	7.4	1.30	30.1	-0.05	0.05	0.06^{N}
	20 × 15	31	4.3	4.5	1.5	7.4	1.34	31.4	0.03	0.03	0.10^{N}
	20 × 20	26	4.4	4.7	1.5	6.8	1.39	31.6	-0.56	-0.45	0.13^{N}
	25 × 5	66	4.8	4.7	1.5	7.4	1.33	27.9	-0.52	0.12	0.08^{N}
	25 × 10	33	4.6	4.5	1.5	7.4	1.45	31.5	-0.15	0.29	0.09^{N}
	25 × 15	24	4.7	4.7	1.5	7.4	1.50	31.9	-0.27	0.08	0.12^{N}
	25 × 20	20	4.7	4.8	1.5	7.4	1.73	36.7	-1.01	-0.02	0.11^{N}
	25 × 25	17	4.6	4.8	1.5	6.8	1.45	31.4	-0.32	-0.45	0.12^{N}
C	5 × 5	221	4.6	4.4	1.1	8.7	1.38	30.3	-0.33	0.26	0.08^{N}
	10 × 5	115	4.7	4.6	1.1	7.6	1.46	31.2	-0.44	0.01	0.06^{N}
	10 × 10	59	4.8	4.6	1.6	7.6	1.50	31.1	-0.56	0.09	0.10^{N}
	15 × 5	75	4.7	4.6	2.3	7.4	1.20	25.7	-0.18	0.48	0.10^{N}
	15 × 10	38	4.8	4.6	2.8	7.3	1.21	25.1	-0.19	0.59	0.19^{N}
	15 × 15	29	4.8	4.8	2.3	7.1	1.23	25.8	-0.26	-0.06	0.08^{N}
	20 × 5	59	4.9	4.8	2.7	7.3	1.41	28.8	-1.17	0.22	0.12^{N}
	20 × 10	30	4.9	4.7	3.0	7.3	1.43	29.0	-1.15	0.41	0.16^{N}
	20 × 15	22	4.9	4.7	3.0	7.3	1.28	26.2	-0.73	0.44	0.10^{N}
	20 × 20	18	5.0	4.8	3.0	7.3	1.40	28.2	-0.75	0.44	0.13^{N}

[a] n: number of points measured. [b] Med: median; Min: minimum value; Max: maximum value; s: standard deviation; CV: coefficient of variation; Kur: kurtosis coefficient; Ske: skewness coefficient. [c] D_{K-S}: calculated values of the Kolmogorov-Smirnov test (K-S); N and NN: follows and does not follow a non-normal distribution, respectively, based on the critical value calculated at 5% significance.

Among the sampling grids studied, only the 30 × 25 m and 30 × 30 m grids in vineyard A did not ensure spatial dependence among the ECa data (experimental semivariograms with PNE; Table 5). The occurrence of PNE, i.e., the non-existence of a sill in the experimental semivariogram, demonstrated that the spacing between samples used was greater than the spatial dependence range (Oliver & Webster, 2014) and insufficient for interpolation based on geostatistical tools (Landim, 2006). Vineyard A presented the lowest values of spatial dependence range in the majority of the sampling grids tested (between 22.8 and 47.6 m: Table 5) in comparison to those of the other vineyards (between 79.4 and 39.9 m for vineyard B and between 74.6 and 32.3 m for vineyard C). Therefore, this resulted in the occurrence of PNE only in this vineyard, when distances beyond 25 m were used between points of ECa measurements.

TABLE 5. Models and their respective parameters to fit the experimental semivariograms of apparent soil electrical conductivity (ECa, mS m^{-1}) and cross-validation parameters for the different sampling grids (SG) and the number of points (n).

Vineyard	SG (m)	n	Model[(a)]	Nugget effect	Sill	Range (m)	DSD[(b)] (%)	Cross-validation[(c)]		
								b	r^2	RMSE
A	6 × 5	511	Exp.	0.40	0.90	36.3	44.2^{M}	1.04	0.35	0.76
	12 × 5	263	Exp.	0.15	0.87	39.6	17.1^{F}	0.90	0.32	0.77
	12 × 10	132	Exp.	0.12	0.89	38.7	13.6^{F}	0.75	0.19	0.85
	18 × 5	190	Sph.	0.23	0.92	35.9	24.8^{F}	0.93	0.38	0.79
	18 × 10	95	Sph.	0.41	0.89	39.6	46.8^{M}	0.90	0.17	0.87
	18 × 15	71	Sph.	0.32	1.11	40.2	28.9^{M}	0.93	0.23	0.95
	24 × 5	143	Sph.	0.26	0.94	22.8	27.5^{M}	0.92	0.30	0.81
	24 × 10	72	Exp.	0.24	1.00	29.4	24.1^{F}	0.63	0.05	0.99
	24 × 15	53	Sph.	0.42	1.08	31.4	38.5^{M}	0.49	0.03	1.07
	24 × 20	42	Sph.	0.39	1.04	39.1	37.5^{M}	0.52	0.02	1.05
	30 × 5	119	Exp.	0.15	0.68	25.3	21.6^{F}	0.99	0.30	0.72
	30 × 10	60	Sph.	0.51	0.79	39.5	64.1^{M}	0.47	0.02	0.92
	30 × 15	44	Sph.	0.24	0.83	47.6	29.3^{M}	0.35	0.03	0.99
	30 × 20	35	Sph.	0.13	0.85	31.9	14.8^{F}	-0.30	0.01	1.05
	30 × 25	30	PNE[(d)]	-	-	-	-	-	-	-
	30 × 30	25	PNE	-	-	-	-	-	-	-
B	5 × 5	321	Sph.	0.95	1.70	71.6	55.8^{M}	1.00	0.27	1.12
	10 × 5	163	Sph.	0.64	1.56	50.2	40.8^{M}	0.94	0.27	1.06
	10 × 10	85	Sph.	0.67	1.51	52.8	44.3^{M}	0.68	0.10	1.19
	15 × 5	110	Sph.	0.96	1.72	79.4	56.0^{M}	0.95	0.16	1.17
	15 × 10	57	Exp.	0.75	1.44	47.2	52.1^{M}	0.31	0.01	1.24
	15 × 15	39	Exp.	0.06	1.60	39.9	3.9^{F}	0.91	0.11	1.19
	20 × 5	86	Sph.	0.68	1.75	53.5	38.7^{M}	0.91	0.29	1.09
	20 × 10	45	Sph.	0.39	1.69	50.4	23.1^{F}	0.83	0.26	1.08
	20 × 15	31	Sph.	0.62	1.63	73.4	38.3^{M}	0.31	0.02	1.27
	20 × 20	26	Sph.	0.16	1.63	45.0	9.9^{F}	1.19	0.24	1.09
	25 × 5	66	Exp.	0.88	1.76	55.2	50.0^{M}	0.85	0.13	1.19
	25 × 10	33	Sph.	1.23	2.09	61.3	59.0^{M}	0.69	0.07	1.38
	25 × 15	24	Sph.	1.34	2.34	60.0	57.4^{M}	-0.87	0.06	1.61
	25 × 20	20	Sph.	1.63	3.25	57.2	50.0^{M}	-0.63	0.04	2.17
	25 × 25	17	Sph.	0.23	1.84	67.9	12.7^{F}	0.76	0.15	2.20
C	5 × 5	221	Exp.	0.38	2.54	71.2	14.9^{F}	1.01	0.48	0.99
	10 × 5	115	Sph.	0.68	2.82	70.6	24.2^{F}	1.01	0.42	1.11
	10 × 10	59	Sph.	0.83	2.96	70.3	28.1^{M}	0.88	0.26	1.29
	15 × 5	75	Sph.	0.37	1.68	68.6	22.3^{F}	0.96	0.45	0.89
	15 × 10	38	Sph.	0.28	1.66	72.0	16.7^{F}	0.96	0.44	0.89
	15 × 15	29	Exp.	0.03	1.54	74.6	2.1^{F}	1.02	0.42	0.92
	20 × 5	59	Sph.	0.68	2.39	58.0	28.5^{M}	0.96	0.43	1.06
	20 × 10	30	Sph.	0.75	2.27	48.4	33.2^{M}	0.93	0.27	1.21
	20 × 15	22	Sph.	0.27	1.68	32.3	15.9^{F}	1.56	0.30	1.08
	20 × 20	18	Sph.	0.90	1.91	34.8	46.9^{M}	0.22	0.00	1.38

[a] Exp. and Sph.: exponential and spherical, respectively. [b] DSD: degree of spatial dependence; S and M: strong and moderate spatial dependence, respectively, according to Cambardella et al. (1994). [c] b, r^2, and RMSE: angular coefficient, coefficient of determination, and root mean square error, respectively, of the cross-validation for the adopted model. [d] PNE: pure nugget effect.

There was a predominance of strong spatial dependence among the sampling grids of vineyard C (Table 5), indicating better estimates by kriging for this vineyard. This is evidenced by the better cross-validation results found in this vineyard, i.e., a higher coefficient of determination (r^2) and angular coefficient (b) closer to unity compared to those of other vineyards.

Generally, the analysis of the cross-validation results (Table 5) revealed that the quality of the fittted semivariogram models gradually decreased with the increase in the spacing between ECa sampling points and reduction in the number of points. According to Oliver &Webster (2014), the number of sampling points is a determining factor in the reliability or accuracy of the experimental semivariogram, presenting in general a direct relationship between the sample size and the accuracy of the semivariogram.

In a more specific assessment of the cross-validation results, vineyard B presented a reduction with increased intensity of b, r^2, and RMSE from 10 m grids in both directions (Table 5). The same result was observed in the other vineyards, in general, for spacing above 20 m in at least one of the directions of the sampling grid, except with spacing of 5 m in the other direction (from 24 × 10 and 20 × 10 m for vineyards A and C, respectively). The increase in spacing between sampling points and the resulting reduction in their number, resulted in a decrease in the number of point pairs used in the calculation of semivariance, which reflected negatively on the confidence interval, and therefore, on the accuracy and reliability of the semivariogram (Webster & Oliver, 1992; Oliver & Webster, 2014).

In all vineyards assessed, when the spacing of 5 m was used in at least one of the directions of the sampling grid, the result of the cross-validation was, in most cases, similar to that observed for the grid with higher sample size (reference) of the same vineyard (Table 5). Moreover, these same grids with 5 m in either direction, frequently presented better cross-validation results compared to other grids with a similar or even higher number. This means that greater reliability and accuracy of the experimental semivariograms can be ensured when reduced dimensions (5 m in this case) in one of the directions of the sampling grid is used. This is due to the greater detail of the variability of the ECa detected by random sampling at a reduced spacing in either direction, which facilitates the structuring of the semivariograms. In addition, this type of sampling grid tends to involve a greater number of points measured, which is also important in the quality of the semivariograms (Oliver & Webster, 2014).

The ECa maps interpolated for the three vineyards based on different sampling grids are shown in Figure 2. From the increase in the spacing between points and decrease in the number of points measured, the maps showed a reduction in the detail of the spatial variability of the ECa, i.e., homogeneous zones of ECa presented greater continuity and gradually smoothed contours. This demonstrated a reduction in the similarity of the maps in relation to the reference because of the decrease in the sample size and the increase in the spacing between points.

FIGURE 2. Spatial distribution of the apparent soil electrical conductivity in three categories of values originating from measurements from different sampling grids and with a different number of points (in parentheses), in vineyards A, B, and C.

From the calculated RDC values (Table 6), the best sampling grids evaluated in vineyard A were of 18 × 10 m and 12 × 5 m (5.65 and 5.77%, respectively). For vineyards B and C, the best grid size among the tested was 10 × 5 m (RDC of 6.64 and 8.56%, respectively). The worst grids identified were 24 × 20 m, 25 × 25 m, and 20 × 15 m for vineyards A, B, and C, respectively. Less reliable maps than the reference map of the three vineyards originated not only from greater spacing and with smaller numbers of points, but in some cases also because of the conformation of the sampling grids. This was not verified in other studies when using the RDC for this type of evaluation, as in those on corn productivity maps (Coelho et al., 2009) and soil chemical attributes (Cherubin et al., 2015), which verified with no exception that reducing the number of points increased the difference with respect to the reference map. The reduced size of the areas evaluated in the present study and the smaller difference in the number of points between evaluated grids may explain this difference with the above mentioned studies.

TABLE 6. Relative deviation coefficient (RDC) and Kappa coefficient of agreement for the maps of apparent soil electrical conductivity generated based on measurements made in different sampling grids (SG) in vineyards A, B, and C.

Vineyard	SG (m)[a]	n[b]	RDC (%)	Kappa	Classification[c]
A	12 × 5	263	5.77	0.53	Moderate
	12 × 10	132	5.92	0.47	Moderate
	18 × 5	190	5.82	0.51	Moderate
	18 × 10	95	5.65	0.44	Moderate
	18 × 15	71	7.28	0.46	Moderate
	24 × 5	143	7.25	0.34	Fair
	24 × 10	72	6.99	0.28	Fair
	24 × 15	53	7.71	0.33	Fair
	24 × 20	42	8.80	0.24	Fair
	30 × 5	119	6.95	0.28	Fair
	30 × 10	60	7.07	0.27	Fair
	30 × 15	44	7.11	0.29	Fair
	30 × 20	35	8.09	0.24	Fair
B	10 × 5	163	6.64	0.45	Moderate
	10 × 10	85	8.38	0.30	Fair
	15 × 5	110	9.01	0.43	Moderate
	15 × 10	57	10.68	0.35	Fair
	15 × 15	39	12.90	0.28	Fair
	20 × 5	86	9.76	0.27	Fair
	20 × 10	45	12.05	0.10	Slight
	20 × 15	31	11.67	0.32	Fair
	20 × 20	26	15.00	0.04	Slight
	25 × 5	66	11.68	0.34	Fair
	25 × 10	33	12.18	0.26	Fair
	25 × 15	24	11.28	0.25	Fair
	25 × 20	20	13.26	0.23	Fair
	25 × 25	17	17.17	0.04	Slight
C	10 × 5	115	8.56	0.63	Substantial
	10 × 10	59	11.66	0.57	Moderate
	15 × 5	75	14.63	0.43	Moderate
	15 × 10	38	16.95	0.22	Fair
	15 × 15	29	14.79	0.40	Fair
	20 × 5	59	14.82	0.46	Moderate
	20 × 10	30	18.49	0.34	Fair
	20 × 15	22	19.22	0.30	Fair
	20 × 20	18	19.05	0.35	Fair

[a] spacing between rows × spacing between plants. [b] n: number of points measured. [c] classification of agreement with the reference map, based on the Kappa coefficient of agreement according to Landis & Koch (1977).

Based on the Kappa coefficient (Table 6), the agreement between the maps generated in different sampling grids and the reference map of the respective vineyard was classified according to Landis & Koch (1977) as substantial only for the 10 × 5 mgrid of vineyard C and slight for the 20 × 10 m, 20 × 20 m, and 25 × 25 m grids of vineyard B. The remaining grids tested resulted in maps with moderate or fair agreement. This shows that from the first reduction (approximately 50%) of the number of points measured from the reference grid to the following grid, a considerable drop occurred in the quality of maps.

When evaluating the variation in the RDC and Kappa coefficients according to the number of points measured jointly in the three vineyards (Figure 3), a trend in the potential reduction of RDC values (Figure 3a) and logarithmic increase of Kappa values (Figure 3b) was observed with the increase in the number of measured points. This confirmed the reduction in the quality of maps with the reduction in the number of measured points as also observed in several studies with varied types of data (Bazzi et al., 2008; Coelho et al., 2009; Nascimento et al., 2014; Cherubin et al., 2015).

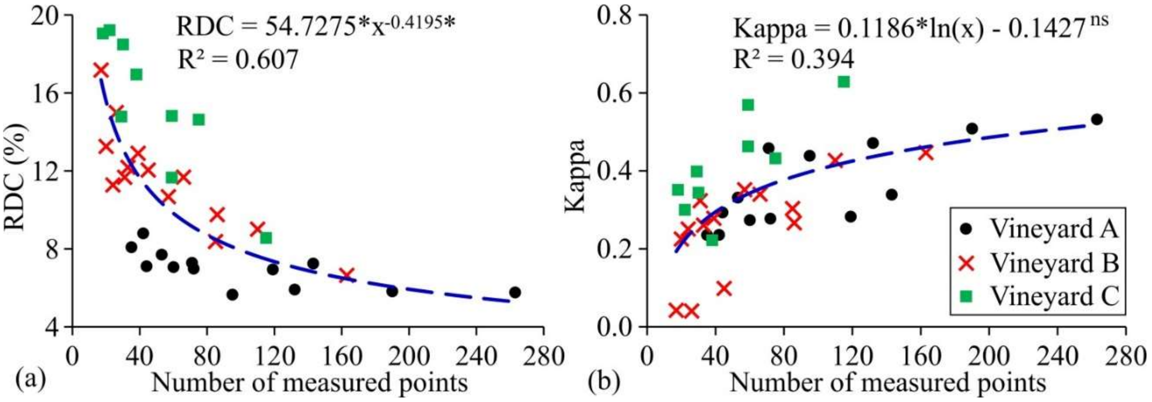

FIGURE 3. Relative deviation coefficient (RDC) (a) and Kappa coefficient (b) according to the number of measured points of apparent soil electrical conductivity in the different sampling grids established in vineyards A, B, and C. * and ns: significant and not significant at 5% by the t-test, respectively.

According to Oliver &Webster (2014), less than 100 sampling points results in unreliable semivariograms because below this value a considerable increase in the confidence interval of the semivariance occurs, which compromises the accuracy of the fitted model (Webster & Oliver, 1992). Based on Figure 3, the lower limit of 100 sampling points should be considered in the planning of future ECa sampling, given that the average rate of change of RDC and Kappa coefficients with the increase in the number of measurements was lower (in module) in the range above 100 points (-0.02 and 7.04×10^{-4} by number of points, for RDC and Kappa, respectively) compared to the range below 100 (-0,11 and 2.53×10^{-3} by number of points, to RDC and Kappa, respectively). This indicated that the maps generated with less than 100 sampling points presented a more accentuated decline in quality. Therefore, to avoid excessively reduced quality in the interpolated maps, the minimum limit of 100 should be used.

Alternatively, high RDC and reduced Kappa values, which identify maps with the greatest divergence from the reference map, did not correspond exclusively to the reduction in the sample size, because some grids were not necessarily better than others because they had a higher number of measured points. For example, the 24 × 5 m grid of vineyard A displayed a lower agreement compared to the 18 × 15 m grid (Table 6), even with a higher number of measured points (143 to 72 points). This indicated that not only should the number of points be considered in the planning of sampling, but also the conformation of the sampling grid (spacing used in both directions).

Figure 4 shows the variation in the Kappa coefficient of agreement as a function of the conformation of the sampling grid used for ECa measurements. It should be emphasized that the region of graphics where the response surface is not visible (upper corner), corresponds to the grids not evaluated in this study.

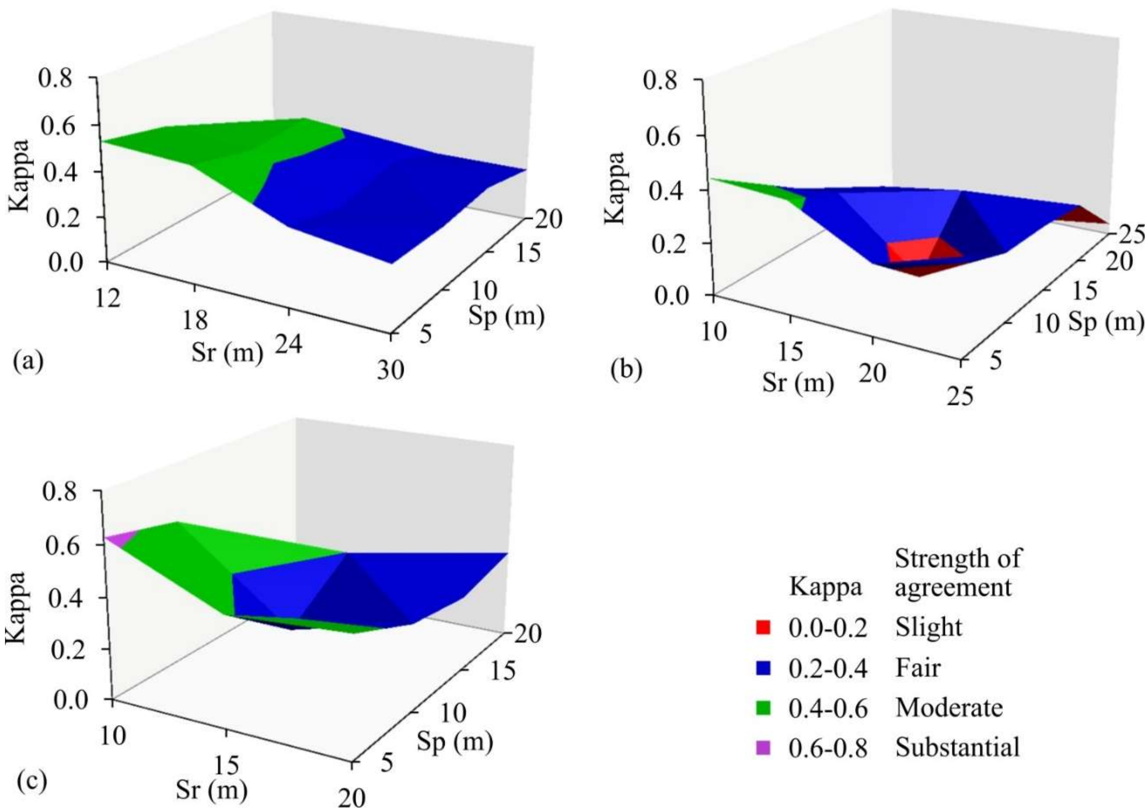

FIGURE 4. Kappa coefficient of agreement according to the spacing of sampling points of apparent soil electrical conductivity in the direction between rows (Sr) and between plants (Sp) in vineyards A, B, and C (a, b, and c, respectively).

A higher decline in the Kappa coefficient was observed in response to the increase in spacing between rows (Sr) in an even spacing between plants (Sp), mainly in vineyards A and C (Figure 4a and 4c). This indicated that the increase in the spacing between ECa measurements in the direction of the slope of the vineyards (spacing of plant rows) may have interfered more strongly with the quality of maps, because the variability of several soil attributes tends to be greater in the direction of the slope, such as that of the presence of clay (Valeriano & Prado, 2001). However, a more detailed study is needed to identify the most appropriate minimum spacing in this direction, because factors peculiar to each vineyard, such as area and slope intensity, influence the variation in the final results.

CONCLUSIONS

The reduction in the number of points measured and the conformation of the sampling grid influenced the quality of maps of apparent soil electrical conductivity (ECa). The sampling grids in vineyard A of 12 × 5 m (263 points) and 18 × 10 m (95 points) and vineyards B and C of 10 × 5 m (163 and 115 points, respectively), resulted in maps more similar to those of the reference grids (6 × 5 m - vineyard A and 5 × 5 m - vineyards B and C).

A minimum limit of 100 sampling points should be considered in the sampling plan to generate spatial distribution maps of the ECa using handheld sensors in vineyards with areas similar to those assessed in this study, close to 1 ha.

The increase in spacing in the direction of the slope of the vineyard (between rows) was more damaging to the quality of ECa maps compared to the increase in the direction of the rows. However, more detailed studies should be carried out to verify the minimum limit more appropriate to spacing in the direction of the slope.

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