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ANALYSIS OF GEOSTATISTICS THROUGH ROUGHNESS DATA SAMPLING OF SOIL AT DIFFERENT SCALES

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Abstract

Erosion is dependent on factors such as volume and intensity of rainfall, the infiltration rate of the soil water storage capacity and surface soil water. In this sense, the study of surface roughness of the soil favors the understanding of a number of factors related to the process of soil erosion, favoring thus reducing the damage caused by degradation by soil erosion. On the other hand, you also need to understand how soil surface roughness manifests itself after the incidence of distinct rainfall because the rainfall intensity also plays an important role on the process of soil degradation. The use of geostatistics to the spatial modeling is based in most cases on the assumption of stationarity of data. The objective of this study was to evaluate the spatial distribution of soil roughness in experimental microplots and validate the intrinsic hypothesis of geostatistics. The soil aggregates of 3-5 cm were collected in the city of Lugo (Spain). In the laboratory experimental plots (200 mm x 200 mm, 400 mm x 400 mm, 600 mm and 600 mm x 800 mm x 800 mm) were constructed using metal base mobile 0.86 mx 0.86 m (0.73 m2), and the roughness of the ground (dm) measured with rugosimeter laser. Os different size plot for determining the soil surface roughness demonstrated stability in statistical and geostatistical parameters, allowing determination of random roughness index (RR) reliably , regardless of portion size. The validation of the intrinsic hypothesis of geostatistics using data from soil roughness was only possible because the data are homogeneous and represent the same phenomenon in a continuous manner.

Keywords: soil management, erosion, soil aggregation, soil sampling.

Introduction

In recent years, geostatistics has been used in several areas of knowledge. Geostatistical analyzes enable efficient mapping and analysis of spatial variability of various attributes.

During the process of geostatistical analysis is necessary to consider their basic assumptions of geostatistics to contemplate whether or not the presence of finite variance. The intrinsic hypothesis is usually the most used because it is less restrictive (DAVID, 1977; Chiles and DELFINER, 1999; VIEIRA, 2000; WENDROTH and NIELSEN, 2003), when compared to other cases of geostatistics. This hypothesis requires only the existence and stationarity of the semivariogram, without any restriction as to the existence of finite variance (VIEIRA, 2000). The stationarity of the data allows an experiment to be repeated, since it believes that all samples are different realizations of the same random function (Siqueira et al., 2011).

Stationarity in all samples belong to the same population, and, regardless of scale, it is expected that the mean is constant, allowing in the same area different sampling schemes can be used to detect the spatial variability of any one attribute (SIQUEIRA et al., 2011).

The surface roughness of the soil consists of microelevações and microdepressions with certain spatial distribution (ALLMARAS et al., 1966; Bertolani et al., 2000; VIDAL VAZQUEZ, 2002), allowing the use of geostatistics for modeling and interpretation of their spatial distribution.

Siqueira et al. (2012) describe the importance of soil roughness on advanced models for predicting soil loss by erosion. In addition to its relationship to maintain and increase infiltration rates and water storage in the soil and in sediment retention, thus helping to reduce erosion rates, according to Paz and Gonzalez Taboada Castro (1996).

Kamphorst et al. (2000) and Vidal Vázquez (2002) describe the surface roughness is influenced by soil tillage and moisture prior to preparation, the amount and type of plant residue, soil type and land slope.

Bertolani et al. (2000), emphasize the importance of knowledge of surface roughness as well as the analysis of their spatial variability by providing knowledge of a lot of important information to the mathematical models of soil loss, using the evolution of surface water retention during distinct episodes of rain. Thus, the use of geostatistics favors knowledge and modeling of spatial variability of soil surface roughness by means of mathematical models, favoring the construction of maps using the process of interpolation by ordinary kriging (CAMBARDELLA et al., 1994; Bertolani et al. 2000; Vieira, 2000; Siqueira et al. 2008).

Thus, the present study aimed to evaluate the spatial distribution of soil roughness on microplot trial and its spatial variability at different scales of sampling to test the hypothesis intrinsic geostatistics.

2. Materials e Methods

This study was conducted using soil from the Province of Lugo (43 º 01 'N and 7 ° 33' W), the Autonomous Community of Galicia (Spain). Clods were collected in the field between 3 and 5 cm, for construction in microplot experimental laboratory for measurement of soil surface roughness.

The soil is classified as a Humic Cambisol (FAO, 1994), whose textural characteristics are presented in Table 1. The geological material in the soil is formed by material Lugo period Precambrian pelitic schists consists of gneisses and amphibolites (IGME, 1973).

Table 1**.** Granulometric composition of the soil in Lugo (Galicia, Spain).

Clay (%) < 0,002 mm	Silt (%) 0,053-0,002 mm	---------------------- Sand (%)----------------------			Textural classification
		Total 2,00-0,053 mm	Thick 2,00-0,21 mm	Thin 0,21-0,053 mm	
15,3	27,8	57,0	19,7	37,3	Franco-arenosa

The climate, according to Köppen, is the type Cs, with an average annual rainfall ranging between 1,000 mm and 1,400 mm. The Haplumbrept sandy loam texture (Lugo) is being kept under fallow in recent years.

In the experimental laboratory was built using mobile metal base of 0.86 x 0.86 m (0.73 m2). The portion was constituted by a plastic screen regular mesh of 0.3 mm, superimposed with a layer of sand 2 to 3 cm. The layer of soil over the sand, containing aggregates had a height of approximately 4-5 cm.

The roughness was measured using a laser roughness meter (simulated surface) on the surface. The laser roughness meter comprises a sensor DME 2000 (SICK Ltda.) providing readings of a simulated surface on decimeter (dm). The readings of the roughness of the soil were taken at regular intervals of 5 mm x 5 mm, with a floor area of 800 mm x 800 mm, totaling 25,600 sampling points. Later, the data were worked in a spreadsheet that allowed the delineation of plots with different scales to test the hypothesis intrinsic geostatistics: 200 mm x 200 mm, 400 mm x 400 mm, 600 mm x 600 mm and 800 mm x 800 mm.

The random roughness index (RR) was calculated according to the methodology proposed by Kamphorst et al. (2000) calculated standard deviation of the heights, rather than the standard error, and using the data of height of ground surface without transforming them to logarithm and without eliminating its extreme values (Equation 1).

$$RR = \sqrt{\frac{\sum_{i=1}^{n}\left(Z_i - \overline{Z}\right)^2}{n}} \quad (1)$$

Where: RR - is the random roughness index (mm) Zi - is the height at each point; Z - Mean height en - number of measured points.

Geostatistics was used to evaluate the spatial dependence of the surface roughness. For this purpose, the set of software Geostat developed by Vieira et al. (2002), for determining the spatial variability by modeling the experimental semivariogram (Equation 2).

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

In equation (2), * (h) is estimated semivariance, N (H) represents the number of pairs of measured values Z (xi), Z (xi + h) separated by the vector (h). In geostatistics name, Z (xi) is described as regionalized variable (Clark, 1979). Thus, we determined the fitting parameters of the semivariogram: nugget (C0) is the discontinuity between samples, ie, the variability is not detected during the sampling process; structure variance (C1) which describes the extent to which there correction between samples and scope (a) represents the maximum size of the zones of spatial variability.

The ratio of spatial dependence (RD, Equation 3) between samples was determined according to the procedure described by Cambardella et al. (1994): 0-25% high, 25-75% and 75-100% average low spatial dependence between samples.

$$RD=\left(\frac{C_0}{C_0+C_1}\right)*100 \quad (3)$$

Where: RD is the ratio of spatial dependence; C0 is the nugget effect, C1 and structural variance.

The software SURFER 7.0 (GOLDEN SOFTWARE, 1999) was used to construct maps of soil surface roughness before and after the start of simulated rainfall.

3. Results and discussion

The average values (Table 2) show that for all plot sizes used there is no big difference in the values of average, with the lowest mean value for the parcel of 3.409 dm (400 mm x 400 mm), while the largest average value was 3.471 dm (800 mm x 800 mm).

It appears that there is an increase in the values of the variance by increasing the size of the parcel. In this case, it was expected that the sample variance value decreased with increasing portion under study, since there is an increase in the number of measurements reaching a peak of 25 599 points read with a laser roughness meter. This fact is because with the increased number of measurements increases the likelihood of outliers or outliers, where the probability of occurrence of an expected value near the average decreases with the increase of the number of reading, since the roughness of the soil varies with other intrinsic and extrinsic parameters to soil type (SCHICK et al., 2000; VIDAL VAZQUEZ, 2002).

Table 2. Statistical parameters for soil roughness determined in different sized plot.

Parameter	Roughness of the soil in different sizes of plots			
	200x200mm	**400x400mm**	**600x600mm**	**800x800mm**
Number of measures	1.640	6.480	14.520	25.599
Mín	3,166	3,056	3,056	3,056
Max	3,612	3,692	3,744	3,744
average	3,423	3,409	3,446	3,471
Variance	0,010	0,011	0,011	0,012
Standard desviation	0,099	0,104	0,107	0,109
Variance coeficient	2,900	3,000	3,310	3,310
Asymmetry	-0,449	-0,403	-0,387	-0,364
Kurtose	-0,689	-0,325	-0,151	-0,241
D	0,070 Ln	0,058 Ln	0,050 Ln	0,039 Ln

D – Maximum deviation relative to the Kolmogorov-Smirnov with error probability of 1%.

The maximum and minimum value shows that there is a coincidence of occurrence of stabilization or even an increase in the experimental plot is represented by the probability of increasing the size of the portion have the same maximum and minimum values, particularly in the larger plots: 600 mm x 600 mm x 800 mm and 800 mm.

The coefficient of variation (Table 1) found for all attributes in the study are considered low, according to the classification of GOMES (1984). However, it is verified that there is a slight increase in the coefficient of variation with increasing size of the sample portion on the order of 0.200. Accordingly, it can be said that regardless of the size of the used portion of the number of observations was sufficient to ensure the accuracy of the experiment, ensuring the generation of random roughness value (RR mm) with the reliability needed for use in advanced models soil loss by erosion.

The coefficient of skewness and kurtosis shows that all data sets have log normal frequency distribution. The proximity of skewness and kurtosis values of 0 and 3 (respectively) is an indication of the normal frequency distribution, as reported by Carvalho et al. (2002).

The normality test of Kolmogorov-Smirnov (D) with probability of error of 1% (Table 1) confirms that all attributes studied showed log normal frequency distribution. This fact does not interfere with geostatistical analysis, because the amount of data involved in this study is sufficient to ensure the spatial modeling and estimation with minimum variance, not by offering underestimation or overestimation derived from data or noise arising from sampling errors.

The fitting parameters of the experimental semivariogram (Table 3) show that all the attributes under study adjusted the spherical model. The values of nugget effect (C0) were low (zero) to the soil surface roughness (dm) for treatments with the following dimensions of parcels: 200 mm x 200 mm, 400 mm x 400 mm and 800 mm x 800 mm. The experimental plots of 600 mm x 600 mm showed a value of nugget (C0) of 4.5, indicating an increase in noise or error in this treatment. This may be related to the increase or decrease of micro elevations this treatment, making the spatial variability is affected when compared to other treatments that had a value close to zero, indicating greater homogeneity in these treatments when compared with the portion 600 mm x 600 mm.

Table 3. Parameters of the semivariogram and random roughness index (RR).

	Model	**C_0**	**C_1**	**a (mm)**	**RD (%)**	**RR (mm)**
200 x 200 mm	Esférico	0,0	9,2	35,0	0,00	10
400 x 400 mm	Esférico	0,0	9,5	34,0	0,00	11
600 x 600 mm	Esférico	4,5	5,5	40,0	0,00	11
800 x 800 mm	Esférico	0,0	9,0	32,0	0,00	12

C0: nugget effect, C1: structural variance, a: range (mm) RD: spatial dependency ratio (%) and RR: random roughness index (mm).

Regarding the spatial structure of the pairs of semivariance did not detect any discrepancies in their distribution, being the spatial pattern held in all sizes of plot, as can be seen in Figure 1. There is only one greater dispersion semivariance in pairs with increasing distance separating the samples.

Values range (mm) show values ranging between 32.0 mm and 40.0 mm, the lowest value range described for the portion with 800 mm x 800 mm and greater value for the parcel with 600 mm x 600 mm.

All sizes of plots studied showed ratio values high spatial dependence, according to the classification proposed by Cambardella et al. (1994), indicating a strong relationship between samples in all plot sizes.

The random roughness index (RR, Table 2) did not vary among different treatments under study for supporting the idea that random roughness index was not affected by this aspect, since it depends mainly on the intrinsic characteristics of each soil type as texture, soil organic matter content, bulk density, structure, etc.. (ALLMARAS et al. 1966; COGO, 1981; KAMPHORST et al. 2000; Schick et al. 2000; VÁZQUEZ VIDAL 2002).

Regarding the size of the portion and the index of random roughness (RR) may also be inferred that there is no large change in the value thereof, since the number of samples in each plot sizes is considerably high, contributing so that no such variation in roughness values.

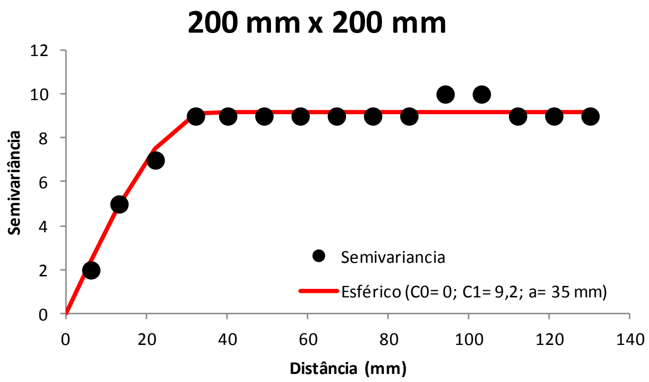
It is important to note that a relationship exists with increasing values of coefficient of variation (CV,% - Table 1) and the random roughness (RR, mm - Table 2), where it is found that with increasing portion size is an increase in the coefficient of variation (CV) and random roughness (RR). This fact can be explained with the increased likelihood of micro elevations and micro depressions with increasing plot. It is known that the surface roughness of the soil has determined spatial distribution (ALLMARAS et al., 1966; Bertolani et al., 2000; VIDAL VAZQUEZ, 2002), however, it is not possible to infer whether there is any relationship between the coefficient values of variation (CV) and random roughness (RR) and the fitting parameters of the semivariogram. However, it can be said that the number of samplings in each plot size was sufficient to detect the spatial variability in all treatments and spatial dependence of the ratio (RD) demonstrates that even smaller portions at elevated occurs spatial dependence between samples, which corroborates the fact that regardless of the number of samples involved in this study the random roughness of the soil was only affected by higher probability of micro elevations and micro depressions.

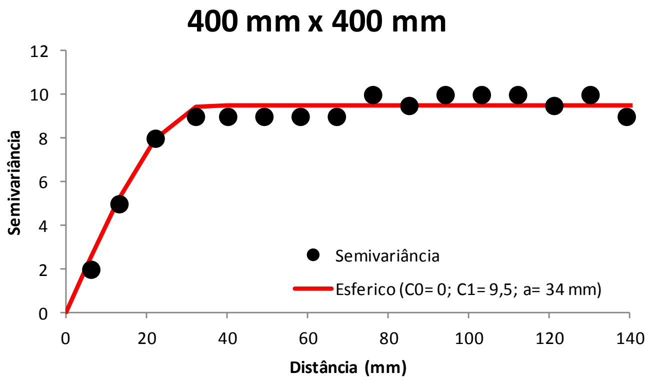
It is noteworthy that not been verified differentiation between different sizes of plots in both statistical analysis, as the geostatistical analysis, which reinforces the idea that the intrinsic hypothesis of geostatistics is valid. According Hamlet et al. (1986) and Smith et al. (2011) the intrinsic hypothesis of geostatistics is more exception than rule. However, in this study it can be said that due to the high number of samples was possible to find a standard statistical and geostatistical justifying the intrinsic hypothesis of geostatistics.

Siqueira et al. (2011) studied the intrinsic hypothesis of geostatistics through data density of soil using soil aggregates with different sizes (3, 5 and 7 cm) could not verify the presence of stationarity of the data. However, this study can be inferred that the intrinsic hypothesis is valid, because the data are homogeneous and represent the same phenomenon in a continuous manner. This fact can be confirmed by analysis of Figures 2 and 3 show that the maps of spatial variability for all plot sizes under study.

The maps of spatial variability show that with increasing portion phenomenon becomes less stable, ie the effect of smoothing the distribution of lines in contour maps constructed using the technique of kriging interpolation considering the setting parameters of semivariogram for each set of experimental data.

It is difficult to say to what extent the maps were influenced by minimizing the variance in the estimate of the error on the assumption of no bias estimator (Carvalho and ASSAD, 2005) by kriging interpolation technique. The visual analysis of maps of spatial variability demonstrates the presence of a smooth contour lines with increasing portion size, and difficult to describe if there is a relation of this phenomenon to the presence or not of stationarity of the data, because it is analysis empirically.





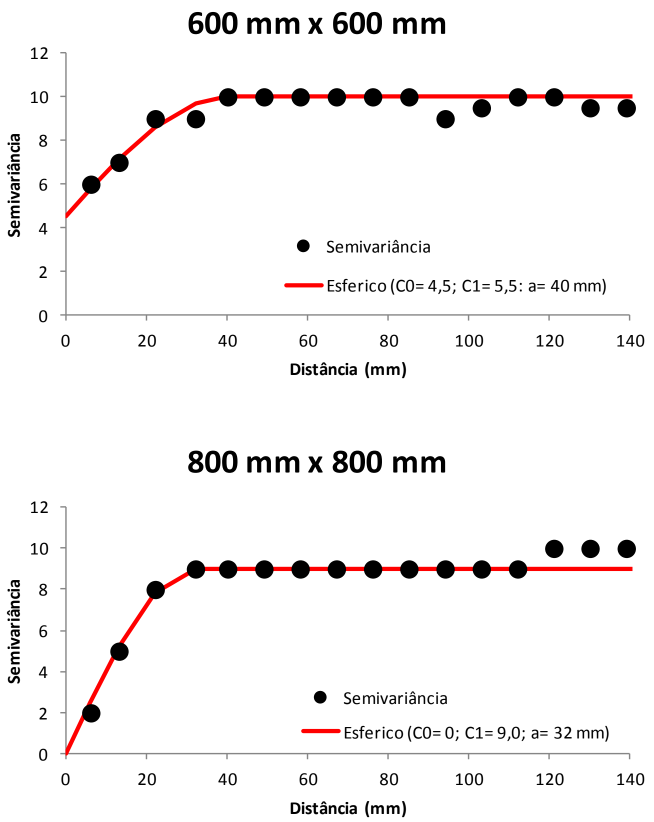


Figure 1. Semivariograms for the attributes set in study.

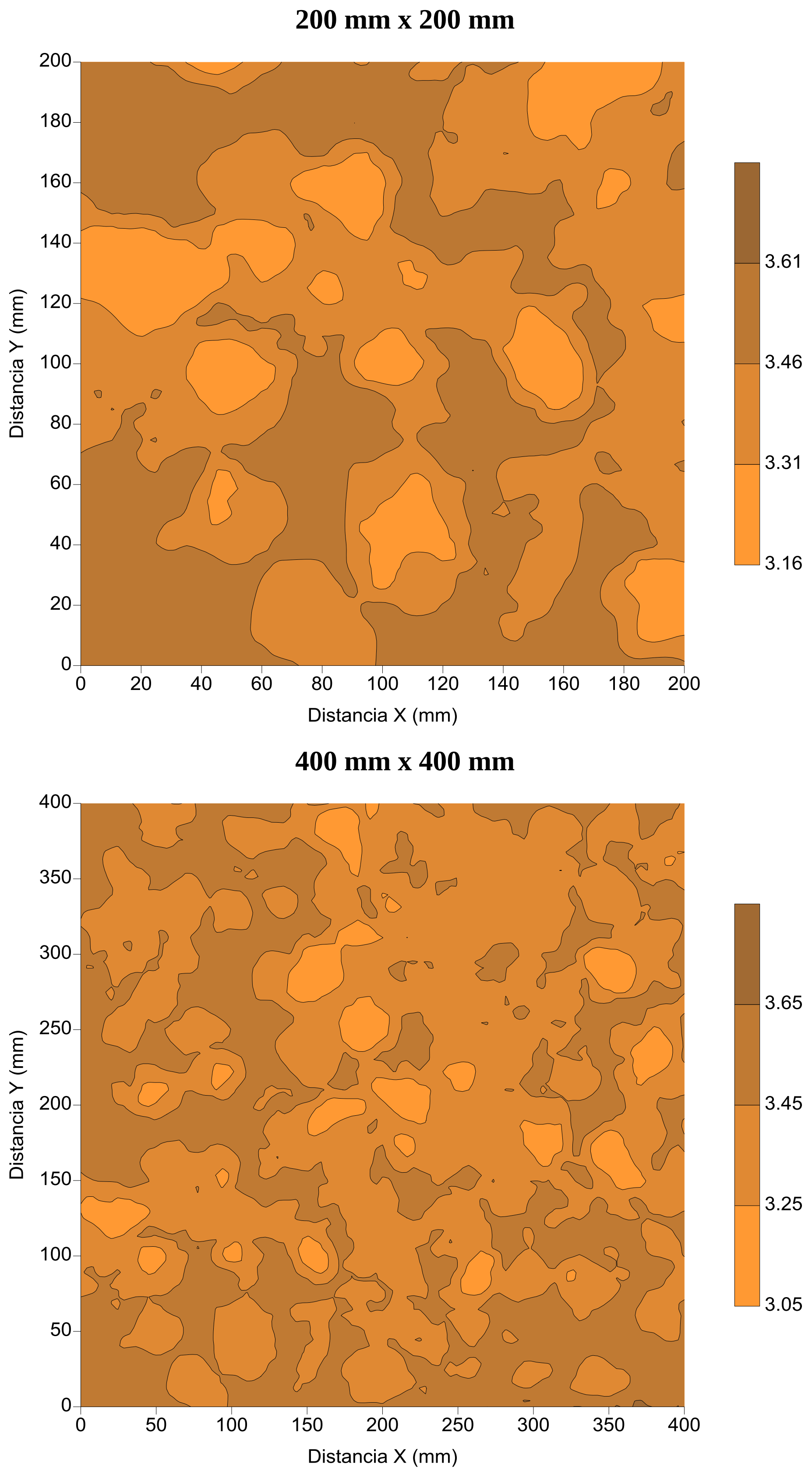
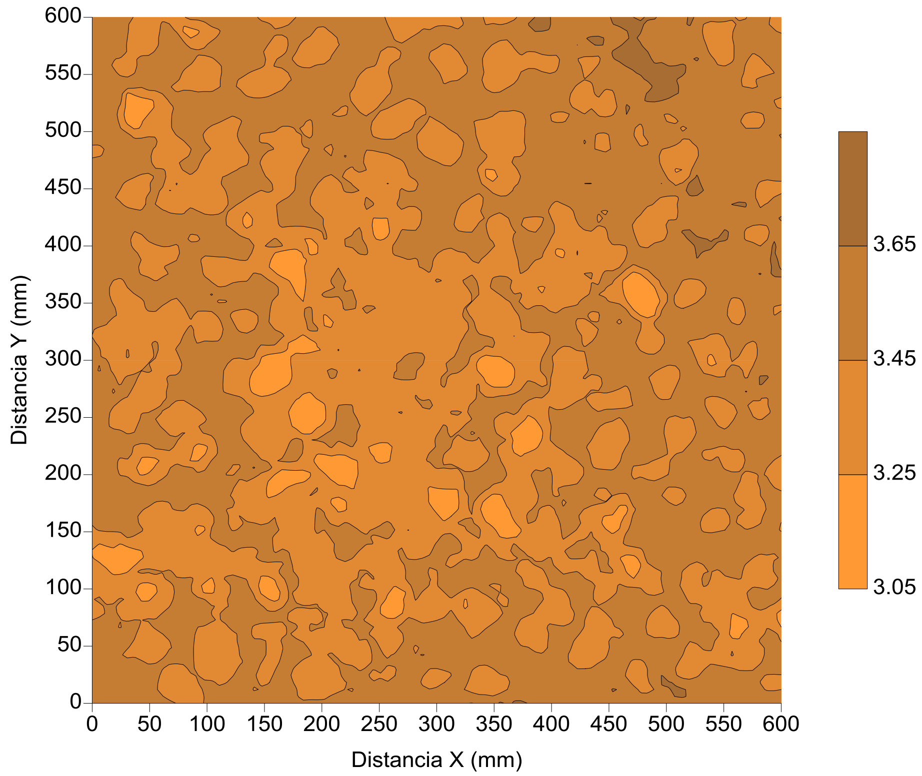


Figure 2. Maps of spatial variability of soil surface roughness determined in plot 200 mm x 200 mm and 400 mm x 400 mm.

600 mm x 600 mm



800 mm x 800 mm

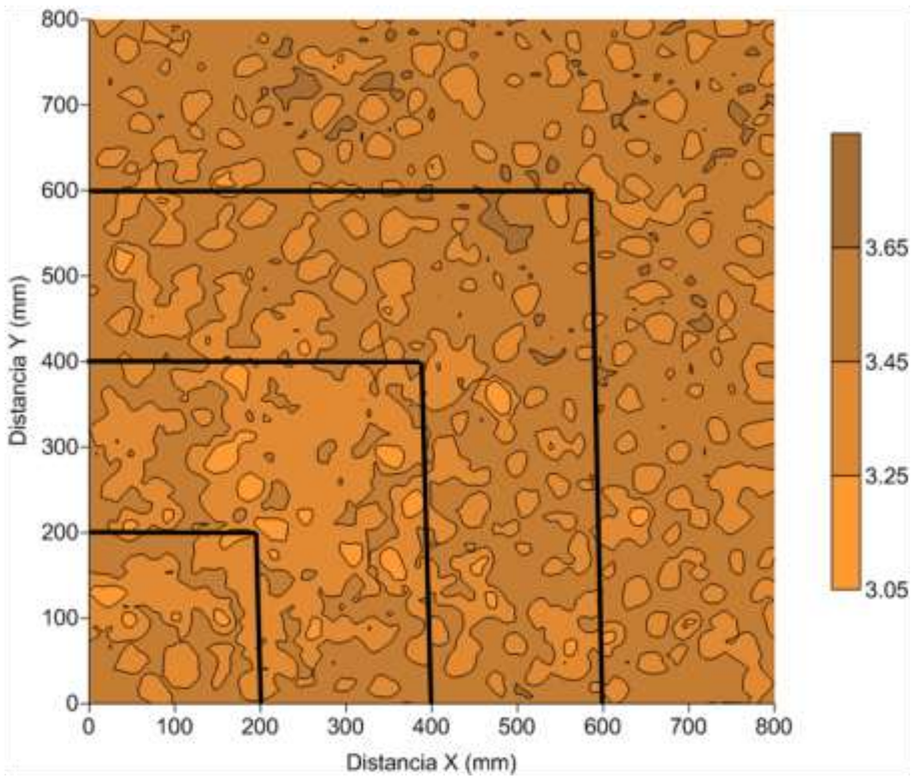


Figure 3. Maps of spatial variability of soil surface roughness determined in plot 600 mm x 600 mm and 800 mm x 800 mm.

4. Conclusions

The different plot sizes for experimental determination of surface roughness of the soil showed stability in statistical and geostatistical parameters, allowing the determination of the index random roughness (RR) with reliability, regardless of portion size.

The coefficient of variation (CV) and index random roughness (RR) were directly related to the increase in portion size, with increased coefficient of variation (CV) and index random roughness (RR) with increasing portion.

The validation of the intrinsic hypothesis of geostatistics using data from soil roughness was only possible because the data are homogeneous and represent the same phenomenon in a continuous manner.

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