Spatial distribution of clay by classic inference method (Geostatistic)

Sérgio Ricardo Rodrigues de Medeiros[A] and Rubens Duarte Coelho[B]

[A] Escola Superior de Agricultura 'Luiz de Queiroz', University of São Paulo, Piracicaba, SP, Brazil, Email srrdmede@esalq.usp.br
[B] Escola Superior de Agricultura 'Luiz de Queiroz', University of São Paulo, Piracicaba, SP, Brazil,, Email rdcoelho@esalq.usp.br

Abstract
The application of technology associated with spatial and temporal variability is necessary, particularly in agricultural research that studies the soil and its productive capacity (Grego and Vieira, 2005). Soil properties related to moisture retention, permeability and aeration have great influence on water management. In this paper geostatistics was used to analyse the variability and to characterize the spatial dependence of grain size at Areão Farm, an experimental area of Escola Superior de Agricultura 'Luiz de Queiroz', University of São Paulo (ESALQ / USP), based on descriptive statistical analysis and spatial inference by using the classical maximum likelihood method, thereby generating the prediction model and therefore the prediction map.

Key Words
Analysis geostatistics, dispersion of clay, kriging, spacial inference, prediction model, prediction map.

Introduction
Knowledge of the variability of soil properties and crops in space and time, is considered now the basic principle for the precise management of agricultural land, whatever its scale (Grego and Vieira 2005). The variation of the textural characteristics of soil occur in response to the deposition of sediment, vegetation, and relief that governs the time of exposure of materials to the action of weathering (Young and Hammer, 2000) and mainly of original material (Cunha *et al.* 2005). Understanding the behaviour of soil particle size is important to understand the distribution of sediments, the formation dynamics of a case and make inferences about the behaviour of the soil. It is worth noting that the size is also considered a useful tool in the definition of taxonomic classes, on the presence of pedogenic processes, and help to understand the movement of water in the soil, fertilization management, as well as the establishment of conservation practices and environmental planning (Mulla and McBratney 2002). The spatial variability of particle size has been studied in various classes of soils where the presence of spatial dependence have been generally between 15 and 10,500 m (Gonçalves, 1997, Souza *et al.* 1997; Vieira, 1997; Salviano *et al.* 1998; Zimback and Cataneo 1998; Gonçalves and Folegatti 2002; Araújo 2002; Rabah 2002;). To be able to study this spatial variability, based on samples analysis and geographic coordinates , geostatistics techniques were applied by establishing a semivariogram model that best describes the spatial variability of the data, which will be used in the interpolation process (kriging method).

Methods
Experiment area
The work was carried out in an experimental farm of the campus 'Luiz de Queiroz', University of São Paulo (ESALQ-USP) in Piracicaba, Sao Paulo State, located in the geographical coordinates, latitude 22 ° 42'S, Longitude 47 ° 37 'W and altitude of 546 meters.

Process of data collection
The farm is an area of 180 hectares, which was performed using a grid sampling equipment to the global positioning system (GPS). The work was performed with sampling of soil auger sample undisturbed within a radius of 2 meters from the intersection of a grid with intervals of 100 m, samples were collected at a depth of 0,0-0,30 m, within that radius thus representing the area georeferenced.

Laboratory analysis of samples
The particle size was determined by the pipette solution using 0.1 N NaOH as dispersing chemical and mechanical stirring apparatus at low speed for 16 hours, following the method proposed by (EMBRAPA, 1997), with modifications. The clay fraction was separated by sedimentation according to Stokes law, and the silt and then sand and the fraction determined by difference.

Analysis Descriptive statistics and spatial
The texture attributes were analyzed using descriptive statistical analysis (Table 1) by calculating the mean, median, standard deviation, variance, coefficient of variation, coefficient of skewness and kurtosis coefficient. Then the variable clay, the object of study was analysed using the technique of geostatistics by GeoR package of free software R, the classical inference to achieve the prediction map.

Analysis by classical inference
Box-Cox transformation was performed so that the data follow a normal distribution. For this it used the value of λ near the maximum likelihood. In the case of clay the value of $\lambda = -1$ was used for the transformation. Then we analyzed the spatial dependence and tests of effect in the trend of the coordinates between the coordinates and the sampled data, including coordinates and density as a covariate, and between the coordinates and a trend model of first degree and also with a model without trend. The effects were not significant and do not change the distribution of sample data of clay. The process of analysis continued without effect on the trend for the generation of the semivariogram to estimate the dependence between samples.

Results
The analysis of the semivariogram (Figure 1) indicates that the values of the attributes studied present a weak spatial dependence, ie, has randomized the sampling spacing used was higher than necessary to reveal the spatial dependence, with a higher than τ^2 σ^2.

In the data analysis by the method of maximum likelihood models were analyzed with kappas (0.5, 1.5 and 2.5) without trend and the trend in the role of first degree (1st) and function of second degree (2sd) which could be compared and which had the best log likelihood (table 2).

The model with Kappa 2.5 and with a tendency to first degree was presented the best fit within the criteria AIC, not taking the BIC as a criterion for estimating the models, a more rigorous and take into account the number of samples .

By comparing the best kappa according to the data is 2.5, more like the arrangement of the sample data are very widely spaced, they contribute to a behavior of a sigmoid, but was chosen kappa 0.5, for have a more practical sense, based on previous work, thus generating a behavior of a less smooth curve and minimize the parameter estimate τ^2.

Estimates of the adjusted model were:
$$\beta_0 = -0,9992 , \beta_1 = -0,0004, \beta_2 = 0,0003, \sigma^2 = 0,0102, \phi = 108,6315 \text{ e o } \tau^2 = 0,0385 \tag{1}$$

Based on the maximum likelihood method by the criteria AIC and BIC model without spatial dependence is best fit to the data, based on more work done with clay dispersion in agricultural areas, but there is spatial dependence in this case, the dependency exists and is justified because the sampling interval of data is 100 by 100 meters and that the explanation may involve only part of the behavior of the semivariogram (τ^2 is much higher than the σ^2) and therefore, assumes the model to take spatial dependence regardless of the criteria AIC and BIC.

After that, it was estimated the values at positions not sampled in the field using the technique of kriging generating thus the map (Figure 2) clay in the area based on the model set and selected earlier.
The Kriging in geostatistics is used to estimate values of variables to places where they were not measured from the adjacent values (neighbors) interdependent. To use this tool is necessary to have spatial dependence defined by the semivariogram (Salviano, 1996).

The kriging equation used was as follows:
$$\hat{Z}(s_0) = \sum_{i=1}^{k} \lambda_i z(s_i) \tag{2}$$
being:
$\hat{Z}(s_0)$ - is the estimator for the point s_0 of the region and k is the number of neighbours used in estimation;

λ - is the weight assigned to each neighbour $z(s_i)$ is the value observed in each neighbour.

Table 1. Descriptive statistics for the variables: clay, silt and sand (g kg-1), the samples collected at the crossing points of the mesh.

Descriptive Statistics	Attributes granulometric		
	Clay	Silt	Sand
		g/kg	
		Depths of 0,0 to 0,30 m	
Average	50.53	18.12	31,35
Median	51,27	17.46	30,61
Variance	90,65	28,50	47,42
Standard deviation	9,52	5,34	6,88
VC (%)	19	29	22
Asymmetry coefficient	-1,94	0,74	0,90
Coefficient of Kurtosis	11,87	4,25	7,04

Table 2. Comparison of Models by the logarithm of maximum likelihood.

Model considering the effect of linear trend in mean and kappas different		
kappa0.5	kappa1.5	kappa2.5
81.56327	81.61545	81.64824

Comparison of Models by the criteria AIC and BIC

Model considering the effect of linear trend in mean and kappas by different criterion AIC

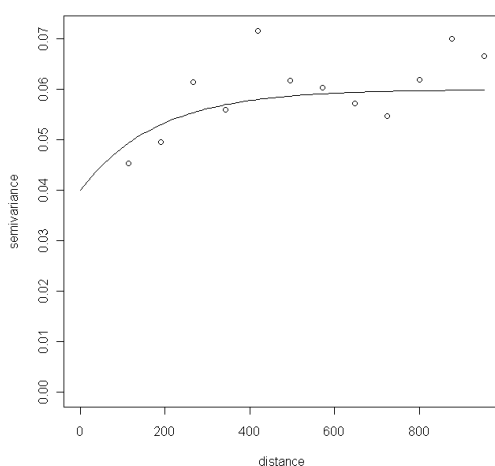| kappa0.5	kappa1.5	kappa2.5
-151.1265	-151.2309	-151.2965

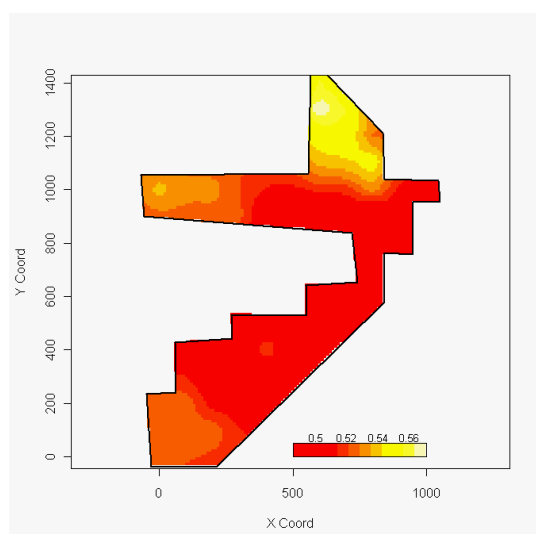**Figure 1. Semivariogram model adjusted second exponential data of clay.**

Figure 2. Map predicting the concentration of clay in the study area obtained by the estimate obtained by the method of maximum likelihood (likfit).

Conclusions

The analysis of the semivariogram indicates that the values of the attributes studied present weak spatial dependence. By comparing the best kappa, a value 0.5 was chosen, for a more practical sense, based on previous work. This generated a less smooth curve and minimized the parameter estimate. Based on the maximum likelihood method by the criteria, AIC and BIC models without spatial dependence are best fit to the data. The spatial dependency exists and is justified because the sampling interval of data is 100 by 100 meters and that the explanation may involve only part of the behavior of the semivariogram.

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