Spatial Variability of Some Soil Physical Characteristics of Al-Khotkhot Experimental Station

A.A. Falatah, M.I. Choudhary, A.A. Shalaby and A.M. Al-Omran
Department of Soil Science, College of Agriculture, King Saud University, Riyadh, Saudi Arabia

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Abstract. Geostatistical theory through the variogram and kriging enables us to obtain information about location in the field that are not actually measured in the field and which we can get through classical statistical methods because it did not consider spatial correlation and the location of the samples. A study was carried out at King Saud Exeperimental Station at Al-Khotkhot, Saudi Arabia using the geostatistical method to delineate soil particle size, $CaCO_3$ and saturation percent (SP). Surface soil samples (0-15 cm) were taken as 10 x 50 m grids from an area of 200 x 300 m. The high coefficient of variation (CV) of gravel, silt and clay percentage indicated that soil was highly variable with respect to these soil properties. The semivariograms of these properties showed strong spatial relationship and the range was 140 m. Contour maps were generated by block kriging based on the semivariogram models of these properties. The kriged maps obtained in this study could provide useful information for designing experimental lay out, selecting plot size and sampling strategy at Al-Khotkhot Experimental Station.

Introduction

Soil is characterized by several types of variations. These variations might exist within one soil class unit and thus can be classified as homogeneous. The variability in the unit may be large or small depending on different soil forming factors. The spatial variations in physical or chemical soil properties of soils formed on the same parent material may be small but exist within the same soil unit. These properties vary continuously along the field and cannot be measured everywhere. Thus, the understanding of spatial variability of soil properties will allow better management of soil and crop in the field.

mining industry [1, pp281-290; 2, pp225; 3, pp107-125], ground water mapping and modeling [4,5] and in rainfall monitoring [6]. This technique is also being applied in different fields of soil science such as spatial variation in soil physical properties [7,8,9,10] in soil chemistry [11,12], in soil salinity [13,14], soil pH [15,16] and soil fertility [17].

The spatial variability of soil has been studied by soil scientists for many years. During the last 15 years, standard geostatistical technique has been used to describe the spatial variations in soils [13,18-23]. The geostatistical approach is very useful when sample value is expected to be affected by its position and relationship with its neighbors through the semivariograms and variograms. The parameters of variogram provide the essential spatial information for kriging, which is a method of optional estimation of the variable. Kriging is unbiased estimator with a minimum and known variance [2,11,18,19]. Kriged estimates can be made from observations of continuously varying properties on equilateral or square grid [20] or from irregularly scattered data [24].

Applying geostatistical methods in analyzing the data of soil physical properties provide a way to reduce the number of field observations. Vieira *et al.* [7] concluded that a minimum of 128 samples were enough to obtain nearly same information as with 1280 samples in area of 55 x 160 m . Chang *et al.* [14] concluded from their study on EC and sand content that maps generated by kriging could provide useful information for designing experiments such as selecting plot size , plot layout and soil sampling strategy for managing and reclaiming salt affected soils. Also the kriged estimates can be displayed as isoarithmic map to show the variation. Hajrasuliha et al. [13] used maps of estimated kriged of soil salinity to optimize the location of sprinklers for an irrigation system. Many other studies [11,18,19,25] used kriging to map regionalized soil properties.

The purpose of this research is to study the spatial variabilities of soil particle size, $CaCO_3$, and saturation percent (SP) at Al-Khotkhot Experimental Station, Saudi Arabia and to delineate these properties and their variabilties in the area using the kriging technique. Thus, the kriged maps might provide some useful information in designing experiments and determine soil sampling strategy at Al-Khotkhot Experimental Station.

Materials and Methods

The study was conducted at the Center of Desertification Studies for King Saud University at Al-Khotkhot site at 50 km south-east of Riyadh, Saudi Arabia. The studied area is located within the huge sedimentary basin commonly known as the Arabian

Shelf. It is intersected by longitudes 46° 34′ and latitudes 24° 25′ with an average elevation of +580 m a.s.l. The prevailing climatic conditions are very arid -hot , annual rainfall ranges from 50 to 100 mm while evaporation amounts 9.6 mm/day ; average annual soil moisture and temperature regimes are defined as torric-hyperthermic. Temperature is about 27°C natural vegetation is few and scanty, and the soil is utilized by drough resistant range crops which are irrigated by ground water being pumped from deep ells. The soil in the area is classified as Torripsammets.

Soil s_mples were collected from surface (0-15 cm) as 10 x 50 m grids from field measuring 200 x 300 m. The samples were air dried and gravel content was determined as percentage weight. Then the samples were passed through 2-mm sieve. The particle size distribution (sand, silt and clay percentage) was determined using hydrometer method [26, pp. 545-566]. Saturation percent (SP) was determined according to the standard method recommended by Richards [27, p.16]. Total $CaCO_3$ percent was determined using standard calcimeter procedure[26, pp. 1392-1395].

Geostatistical procedure : Geostatistical theory and its application in soil science has been described in detail by Trangmar *et al.* [28] and Webster [29]. Regionalized variables are spatially continuos, but the changes in these variables are too complex to describe with any deterministic function [30, pp.217-247]. Assuming statistical homogeneity of the data, the rate of change of regionalized variable along a specific direction is given by semivariance. The semivariances were used to find the spatial dependence between two adjacent points, which require that the mean and variance of increment are stationary [2, p.225]. The semivariance is a measure of the degree of spatial dependence between observations and calculated as :

$$\gamma(h) = 1/2n(h) \sum_{i=1}^{n(h)} \left[Z(X_i) - Z(X_{i+h})\right]^2 \qquad (1)$$

where $\gamma(h)$ is the semivariance and $n(h)$ is the number of data pairs of soil properties $Z(X_i)$, $Z(X_{i+h})$ which are separated by a distance (h) . As a rule of thumb, according to Journel and Huijbregtts [2, p.225], at least 30 data pairs should be used to calculate $\gamma(h)$. After calculating the semivariance for various lag values, a variogram can be constructed by plotting $\gamma(h)$ versus lag (h). The shape of variogram of any given soil property depends on the sampling distance used in the field. If the sampling distance is too great or the property being measured is not spatially dependent, the variogram can be represented by a horizontal line. Several models have been proposed to describe the relationship between the semivariance and the lag distance (h) as linear, spherical, gaussian and exponential models [30, pp.217-247]. In these models, if some distance points being compared are so far apart that they are not related to each other, the semivariance reaches a constant value. In the spherical model if the semivariance no longer increases, and a flat region which develops is called silt whereas the corresponding lag distance is called range. The range gives an indication of the distance at which the parameter values become independent of each other. When the semivariogram is independent of separation between sampling points, the variable is truly random and is not exhibited at spatial structure.

If a model of the semivariogram is obtained, then kriging can be used to estimate values of soil properties for locations not sampled. Kriging is an interpolation procedure which uses the variograms to estimate the observations at different points in the field [11,31,pp 279-330, 32,]. Kriging has some advantages over other interpolation techniques because it takes into consideration the number of observations and their neighbors around the estimated point. The kriging estimate can be expressed as:

$$Z(X_0) = \Sigma^{N}_{i=1} \lambda_i Z(X_i) \qquad (2)$$

Where $Z(X_0)$ is the estimator of unknown true value to $Z(X_0)$, λ_i is wighted coefficient to be determined, N is the number of observations used in kriging . The estimated variance at point X_0 is:

$$\sigma^2(X_0) = \mu + \sum_{i=1}^{N} \lambda_i \gamma(X_i - X_0) \qquad (3)$$

Where μ is the lagrangian multiplier obtained from minimizing the kriging variance $\gamma(X_i - X_0)$ is semivariance for Z at distance $(X_i - X_0)$. The experimental variogram is used to solve the kriging system to obtain λ_i and which are used in equation (2) and (3) to calculate the kriged value and its estimation variance, respectively. Further descriptions of kriging are given by Samra *et al.* [25], Issaks and Srivastara [31], Alemi *et al.* [32] and Oliver and Webster [33]. The packaged program used here is of U.S. EPA by England and Sparks [34].

Results and Discussion

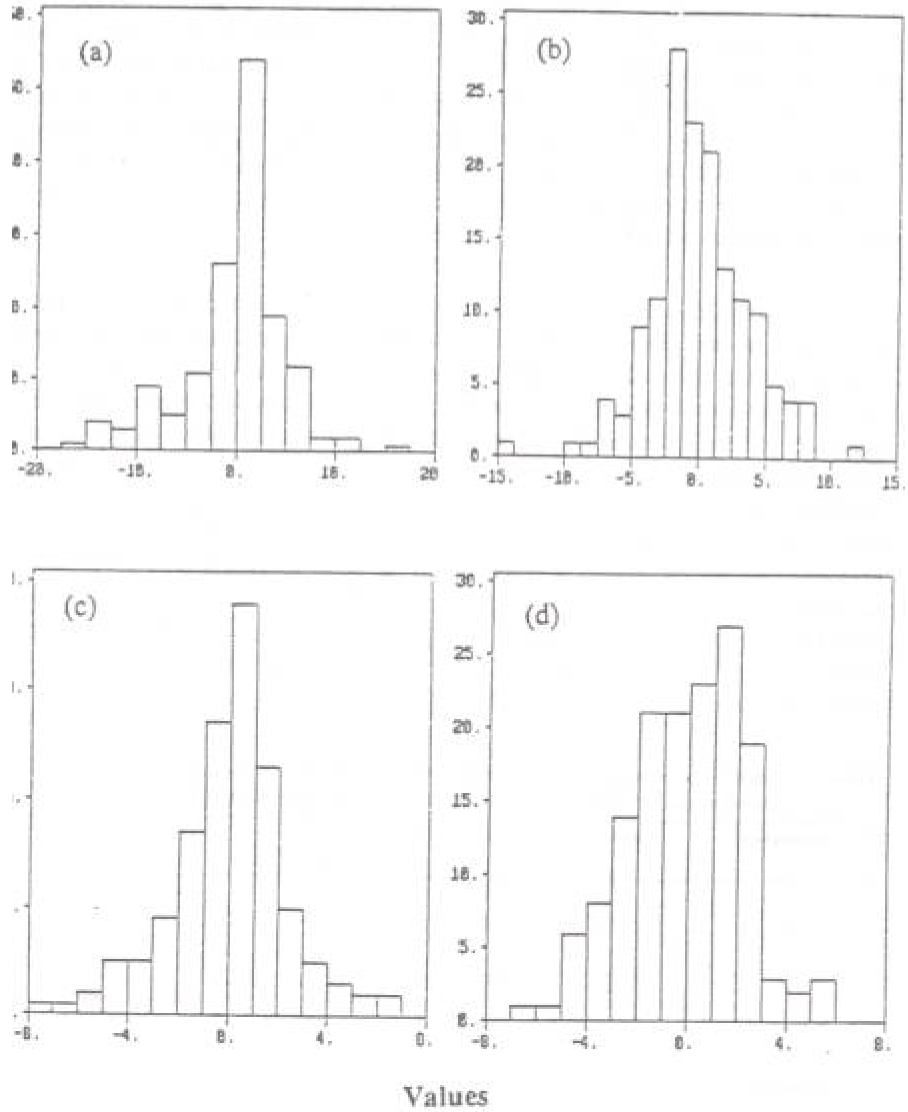
Table 1 summarizes the statistical values of 150 grid samples of gravel, sand, silt and clay; SP and $CaCO_3$ percentage. These properties were shown in Figs.(1&2). Gravel percentage ranged from 0.0 to 29.4 with coefficient of variation of 90 percentage which illustrated the heterogeneity of gravel in the area. Similar results were reported for sand, silt, clay and SP. Content of $CaCO_3$ ranged from 8.6 to 22.10 percentage with a coefficient of variation of 22.0percentage. The data also showed that soils in studied area were of coarse texture and classified as Torripsamment. The variation of data obtained in the study can be attributed to spatial variation in area of these measured parameters. Figures (3&4) show the plot of semivariance versus lag of the soil parameters. The semivariance of gravel percentage indicated that a nugget effect of 17 existed for the data and the distance increased the experimental semivarigram up to 140 m. The same trend was obtained for all the other parameters studied. The variation of all parameters showed a regional trend at distance of 140 m with exception of SP with isotropic variation (semivariograms were similar in all directions).

The variograms of gravel, sand, silt , clay , and $CaCO_3$ exhibited a range of 140 m, while the range of SP was 150 m (Table 2). The values of ratio (C_0/C_1) of studied parameters were presented in Table 2. The data showed that ratio values of clay and $CaCO_3$ were higher than other parameters. These higher values were due to large effect of nugget variance which included the variation that remained unresolved by the sampling interval that due to measurement error , and purely variation [33]. The ratio values of other studied parameters were low. These ratios were 7.84 for SP , 22.6 for gravel percentage and 18.5 for silt percentage.

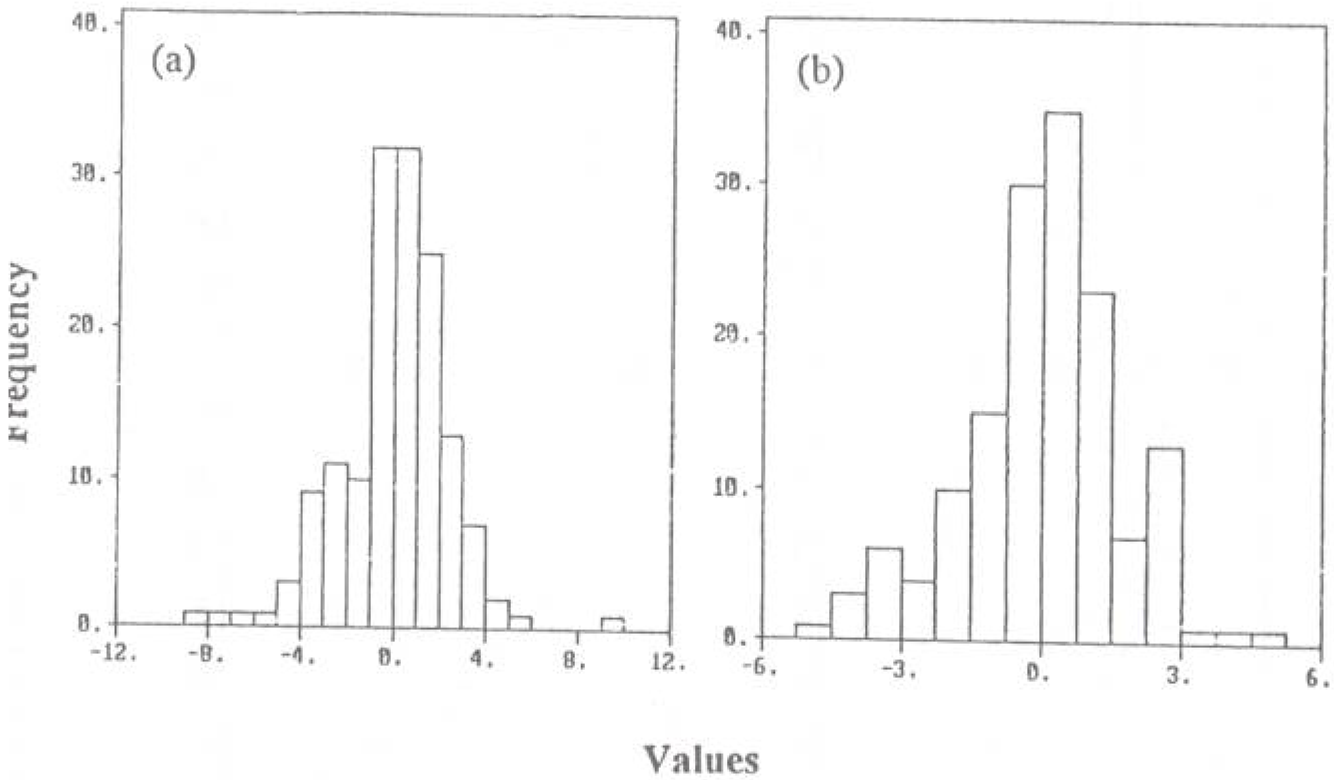
For the variogram models used on the data, cross validation or jacknifing was performed on the data. The results of this procedure for estimated and measured values of gravel, silt, clay, SP and $CaCO_3$ percentasge were shown in Figs. (5&6). The solid line was forced through the origin. Also, Table 3 shows the comparison of means and variances of both measured and estimated kriged values of the studied soil properties. The results indicated that estimated kriged values obviously had lower variances than measured because of neighboring influence of kriging technique. Once the best model for the data was determined, it could be used to predict the values of the given soil properties of an unmeasured location in field. Since kriging was an exact inter-polator, an estimated value should be equal to measured value at the data location. Using the variogram model of each studied soil property, the kriged values were estimated as a block of 10x10 m and performed a contour map of 200x300 m area of all measured soil properties which were illustrated in Figs. (7&8).

Table 1. Mean (X), variance (S^2), coefficient of variation (CV), minimum and maxmimum values for gravel, sand, silt, caly, saturation percentage (SP) and $CaCO_3$ of the soil

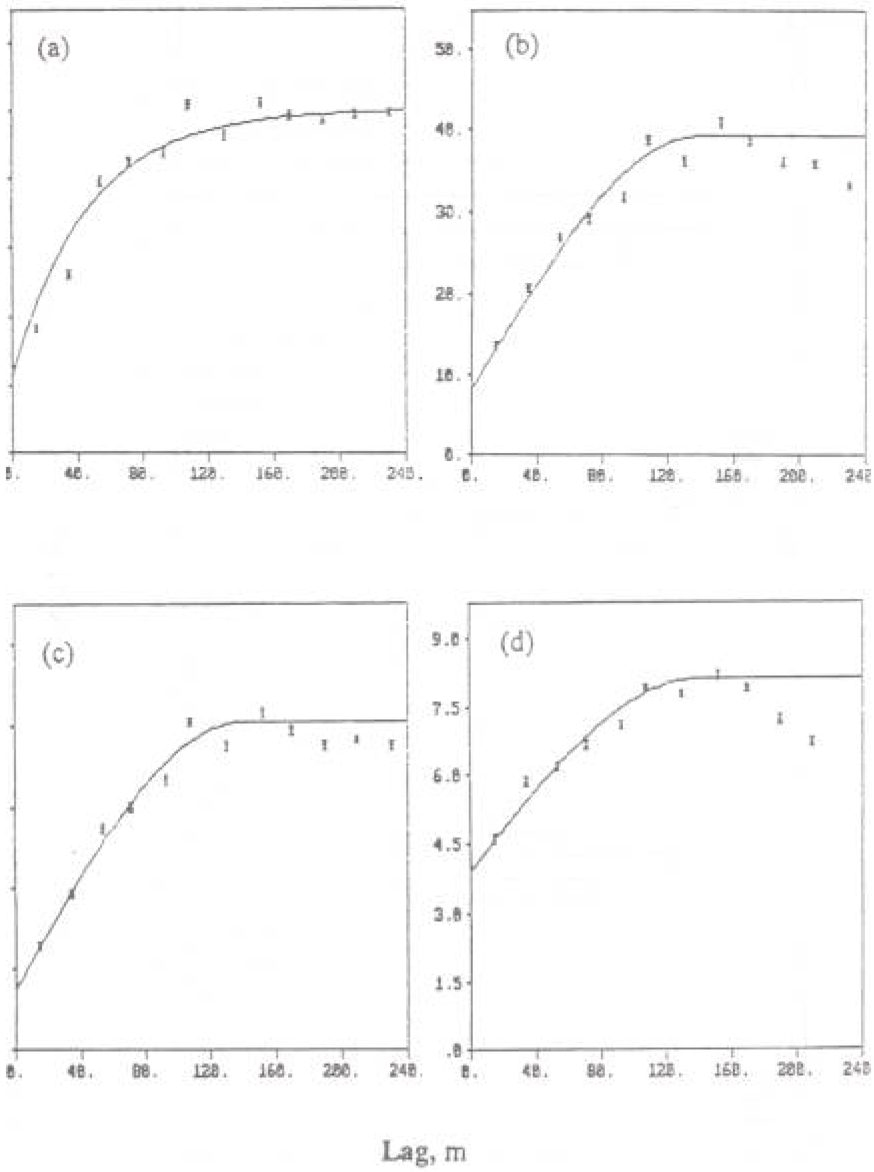
Parameters	Gravel	Sand	Silt percentage	Clay	SP	$CaCO_3$
X	9.09	85.73	5.62	8.62	22.54	13.66
S^2	67.99	33.77	14.10	7.06	11.01	9.76
CV	0.90	0.07	0.66	0.30	0.14	0.22
minimum	0.00	71.00	1.00	3.00	16.00	8.60
maximum	29.40	95.00	14.00	15.00	30.00	22.10



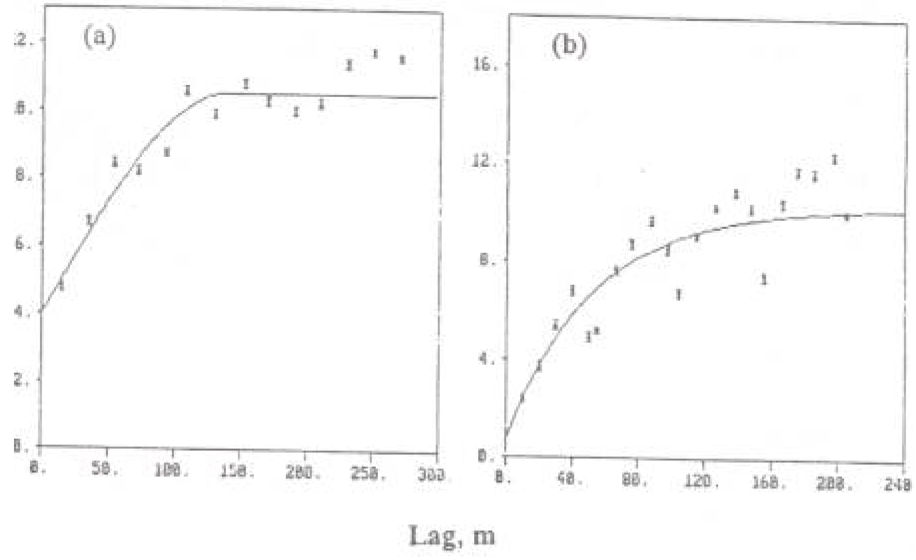
requency distribution of (a) Gravel (b) Sand © Silt (d) Clay.



ig. 2. Frequency distribution of (a) $CaCO_3$ (b) SP.



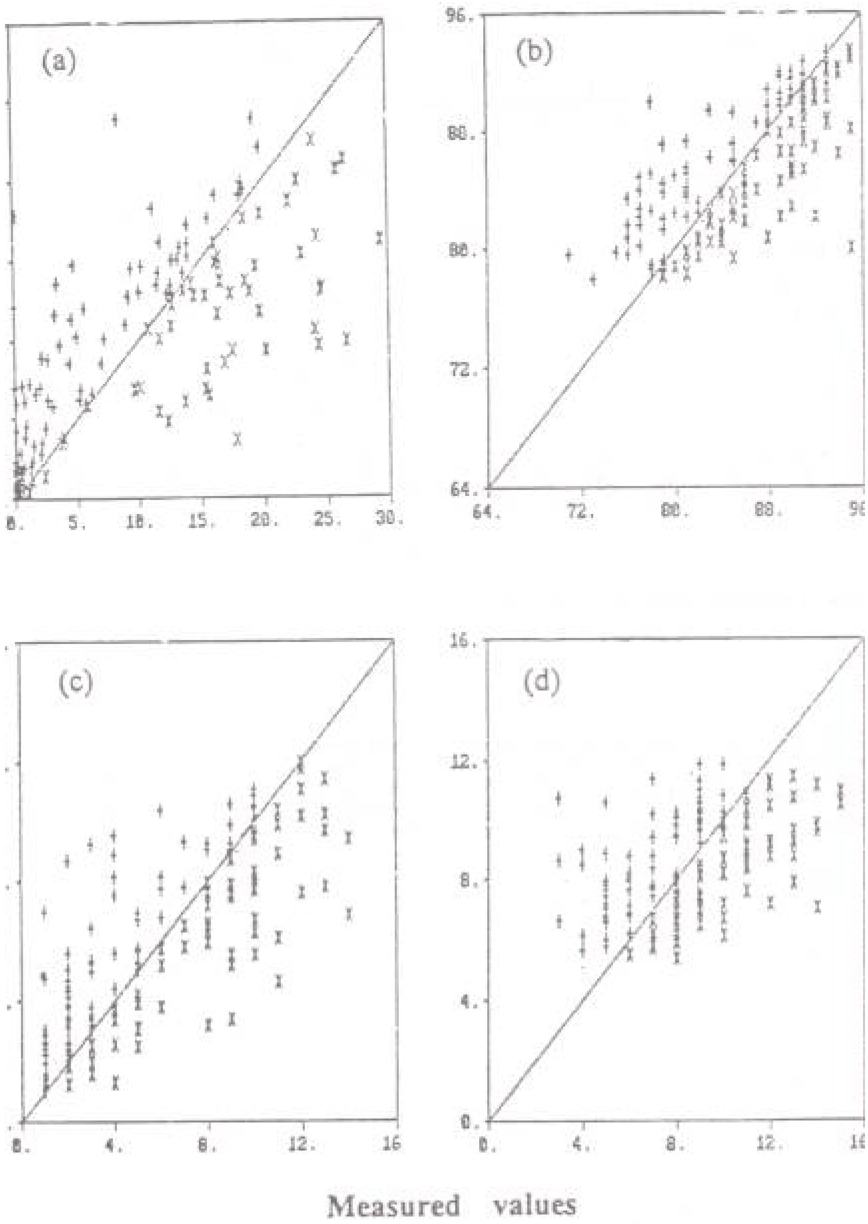
Variograms of (a) Gravel (b) Sand © Silt (d) clay.



. Variograms of (a) $CaCO_3$ (b) SP.

2. Parameters of the models used for kriging soil properties

property	Model	Nugget effect (c_0)	Structural components c_1	c_0/c_1	Range	Sill
Gravel	Exp.	17.0	58.0	22.6	140	75
Sand	Spherical	8.3	31.0	21.1	140	39.3
Silt	"	3.0	13.2	18.5	140	16.2
Clay	"	3.9	4.2	48.1	140	8.1
SP	Exp.	0.8	9.4	7.8	150	10.2
$CaCO_3$	Spherical	4.0	6.5	38.1	140	10.5



'he scatter diagram of the estimated and measured values of (a) Gravel (b) Sand © Suit (d) Clay.

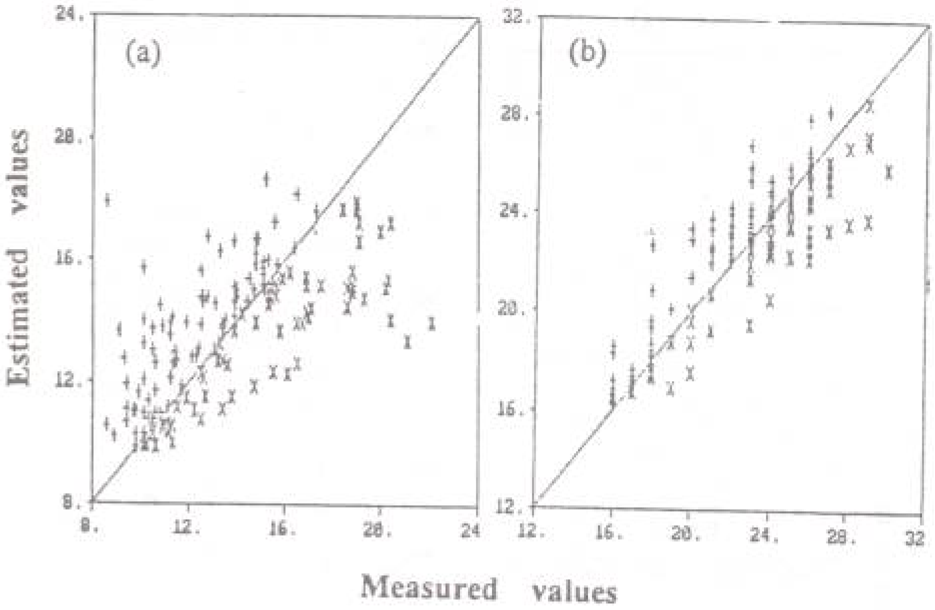
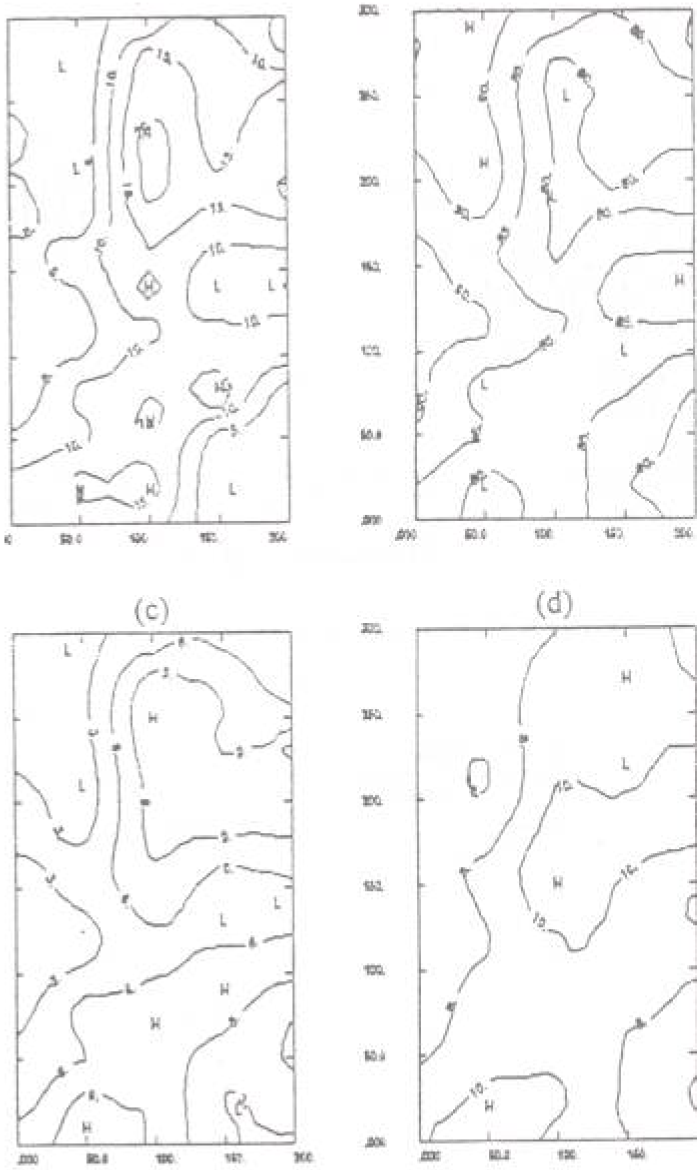


Fig. 6. The scatter diagram of the estimated and measured values of (a) $CaCO_3$ (b) SP.

Table 3. Comparison of means and variances of measured and kriged values of soil properties

Soil property	mean		variance	
	measured	kriged	measured	kriged
Gravel	9.09	9.15	67.99	41.8
Sand	85.73	85.70	33.76	20.08
Silt	5.62	5.65	14.10	8.95
Clay	8.63	8.62	7.07	2.54
SP	22.54	22.56	11.01	8.28
$CaCO_3$	13.67	13.68	9.76	4.73



Distance, m

. (10 x 10m) kriged map of (a) Gravel (b) Sand (c) Silt (d) Clay.

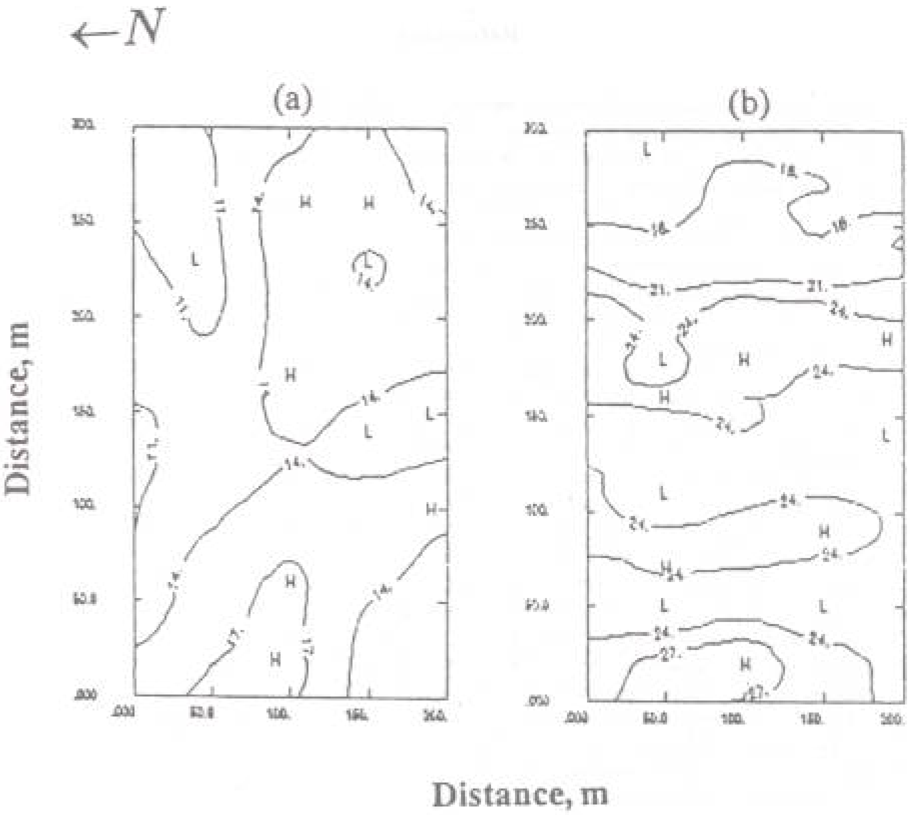


Fig. 8. Block (10 x 10m) kriged map of (a) $CaCO_3$ (b) SP.

Conclusions

The high coefficients of variation (CV) in gravel, silt and clay percentage indicated that the soil of the Experimental Station was highly variable with respect to these soil properties. The spatial variability of some soil physical properties on 10 x 50 m grids in field of 200x300 m was investigated using geostatistical technique to develop variograms for measured properties. The best model selected was based on a better fit and jackknifing procedure. The cross validation provided the appropriate model selected for these properties. The semivariograms of these properties showed strong spatial relationships and the range was 150 m. Then the models were used to estimate kriging values on 10x10 m grids in field and a contour map was developed for each soil property measured in the area. The kriged maps obtained can provide useful informations for designing research at the Experimental Station.

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