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Assessment of soil property spatial variation based on the geostatistical simulation

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Abstract

The main objective in the present study was to assess the spatial variation of chemical and physical soil properties and then use this information to select an appropriate area to install a pasture rehabilitation experiment in the Zereshkin region, Iran. A regular 250 m grid was used for collecting a total of 150 soil samples (from 985 georeferenced soil pits) at 0 to 30, and 30 to 60 cm layers. Soil samples were analyzed for pH, EC, N, K, P, Na, Ca, Mg and SAR. Conventional statistical methods and geostatistics were performed in order to analyze soil properties spatial dependence. Mean, standard deviation, skewness, and kurtosis for all measured variables were evaluated. All variograms generally were well structured with a relatively large nugget effect. Soil properties such as pH, P semivariograms were best fitted by spherical models, while SAR, Na were best fitted by spherical models. In the beginning kriging were performed in order to analyze spatial variation of chemical and physical soil properties, then for enhancing estimation accuracy and comparing results we used cokriging technique. Comparison of the results using statistical techniques showed that kriging technique has acceptable accuracy in characterizing the spatial variability. Also results showed that although kriging technique has acceptable accuracy in characterizing the spatial variability of soil properties but if higher accuracy is needed, cokriging is preferred to kriging particularly when the extra variable has been used.

Keywords: Geostatistics; Kriging; Cokriging; Soil properties; Spatial variation; Variogram

1. Introduction

The need to take account of spatial variability when modeling soil forming and environmental processes is now abundantly clear. Understanding the distribution of soil properties in the field is important in refining agricultural management practices (McBratney and Pringle, 1999) while minimizing environmental damage. Soil property variation within a field often has been described by classical statistical methods assuming a random distribution (Goovaerts, 1999; Webster, 2000; Conant and Paustian, 2002). Determining the risk of exceeding a threshold, or more generally estimating a function of a soil property, can be dealt with either stochastic simulations or nonlinear geostatistical methods like indicator kriging or disjunctive kriging, which have found wide acceptance in soil science (Webster and Oliver, 1989, 2001; Wood et al., 1990; Oliver et al., 1996; Van Meirvenne and Goovaerts, 2001; Lark and Ferguson, 2004). An alternative to indicator and disjunctive kriging is the

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conditional expectation estimator. However, in practice this estimator is hardly used, except in the scope of the multigaussian model (Goovaerts, 1997, p. 271; Chile`s and Delfiner, 1999, p. 381).

Natural soil spatial variation occurs primarily from pedogenetic factors (Trangmar et al., 1985). In addition, variation can occur as a result of land use and management (Paz-Gonza´lez et al., 2000; Stenger et al., 2002). As a consequence, soils usually exhibit marked spatial variation on macro (White et al., 1997) and micro scales (Yang et al., 2001). In many instances, spatial variation is not random but tends to decrease as distances diminish between points in space (Goovaerts, 1998; Webster, 2000). Spatial dependence has been observed for a wide range of soil physical (Mapa and Kumaragamage, 1996; Castrignano et al., 2000), chemical (Boyer et al., 1996; Bragato and Primavera, 1998) and biological properties (Robertson et al., 1997; Goovaerts, 1998; Gaston et al., 2001), but typically the size of the studied area is relatively small, commonly ranging from 1 m^2 to 1 ha.

Increasingly geostatistical techniques are being used in soil science for spatial variation studies on scales ranging from centimeters to kilometers (White et al., 1997; Goovaerts, 1998; Castrignano et al., 2000; Yang et al., 2001). These techniques have provided the means to characterize and quantify spatial variation have been used to process this information for rational interpolation, and have been applied to estimate the variance of interpolated values (Isaaks and Srivastava, 1989; McBratney and Pringle, 1999; Webster, 2000; Gaston et al., 2001; Stenger et al., 2002).

Despite the predominance of degraded pasture areas, little information exists about the spatial variation of soil properties including nutrients and carbon. The first results obtained at a regional scale have shown large variations of C, N, Ca and pH, due to vegetation and soil type (Bernoux et al., 1998; Cerri et al., 1999). At the field scale, variation s may also occur and have to be better understood. Indeed, it is in that scale that agronomic experiments have been installed and carried on to support strategies for conservation practices and policies. However, soil property variation has been a familiar problem to agricultural scientists who must constantly deal with cumulative effects of micro and macro variation that can easily mask treatment differences in agronomic experiments (Perrier and Wilding, 1986; Goovaerts, 1999). An ideal experimental field is a land area in which the plot size and soil variability have been minimized for a specific plant or soil physical/chemical treatment (Davis, 1986). It should have a minimum point-to-point variability (Trangmar et al., 1985). In addition, proper interpretation of experimental data largely depends on the ''best'' estimation of experimental error (Webster, 2001).

MC Bratney et al (2003) developed comprehensive biological and chemical maps by using geostatistics methods, GIS and remote sensing. Neal et al (2004) used geostatistics methods to interpolate response of soil quality indicators and their spatial variability to land degradation in central Iran. Pcerri et al (2004) assessed soil property spatial variation in an Amazon pasture. Stark et al (2004) estimated small scale spatial variability of selected soil biological properties by using geostatistics methods. Barens et al (2006) estimated azotobacter abundance and soil properties by using Ph, soil water volume and geostatistics methods. Cheng et al (2006) investigated spatial relationships among species aboveground biomass, N, P in degraded grassland in ordos Plateau. Robinson et al (2006) tested the performance of spatial interpolation techniques (normal kriging and log normal kriging) for mapping soil properties and obtained acceptable results.

For correct watershed management planning, the maps of important characteristics of soil resources such as: pH, EC, N, K, P, Na, Ca, Mg and SAR should be used. The use of current and traditional methods for investigation of changes of spatial structure of soil variables are expensive and time-consuming methods. On the other hand classic statistics can not consider spatial changes of variables. Physical and chemical characteristics of soil resources change in time and place, even spatial structure of soil variables change in various geographic directions. Therefore, in this research geostatistical methods are used that consider spatial structure and changes of soil properties.

Our main objective in the present study was to assess the ability of kriging and cokriging techniques to predict spatial variation of chemical and physical some of the soil properties such as texture, gravel, hardness and organic mater in selected soil samples from Zereshkin area in north of Iran, Mazanderan province.

2. Material and Methods

2.1. Study area

The study area is Zereshkin basin with 2345 ha area located on 65 km southwest of Savadkooh town. The geographic location of the study area is 35° 55′ 51” to 35° 58′ 40” northern latitude and 52° 52′ 58” to 52° 56′ 52” eastern longitude. The minimum temperature in the area is -2°C in winter while it reaches to higher than 41° C in summers since 1980-2006. The climate of study area is mostly humid and the mean annual precipitation is 415 mm. The mean average of the study area from sea level is 2445 m (The mentioned data have been obtained from Savadkooh climatologic station).

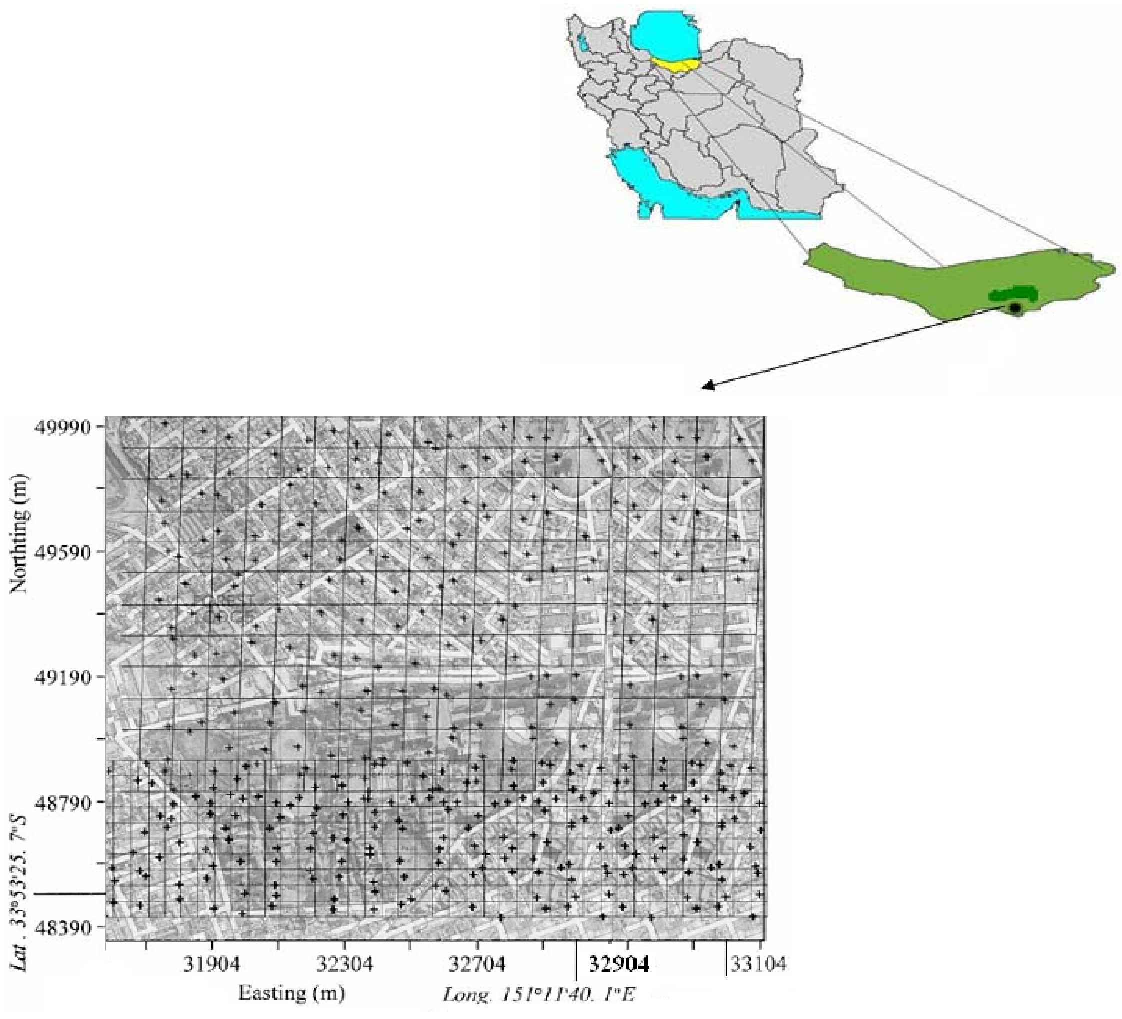


Fig.1. Location of study area in Mazanderan province and sampling design

2.2. Sampling Method

Different sampling methods are used for developing soil maps. Soil was sampled from the inner Zereshkin with a stratified random sampling design to select site locations within an area covering 2.3 km^2. The area was divided into 100- by 100-m cells with one site in each cell selected at random. There were a total of 227 sites, eight of which were not sampled because of an absence of soil. These have been recorded as "no data" points. To determine the extent of spatial variation, two samples 1 m apart were taken at each site and analyzed separately. A total of 438 topsoil samples (surface 10 cm) were collected for analysis.

Descriptive statistics were applied to all nine-soil properties (pH, EC, N, K, P, Na, Ca, Mg and SAR) at each depth. We evaluated all data together (Table 1), and afterwards, the modeling set data and the validation set data were separately considered. Analyzing the data using a classical approach, no discrepant values were observed.

Table 1. Basic statistics of the variables under the study area for 0-30, 30-60 cm layers

Variable	n	Mean	S.D.	CV	Min	Max	Skewn
0-30 cm layer							
pH	75	5.71	0.44	7.70	4.18	7.95	0.42
EC (%)	75	5.04	0.45	8.89	3.87	7.69	0.87
N (%)	75	8.47	1.34	15.79	3.78	15.42	0.12
K (%)	75	21.47	1.55	7.13	10.55	32.21	0.35
P (%)	75	10.2	0.44	29.53	4.25	21.55	1.25
Na (%)	75	13.2	0.03	25.50	7.54	23.10	2.01
Ca (%)	75	11.5	4.83	19.52	6.32	18.24	0.45
Mg (%)	75	7.5	5.16	7.42	2.51	12.32	0.55
SAR (%)	75	8.1	9.2	8.65	4.12	10.71	0.84
30-60 cm layer							
pH	75	5.33	0.47	8.77	3.55	7.94	0.12
EC (%)	75	4.86	0.43	8.48	2.17	6.25	0.26
N (%)	75	10.95	1.00	9.15	4.53	17.24	1.32
K (%)	75	22.5	1.31	5.68	12.25	29.44	1.20
P (%)	75	0.88	0.24	27.53	0.08	1.02	0.87
Na (%)	75	0.08	0.02	23.29	0.01	0.84	0.71
Ca (%)	75	28.26	5.31	18.78	13.24	37.14	2.01
Mg (%)	75	7.01	3.22	8.24	3.12	13.47	0.55
SAR (%)	75	7.5	10.2	9.15	2.11	11.58	0.67

S.D.: standard deviation, CV: coefficient of variation, Skewn: standardized Skewness, Min.: minimum, Max.: maximum.

2.3. Methods

Geostatistical prediction includes two stages which is first identification and modeling of spatial structure. At this stage continuity, homogeneity and spatial structure of a given variable is studied using variogram. Second stage is geostatistical estimation using kriging technique which depends on the properties of the fitted variogram which affects all stages of the process. It should be mentioned that the results of the study were obtained using GS+ software.

2.4. Criteria for Model Evaluation

A variety of verification criteria which could be used for evaluation and inter comparison of different models were proposed by World Meteorological Organization WMO and other investigators Nash and Sutcliffe 1970; WMO 1975; ASCE Task Committee on Definition of Criteria for Evaluation of Watershed Models 1993 . Of the several numerical indicators, the two important ones selected for the present study are the root-mean-square error RMSE and the MAE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(z^*(xi) - Qz(xi))^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|z^*(xi) - z(xi)\right|$$

3. Results

The first step in the use of geostatistics methods is the investigation of spatial structure existence among data by using variogram analysis. Normal data should be used for this analysis. For this purpose normal test was performed for data and some data series that have high skewness were recognized and they were normalized by using the relevant normalizing methods. Then variogram analysis was done for each soil property at 0-30 cm and 30-60 cm layers and the mean depth of these two layers (Table 2).

Table 2. The properties of suitable variogram model of variables

Variable	Model	Nugget	Sill	R_o	C_o/C_o+C
Mean pH	Exponential	3.71E-0.004	1.407E-0.003	24549	0.736
pH at 0-30 cm layer	Exponential	1.000E-0.006	6.01E-0.004	1530	0.998
pH at 30-60 cm layer	Exponential	0.029	0.0901	24141	0.671
Mean EC	Spherical	0.00486	0.03122	1791	0.844
EC at 0-30 cm layer (ds/m)	Exponential	0.0001	0.042	3366	0.713
EC at 30-60 cm layer (ds/m)	Exponential	0.0235	0.082	22917	0.998
Mean N (me/l)	Exponential	0.1462	0.3384	24450	0.568
N at 0-30 cm layer (me/l)	Spherical	0.042	0.2178	2569	0.808
N at 30-60 cm layer (me/l)	Linear	0.214	0.214	3476	0
Mean K	Linear	0.23	0.23	3476	0
K at 0-30 cm layer (me/l)	Linear	0.24	0.24	3476	0
K at 30-60 cm layer (me/l)	Linear	0.33	0.33	3476	0
Mean P (me/l)	Exponential	0.2	0.4	20097	0.501
P at 0-30 cm layer (me/l)	Exponential	0.114	0.2288	4278	0.502
P at 30-60 cm layer (me/l)	Exponential	0.2883	0.5776	31036	0.501
Mean Na(me/l)	Spherical	0.0002	0.00084	9110	0.752
Na at 0-30 cm layer (me/l)	Exponential	0.0001	0.02922	1773	1
Na at 30-60 cm layer (me/l)	Spherical	0.0076	0.024	3277	0.689
Mean Ca (me/l)	Spherical	0.0001	0.0427	2122	0.998
Ca at 0-30 cm layer (me/l)	Spherical	0.0114	0.0694	2592	0.836
Ca at 30-60 cm layer (me/l)	Linear	0.0482	0.0482	3476	0
Mean Mg (me/l)	Linear	0.395	0.395	3476	0
Mg at 0-30 cm layer (me/l)	Exponential	0.225	1.206	25161	0.813
Mg at 30-60 cm layer (me/l)	Linear	2.11	2.11	3476	0
Mean SAR (me/l)	Spherical	0	0.0002	2477	1
SAR at 0-30 cm layer (me/l)	Spherical	0	0.00027	1805	1
SAR at 30-60 cm layer (me/l)	Spherical	0.00001	0.00032	26.9	0.984

Table 3. The properties of suitable variogram model of variables

Variable	Model	Nugget	Sill	R_o	C_o/C_o+C
Mean Co3 (me/l)	Exponential	0.0427	0.0855	27330	0.501
Co3 at 0-30 cm layer (me/l)	Linear	0.057	0.057	3476	0
Co3 at 30-60 cm layer (me/l)	Linear	0.195	0.195	3476	0
Mean Hco3 (me/l)	Exponential	0.131	0.466	26624	0.719
Hco3 at 0-30 cm layer (me/l)	Spherical	0.098	1.506	9110	0.935
Hco3 at 30-60 cm layer (me/l)	Linear	0.33114	0.35814	3476	0.075
Mean Cl (me/l)	Linear	0.11	0.11	3476	0
Cl at 0-30 cm layer (me/l)	Linear	0.11372	0.11372	3476	0
Cl at 30-60 cm layer (me/l)	Linear	0.13	0.13	3476	0

Results show that other than N, K, Mg and Co_3^{2-} that did not have any spatial structure, in other cases, strong spatial structure has been recognized among data. Interpolation was performed by using kriging technique and then RMSE and correlation factor were used to assess results (Table 3,4).

Acceptable estimation has been obtained according to low value of RMSE and high value of R. Suitable estimation has not been obtained for sand according to low values of RMSE and R. Same results especially for surface layers have been obtained for silt and sand. On the subject of hardness there is not any spatial structure among data with due attention to variogram analysis.

Cokriging were used to assess mean amounts of soil properties by using surface amounts of soil properties. For this purpose cross semi-variogram was formed between mean and surface amounts of each soil property (Table 2).

Results show appropriate confrontation among data except for clay. Data interpolation by using cokriging technique shows error value has been decreased in the whole of soil properties whereas correlation value has been increased among observed and approximate quantities (Table 4).

Table 4. The results of cross semi-variogram analysis

Variable	Model	Co	Sill	EiR	Co/Co+C
Correlation of mean and surface pH	Exponential	2.17 E-0.003	9.64 E-0.003	24123	0.775
Correlation of pH and Ec	Exponential	2.89 E-0.003	1.065 E-0.002	24639	0.729
Correlation of mean and surface EC	Spherical	0.0067	0.032	2983	0.791
Correlation of mean and surface N	Spherical	0.016	0.506	2530	0.676
Correlation of mean and surface K	Linear	0.3	0.2	3476	0
Correlation of mean and surface P	Exponential	0.1642	0.3294	16140	0.502
Correlation of mean and surface Na	Exponential	0.0013	0.00735	26925	0.823
Correlation of Na and Ec	Spherical	0.0022	0.0067	9110	0.668
Correlation of mean and surface Ca	Spherical	0.0001	0.047	2440	0.998
Correlation of Ca and pH	Spherical	0.000344	-0.00128	3295	0.731
Correlation of mean and surface Mg	Spherical	0.0001	0.1822	1388	0.999
Correlation of Mg and EC	Linear	0.0186	0.0186	3476	0
Correlation of Mg and Ph	Linear	0.247	0.247	3476	0
Correlation of mean and surface SAR	Spherical	0	0.00018	2326	0.999
Correlation of SAR and EC	Spherical	0	0.00044	3876	0.998
Correlation of SAR and pH	Spherical	0	-0.00021	8244	1
Correlation of mean and surface Co3	Spherical	0.00001	0.027	0	1
Correlation of Co3 and EC	Spherical	0	0.0907	1903	0.999
Correlation of Co3 and pH	Spherical	0.0001	0.409	0	0.998
Correlation of mean and surface Hco3	Spherical	0.117	0.644	8582	0.818
Correlation of Hco3 and EC	Spherical	0.0133	0.0935	9110	0.858
Correlation of Hco3 and pH	Spherical	0.0001	0.137	0	0.999
Correlation of mean and surface Cl	Linear	0.107	0.107	3476	0
Correlation of Cl and EC	Linear	0.021	0.021	3476	0

Descriptive statistics were applied to all twelve-soil properties (Ec, N, K, P, Mg, Na, pH, SAR, Ca, Co3, Hco3, and Cl) at each depth. We evaluated all data together (Table 1), and afterwards, the modeling set data and the validation set data were separately considered. Analyzing the data using a classical approach, no discrepant values were observed. Data followed the same behavior approximately (Table 1). At the study area, soil pH had the same behavior. At 30-60 cm layer the pH was greater (about 0.1 units) than in the 0-30 cm layer.

Results show that the use of Ec data for the estimation of Na amounts at soil layers has increased the accuracy of estimation. Also the use of surface data of each soil property has yielded better estimation of mean amount of the soil property with the exception of P, Cl.

3.1. Variograms

In the references, spatial interrelationship of data is assessed by ($C/C+C_0$), and if this parameter is close to 1, spatial interrelationship is suitable and if the mentioned parameter is close to 0 spatial interrelationship is weak and the value of nugget effect is high. All of physical and chemical soil factors that have been investigated in this research (according to table 2, 3, 4), have high value of mentioned parameter ($C/C+C_0$), and this issue justifies the use of geostatistical techniques. According to table 2, 3, 4 spatial interrelationships of Mg and Ca data are higher than the other variables.

As seen in the variogram results (Table 2, 3, 4) the most appropriate models fitted to groundwater quality variables are spherical and linear models. However the results of current study show high spatial structure of the variable data but the most appropriate results based on the statistical comparisons showed high capability of kriging technique.

Fig.2. shows the variograms of physical and chemical soil factors that have been investigated in this research.

Assessment of effective range of various parameters show that some variables like EC and SAR have short effective range and for their assessment, we should prepare grading with short distance, If we want to calculate sampling distances (grading) for these two variables (EC and SAR) is 2/3 effective range (about 7 km), for Mg, Ca and PH, sampling distance is about 37 km and for SAR, Na and cations, it is about 74 km.

Table 5. The results of estimation of different geostatistical techniques (kriging and cokriging)

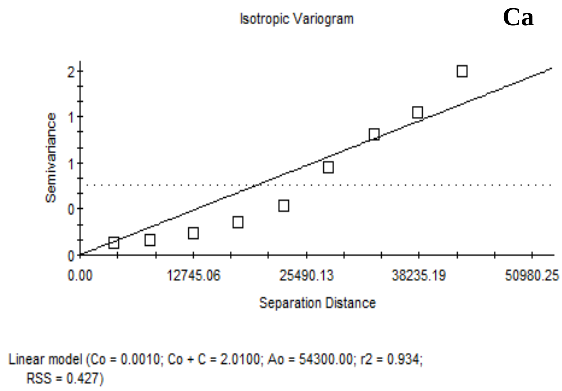
Variable	Mean	Skewness	RMSE	R
pH at 0-30 cm layer	7.23	0.17	0.18	0.14
pH at 30-60 cm layer	7.28	-0.08	0.22	-0.173
Mean pH	7.26	0.23	0.18	0.067
Correlation of mean and surface pH	-	-	0.18	0.25
Correlation of pH and Ec	-	-	0.18	0.25
EC at 0-30 cm layer (me/l)	0.254	0.78	0.037	0.54
EC at 30-60 cm layer (me/l)	0.25	1.69	0.05	0.18
Mean EC (me/l)	0.25	0.57	0.034	0.56
Correlation of mean and surface EC (me/l)	-	-	0.034	0.56
N at 0-30 cm layer (me/l)	0.22	1.12	0.07	0.66
N at 30-60 cm layer (me/l)	0.2	1.05	0.1	-0.74
Mean N (me/l)	0.21	0.97	0.09	0.23
Correlation of mean and surface N (me/l)	-	-	0.082	0.47
K at 0-30 cm layer (me/l)	0.15	0.81	0.067	0.34
K at 30-60 cm layer (me/l)	0.15	1.38	0.082	-0.37
Mean K (me/l)	0.15	1.29	0.055	0.065
Correlation of mean and surface K (me/l)	-	-	-	-
P at 0-30 cm layer (me/l)	13.26	1.25	5.45	0.53
P at 30-60 cm layer (me/l)	11.6	2.06	8.53	0.31
Mean P (me/l)	12.4	1.76	6.9	0.41
Correlation of mean and surface P (me/l)	-	-	6.65	0.45
Na at 0-30 cm layer (me/l)	0.17	0.65	0.03	0.19
Na at 30-60 cm layer (me/l)	0.16	0.39	0.02	0.44
Mean Na (me/l)	0.165	0.07	0.019	0.28
Correlation of mean and surface Na (me/l)	-	-	0.02	0.13
Correlation of Na and Ec (me/l)	-	-	0.022	0.13
Ca at 0-30 cm layer (me/l)	3.9	0.26	0.7	0.6
Ca at 30-60 cm layer (me/l)	4.11	1.7	1.04	-0.75
Mean Ca (me/l)	4.01	1.15	0.59	0.65
Correlation of mean and surface Ca (me/l)	-	-	0.56	0.69
Correlation of Ca and pH (me/l)	-	-	1.41	0.69
Mg at 0-30 cm layer (me/l)	2.12	1.03	1.2	-0.1
Mg at 30-60 cm layer (me/l)	2.12	0.82	0.89	-0.32
Mean Mg (me/l)	2.12	0.83	0.99	-0.52
Correlation of mean and surface Mg (me/l)	-	-	0.89	0.2
Correlation of Mg and EC (me/l)	-	-	0.013	0.2
SAR at 0-30 cm layer (me/l)	0.099	-0.15	0.014	0.51
SAR at 30-60 cm layer (me/l)	0.095	-0.39	0.012	0.46

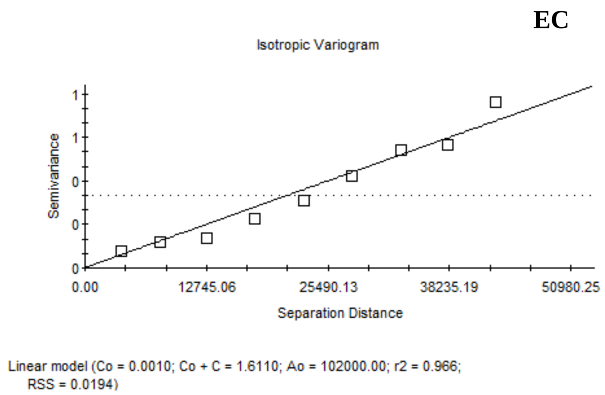
Table 6. The results of estimation of different geostatistical techniques (kriging and cokriging)

Variable	Mean	Skewness	RMSE	R
Mean SAR	0.097	-0.22	0.011	0.45
Correlation of mean and surface SAR (me/l)	-	-	0.011	0.48
Correlation of SAR and EC (me/l)	-	-	0.011	0.48
Correlation of SAR and pH (me/l)	-	-	0.013	0.48
Co3 at 0-30 cm layer (me/l)	1.002	0.17	0.23	-0.5
Co3 at 30-60 cm layer (me/l)	1.03	-0.19	0.42	-0.67
Mean Co3 (me/l)	1.02	0.99	0.25	-0.4
Correlation of mean and surface Co3 (me/l)	-	-	0.26	0.09
Correlation of Co3 and EC (me/l)	-	-	0.25	0.09
Correlation of Co3 and pH (me/l)	-	-	-	-
Hco3 at 0-30 cm layer (me/l)	1.37	-0.23	0.57	0.63
Hco3 at 30-60 cm layer (me/l)	1.56	1.35	1.78	-0.33
Mean Hco3 (me/l)	1.46	0.9	1.05	0.39
Correlation of mean and surface Hco3 (me/l)	-	-	0.99	0.48
Correlation of Hco3 and EC (me/l)	-	-	0.99	0.48
Correlation of Hco3 and pH (me/l)	-	-	-	-
Cl at 0-30 cm layer (me/l)	0.942	-0.29	0.27	-0.3
Cl at 30-60 cm layer	1.04	-0.28	0.33	-0.7
Mean Cl (me/l)	0.99	-0.54	0.28	-0.7
Correlation of mean and surface Cl (me/l)	-	-	-	-
Correlation of Cl and EC (me/l)	-	-	0.35	-0.28

All of physical and chemical soil factors that have been investigated in this research have high value of (C/C+C0) parameter, and this issue justifies the use of geostatistical techniques.

In (Fig.3) average concentration distribution maps of: EC (a), Ca (b), SAR (c), Mg (d), Na (e) and pH (f) in Zereshkin basin, since (1999-2006) have been shown.





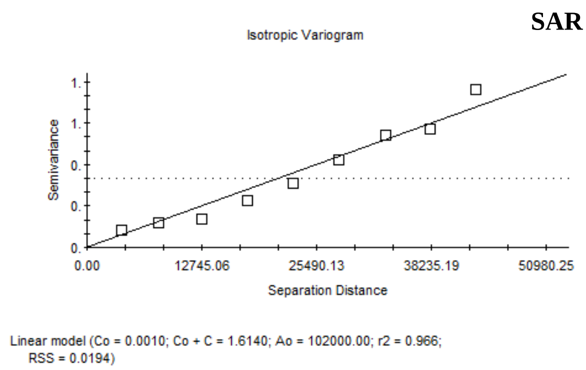
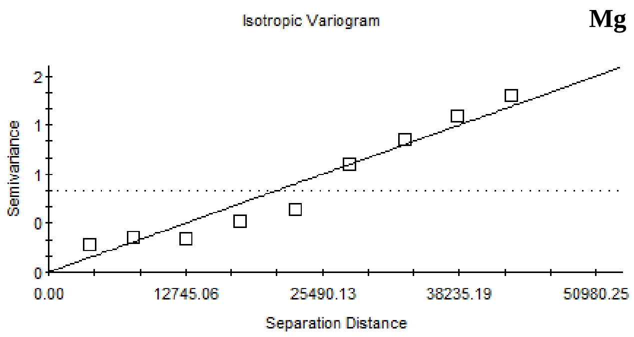
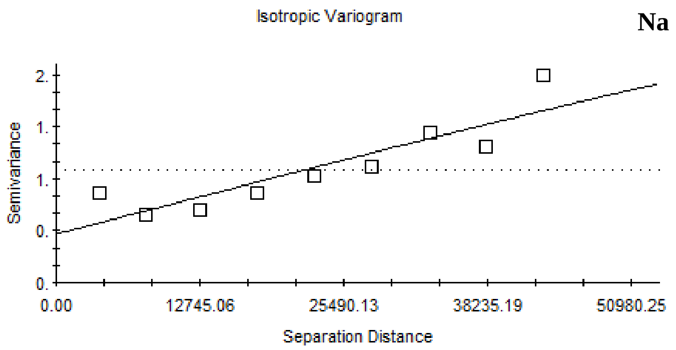


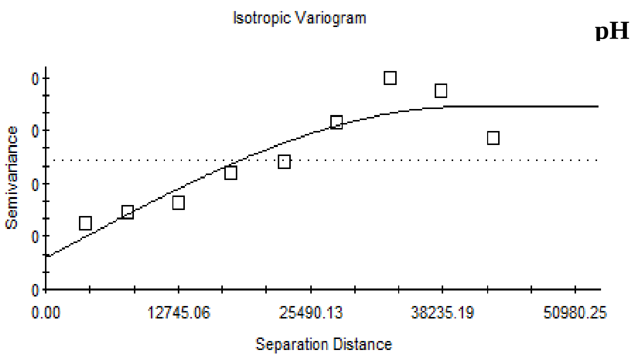
Fig.2. Variograms of the studied variables



Linear model (Co = 0.0010; Co + C = 2.0110; Ao = 55200.00; r2 = 0.941;
RSS = 0.147)



Spherical model (Co = 0.3800; Co + C = 2.7700; Ao = 155700.00; r2 = 0.796;
RSS = 0.196)



Spherical model (Co = 0.0146; Co + C = 0.0857; Ao = 40400.00; r2 = 0.849;
RSS = 7.372E-04)

Fig.2. Variograms of the variables

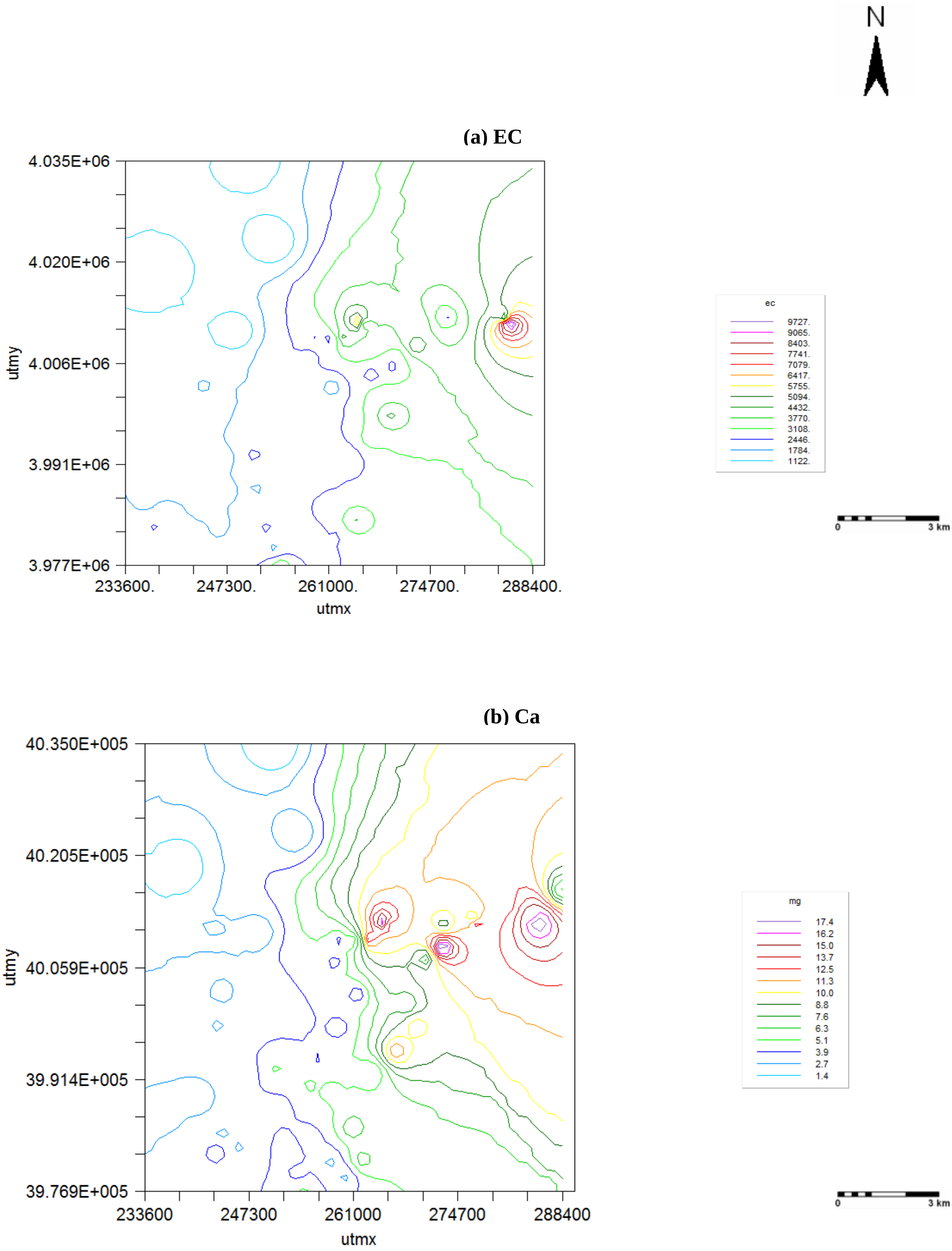
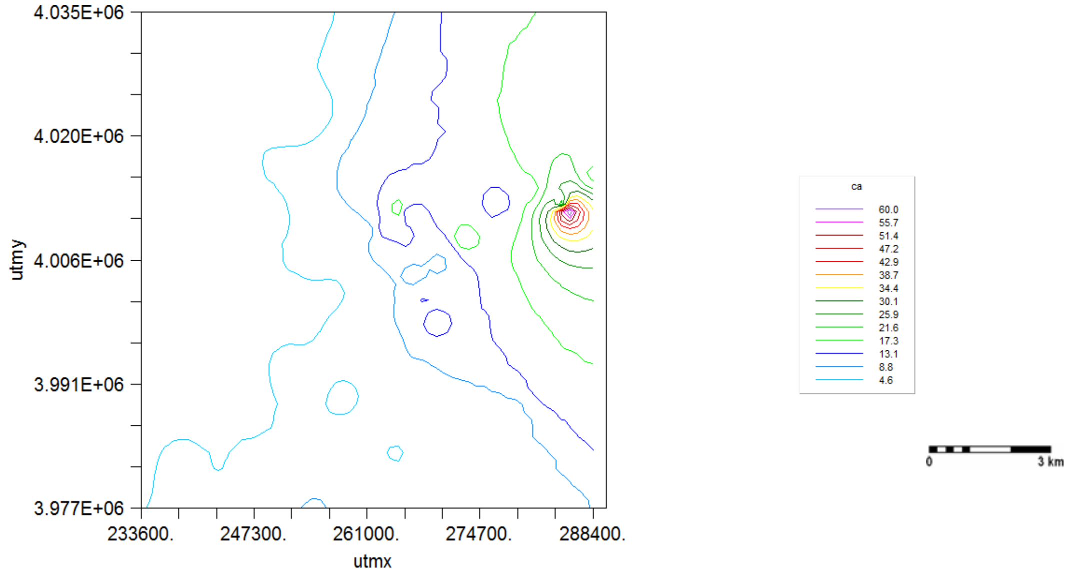


Fig.3. Average concentration distribution maps of: EC (a), Ca (b) , SAR (c), Mg (d), Na (e) and pH (f) in Dameghan plain (1999-2006)

N

(c) SAR



(d) Mg

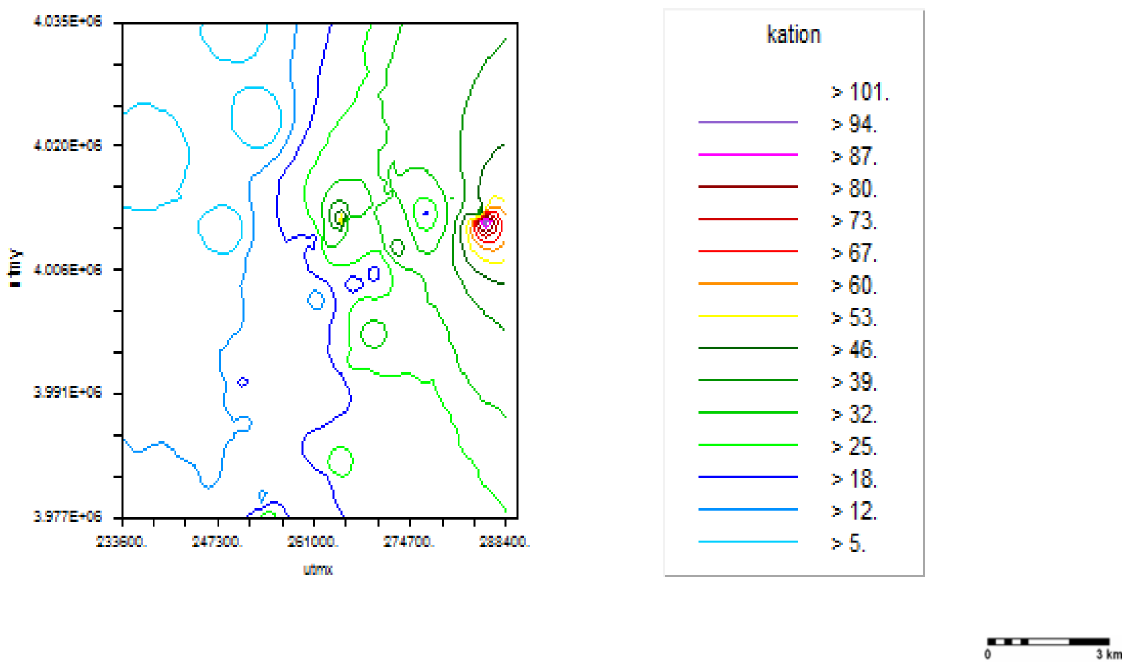
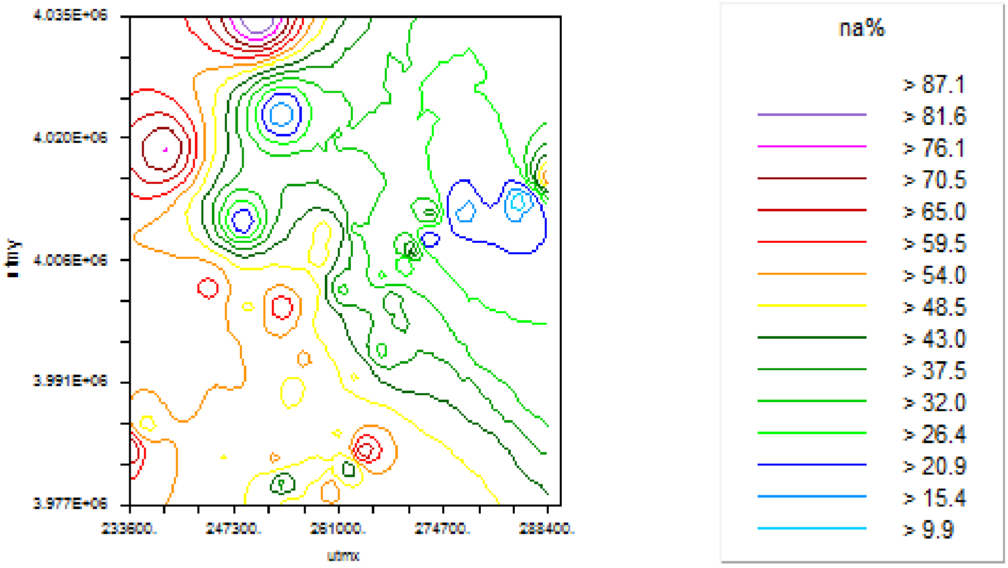


Fig.3. Average concentration distribution maps of: EC (a), Ca (b), SAR (c), Mg (d), Na (e) and pH (f) in Dameghan plain (1999-2006)

(e) Na



(f) PH

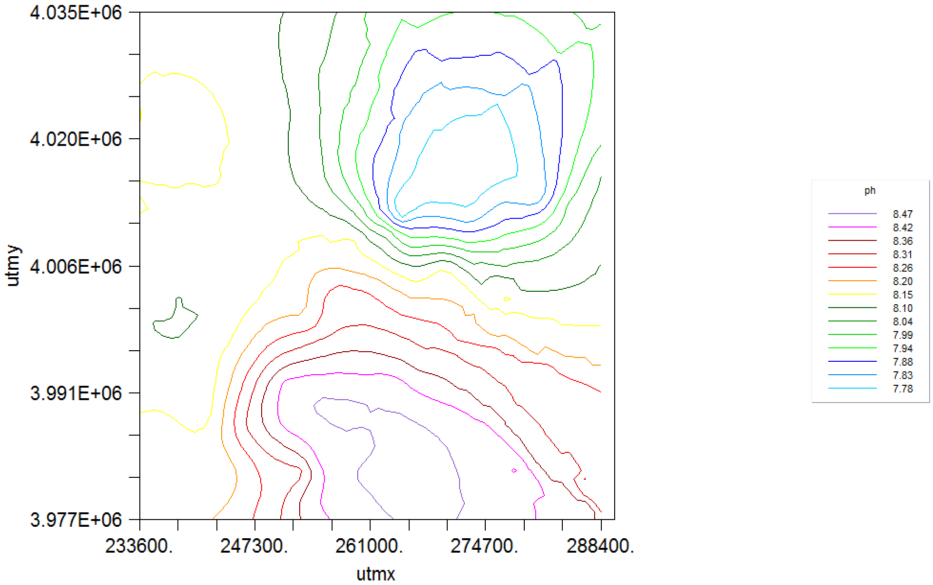


Fig.3. Average concentration distribution maps of: EC (a), Ca (b) , SAR (c), Mg (d), Na (e) and pH (f) in Dameghan plain (1999-2006)

4. Discussion

Results show there is high value of skewness among some soil properties amounts due to intrinsic characteristics of variables, environmental conditions like human activities, sampling methods and number of samples. In this study transect method was selected for sampling and a minimum of samples was tried to take for economizing on time and expenses.

We found a large amount of spatial heterogeneity in this study area, despite the fact of the site appears to be as homogeneous as any pasture field in the region. The site had been cleared of original vegetation and used as a pasture for several decades prior to the start of this study, with neither chemical fertilizer added nor mechanized agricultural practices adopted. We thus did not expect to find very large differences in important soil properties across the site. The present study illustrates that substantial soil property spatial variation existed in the study area, and that the structure of the variation could be determined using semivariograms. Variation differed among the soil properties and these differences may reflect the impacts of plants, soil fauna, and/or precipitation and also highly influenced by topography and management adopted in the area.

Using grid sampling can decrease data skewness value, but this method cause to increase numbers of samples and therefore more spending money and time is needed. In the current study the use of appropriate methods for changing data to normal condition has solved some problems but some data have high skewness values as before. Other method like WMI, Spline, and Surface Trend can be used for such data. In our study the use of kriging method has given acceptable estimation, but application of cokriging method has increased the estimation accuracy. Amini et al (2002) reported cokriging does not have any preference to kriging if cross semi-variogram is well proportioned to single variogram. Despite the fact that calculated variograms follow similar pattern, but cokriging has given more accurate estimation than kriging.

Generally accurate and clear spatial data of soil properties will be useful for natural resources management and sustainable development.

Examined with other studies of soil property variability, our results provide further evidence that soils are highly structured spatially, and that this structuring should be considered when designing both agronomic experiments and management strategies. Although knowledge about the heterogeneity of some properties at a specific point in time may be insufficient to guide management decisions later, it is nevertheless apparent that spatially explicit information about some properties (e.g., soil P content or soil Cl) should be useful to support policy decision makers in natural resource improvement.

With greater recent emphasis placed on regionalized variable analyses, the choice of an adequate area for a field experiment must not be arbitrary, but rather must be based on measured variance and spatial correlation structures. This is in addition to the usual considerations such as equipment availability, number of treatments or sub treatments, irrigation systems, and land area available for the experiment. Plot arrangement should also be based on magnitudes of the spatial correlation lengths associated with observations of the soil attributes being investigated.

At the end of the article these issues are suggested for next studies:

1) The other sampling methods should be used and obtained results should be compared with transect method.

2) The other interpolation methods should be applied to estimate soil properties.

3) The other supplementary variables like satellite data can be utilized in cokriging method.

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References

Amini, M., Khadi, H., Fathianpour, N. 2002. Comparison of kriging and co-kriging methods for estimating Cl- concentration of soil, Iranian Journal of Agricultural Science (In Persian), Vol. 33: 4:741-748.

Azimzadeh,H.R., Ekhtesasi, M.R., Mohammadi, J., Refahi, H. 2005. Application of geostatistics using kriging method for estimating desert pavement and wind erosion threshold (In Persian), First National Conference of Wind Erosion.

Barnes, R.J., S.J. Baxte , R M.Lark, 2006. Spatial Covariation of Azotobacter abundance and soil properties, soil biology & biochemistry 42:475-482.

Bernoux, M., Arrouays, D., Cerri, C.C., Grac ßa, P.M. de A., Volkoff, B., Trichet, J., 1998. Estimation des stocksde carbone des sols du Rondoˆnia (Amazonie bre´silienne). E´tude et Gestion des Sols 5, 31 – 42.

Boyer, D.G., Wright, R.J., Feldhake, C.M., Bligh, D.P., 1996. Soil spatial variability relationships in a steeply acid soil environment. Soil Sci. 161 (5), 278 – 287.

Bragato, G., Primavera, F., 1998. Manuring and soil type influence on spatial variation of soil organic matter properties. Soil Sci. Soc. Am. J. 62, 1313 – 1319.

Castrignano, A., Giugliarini, L., Risaliti, R., Martinelli, N., 2000. Study of spatial relationships among soil physico-chemical properties of a field in central Italy using multivariate geostatistics. Geoderma 97 (1–2), 39 – 60.

Cerri, C.C., Bernoux, M., Arrouays, D., Feigl, B.J.,Piccolo, M.C., 1999. Carbon stocks in soils of the Brazilian Amazon. In: Lal,R., Kimble, J., Follet, R., Stewart, B.A. (Eds.), Global Climate Change and Tropical Ecosystems.Advances in Soil Science.

Cheng, X., S. An, J. Chen, B. Li, 2006.Spatial relationships among species above-ground biomass, N, P in degraded grassland in ordos Plateau, Journal of arid environment.

Chile`s, J.P., Delfiner, P., 1999. Geostatistics: Modeling Spatial Uncertainty.Wiley, New York.

Chile`s, J.P., Liao, H.T., 1993.Estimating the recoverable reserves of gold deposits: comparison between disjunctive kriging and indicator kriging. In: Soares, A. (Ed.), Geostatistics Troia'92.

Conant, R.T., Paustian, K., 2002. Spatial variability of soil organic carbon in grassland: implications for detecting change at different scales. Environ. Pollut.116, S127 – S135.

Cressie, N., 1990.Statistics for Spatial Data.Revised Edition. Wiley, New York, USA. 900PP.

Davis, J.C., 1986. Statistics and Data Analysis in Geology. Wiley, New York.

Douaoui, A.E.K., H. Nicolas, C. walter, 2006. Detecting Salinity hazard Within a semi arid context by means of combining soil and remote – sensing data, Geoderama 134 :217-230.

Duffera, M., j.G. White, R. weisz, 2006. spatial variability of southwestern U.S. Coastal plain soil physical properties, Geoderama.

Gaston, L.A., Locke, M.A., Zablotowicz, R.M., Reddy, K.N., 2001.Spatial variability of soil properties and weed population in the Mississippi delta. Soil Sci. Soc. Am. J. 65, 449 – 459.

Goovaerts, P., 1997.Geostatistics for Natural Resources Evaluation. Oxford University Press, New York.

Goovaerts, P., 1998. Geostatistical tools for characterizing the spatial variability of microbiological and physico-chemical soil properties. Biol. Fertil. Soils 27, 315 – 334.

Goovaerts, P., 1999. Geostatistics in soil science: state-of-the-art and perspectives. Geoderma 89 (1-2), 1-45.

Hasanipak, A., 1988, Geostatistics (In Persian), University of Tehran Press 314pp.

Isaaks, E.H., Srivastava, R.M., 1989.An Introduction to Applied Geostatistics. Oxford Univ. Press, New York. 561 pp.

Lark, R.M., Ferguson, R.B., 2004. Mapping risk of soil nutrient deficiency or excess by disjunctive and indicator kriging. Geoderma 118, 39 – 53.

Mapa, R.B., Kumaragamage, D., 1996. Variability of soil properties in a tropical Alfisol used for shifting cultivation. Soil Technol. 9,187 – 197.

McBratney, A.B., Pringle, M.J., 1999. Estimating average and proportional variograms of soil properties and their potential use in precision agriculture. Prec. Agric. 1, 125 – 152.

McBratney, A.B., M .L. Mendonca , B. Minasny, 2003. on digital soil mapping, Geoderama 117:3-52.

Neal, M.,H. Khademi, M .A .Hajabbasi, 2004. Response of Soil quality indicators and their spatial Variability to land degradation in central Iran, Applied soil ecology 27:221-232.

Oliver, M.A., Webster, R., McGrath, S.P., 1996. Disjunctive kriging for environmental management. Environmetrics 7 (3), 333 – 357.

Panagopoulos, T., J. Jesus, M.D.C. Antunes, J. Beltrao, 2006. Analysis of spatial interpolation for optimizing management of a salinized field cultivated with lettuce, European j. of Agronomy 24:1-10.

Paz-Gonza´lez, A., Vieira, S.R., Taboada Castro, M.T., 2000. The effect of cultivation on the spatial variability of selected properties of an umbric horizon. Geoderma 97, 273 – 292.

Pcerri, C.E., M .Bernoux , V. Chaplot, 2004. Assessment of soil property spatial variation in an Amazon Pasture, Geodrama 123:51-68.

Perrier, E.R., Wilding, L.P., 1986.An evaluation of computational methods for field uniformity studies. Adv. Agron. 36,265 – 313.

Robertson, G.P., Klingensmith, K.M., Klug, M.J., Paul, E.A., Crum, J.R., Ellis, B.G., 1997. Soil resources, microbial activity,and primary production across an agricultural ecosystem. Ecol.Appl. 7 (1), 158 – 170.

Robinson, T.P., G. metternicht, 2006. Testing the performance of spatial interpolation techniques for mapping soil properties, computer and electronic in agriculter 50: 97-108.

Stark, C.E., L.M. Condron, A. Stewart , H .J. Di , M. Callaghan, 2004. Small scale spatial variability of selected soil biological properties, soil biology & Biochemistry 36:601-608.

Stenger, R., Priesack, E., Beese, F., 2002. Spatial variation of nitrate-N and related soil properties at the plot-scale. Geoderma 105, 259 – 275.

Trangmar, B.B., Yost, R.S., Uehara, G., 1985.Application of Geostatistics to Spatial Studies of Soil Properties. Advances in Agronomy, vol. 38. Academic Press, San Diego, pp. 45 – 94.

Van Meirvenne, M., Goovaerts, P., 2001.Evaluating the probability of exceeding a site-specific soil cadmium contamination threshold. Geoderma 102, 75 – 100.

Webster, R., Oliver, M.A., 1989. Optimal interpolation and isarithmic mapping of soil properties: VI. Disjunctive kriging and mapping the conditional probability. Journal of Soil Sciences 40, 497 – 512.

Webster, R., Oliver, M.A., 2001.Geostatistics for Environmental Scientists. Wiley, New York.

Webster, R., 2001. Statistics to support soil research and their presentation. Eur. J. Soil Sci. 52, 331 – 340.

White, J.G., Welch, R.M., Norvell, W.A., 1997. Soil zinc map of the USA using geostatistics and geograp hic information systems. Soil Sci. Soc. Am. J. 61, 185 – 194.
Wood, G., Oliver, M.A., Webster, R., 1990.Estimating soil salinity by disjunctive kriging. Soil Use and Management 6 (3), 97 – 104.
Yang, J.I., Mosby, D.E., Casteel, S.W., Blanchar, R.W., 2001. Microscale pH variability for assessing of phosphoric acid treatment in lead-contaminated soil. Soil Sci. 66 (6), 374 – 381.