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Applying Spatial Geostatistical Analysis Models for Evaluating Variability of Soil Properties in Eastern Shiraz, Iran

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ABSTRACT- The information on the spatial properties of soil is vital to improve soil management and to increase the crop productivity. Geostatistical analysis technique is one of the most important methods for determining the spatial properties of soil. The aim of this study was to investigate spatial variability of soil chemical and physical attributes for field management in eastern Shiraz, Iran, in 2010. In the study area, for applying geostatistical analysis, eighty soil samples were taken randomly. The variability of saturation percentage (SP), electrical conductivity (EC), soil pH, sand%, silt%, clay%, nitrogen (N), phosphorus (P) and potassium content (K) of the soil used to determine the spatial properties of soil by geostatistical analysis techniques. Soil properties were analyzed both geostatistically and statistically on the basis of the Semivariogram models. Thus, each soil parameter was used for different Semivariogram models such as spherical, circular and exponential because of their different spatial structures. The results showed that the best model to generate soil properties map was ordinary kriging with spherical and exponential Semivariogram models. The best model for soil pH, SP, K and N was the spherical model whereas for sand%, silt%, clay%, EC and P, the best model was the exponential model. Based on the models, the range of spatial dependency was found to vary within soil parameters. EC had the longest (134 meter) and pH had the shortest (19.1 meter) range of spatial dependency. Additionally, spatial patterns may vary among soil parameters in the study area. Therefore, Semivariogram models can be useful tools to determine spatial.

Keywords: Broadcast Planting, Crude Protein, Digestibility, *Medicago* species, Row Planting

INTRODUCTION

Evaluation of the agricultural land management practices requires knowledge of soil spatial variability (8). Wheat is one of the most important food crops in South of Iran such as Fars province. This province is also the largest wheat producer in Iran (14). Thus, studying the spatial soil properties is one of the prime concerns for field management. Spatial variability is used to predict values at unsampled locations within area (2). Natural variability of soil results from complex interactions among topography, parent material, geology, climate as well as soil

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use (17, 28). Therefore, soil properties can exhibit marked spatial variability (3, 37).

Several researchers have demonstrated that soil chemical and physical attributes are correlated with soil spatial distribution (38, 35, 6). The distribution of the attributes may be influenced by soil management which leads to variability that covers an area of cultivated soils (4). Digital soil mapping is characterized as a quantitative geostatistical production of soil properties (25).

Geostatistics has been widely used for quantifying the spatial pattern of environmental variables (27). The Kriging method has been used for Geostatistical interpolation and has been proved to be sufficiently huge for estimating values at unsampled locations based on the sampled data (15, 39, 27). In recent years, soil scientists focused on using geostatistics and different kriging methods to predict soil properties at unsampled locations and to better understand their spatial variability pattern over small to large spatial scale. (7, 35, 40).

The ordinary kriging method is one of the kriging methods (26) which plays an important role in interpolation and mapping of soil properties (1, 31, 20). Triantafilis and Buchanan (34) and Juan et al. (18) used ordinary kriging to study soil. Geostatistical analyses are useful in soil science for mapping spatial variation of soil properties (24). Geostatistics analyses use the modeled variance to estimate values between samples(43).

Accordingly, one of the largest wheat producing regions was located in the east of Shiraz, Fars province. Therefore, the aim of this study was to investigate spatial variability of soil chemical and physical attributes for better field management in the east of Shiraz, Iran.

MATERIALS AND METHODS

Study area

The study area was located in the east of Shiraz, Iran, between latitudes 29° 62' 00" N- 29° 54' 00" N and longitudes 52° 86' 00" E- 53° 02′ 00"E with an area 48 km^2 (Fig. 1); the highest elevation is 1677 m above mean sea level with semi-arid climate.

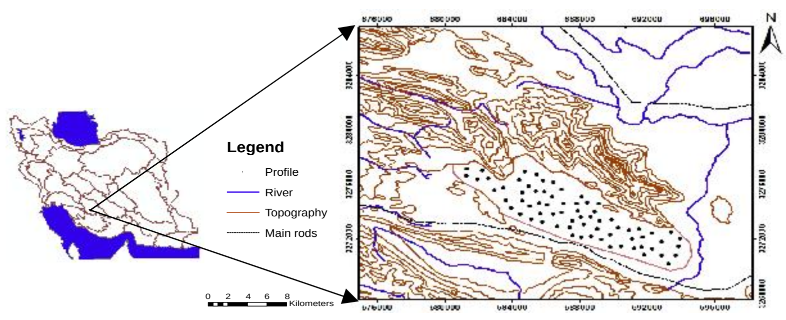


Fig. 1. Geographical location of case study

Data collection and sampling

The dataset was extracted from a land classification study done by the Fars Soil and Water Research Institute in the year 2010 with 80 soil samples consisted of: saturation percentage (SP), electrical conductivity (EC), soil pH, sand%, silt%, clay%, nitrogen, phosphorus and potassium applied to the soil (ppm) [(Department of Natural Resources and Watershed of Fars province, 2010), 12].

Geostatistical analysis models

Geostatistical models, including analyses of Semivariograms models, kriging and mapping of kriged estimates (15), were used to determine the variance structure of the soil properties measurements. The soil properties were analyzed using geostatistics models. Semivariance is defined by the following Eq. (15, 26, 21):

$$\gamma(h) = \frac{1}{2} \cdot \frac{1}{n(h)} \sum_{i=1}^{n(h)} (z(x_i + h) - z(x_i))^2 \tag{1}$$

Where γ (h) is the Semivariogram models for a lag distance *h* between observations z(xi) and z(xi+h), z(xi) represents the measured value of the soil property at location xi, and *n(h)* is the number of data pairs separated by a lag distance equal to *h*. Three models were fitted to the experimental Semivariograms (circular, spherical and exponential). The study area were calculated using three types of kriging for estimate soil properties.

Geostatistical procedures were assessed using parameters nugget, sill and range which helped to choose the most appropriate model to predict soil parameters. In Fig. 2, the value at which the Semivariogram model attains the range, representing the value on the y-axis,is called the sill. A partial sill is the sill minus thenugget. (30).

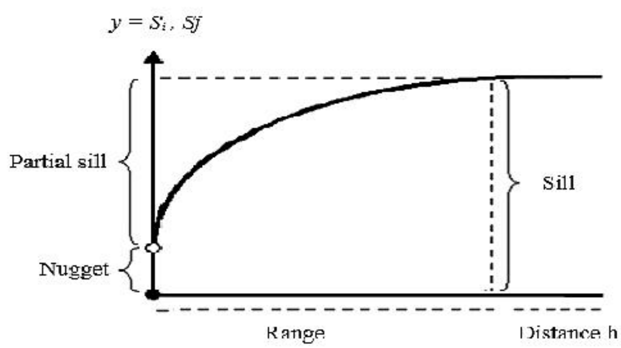
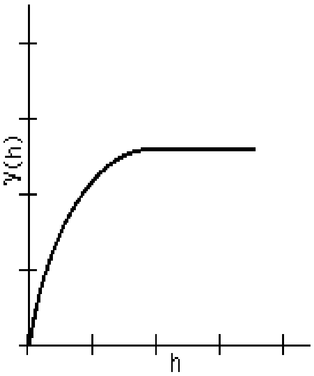


Fig. 2. Semivariogram model

Several Semivariogram models functions, such as spherical model, exponential model and circular model, were evaluated to choose the best fit with the data. Spherical or exponential models were fitted to the empirical Semivariograms models (Fig. 3 to 5), defined in the following Eq.s of2 to 4 (30):

Several classes of spatial dependence for the soil parameters were evaluated by the ratio between the nugget Semivariance and the total Semivariance (5). For the ratio of 100%, soil variable was close to zero; for the ratio greater than 75%, the soil variable was considered weakly spatially dependent; for the ratio between 26 and 75%, the soil variable was considered to be moderately spatially dependent and for the ratio lower than 25%, the variable was considered to be strongly spatially dependent, or strongly distributed in patches(10, 11).

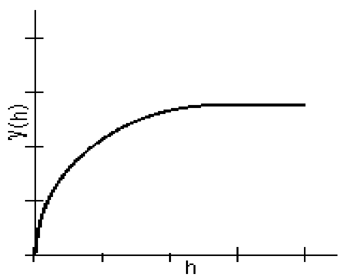
Spherical model



$$\gamma(h) = c_0 + c\left(\frac{3h}{2\alpha} - \frac{1}{2}\left(\frac{h}{\alpha}\right)^3\right) \quad 0 < h \leq \alpha$$
$$\gamma(h) = c_0 + c \quad h > \alpha \tag{2}$$
$$\gamma(0) = 0$$

Fig. 3. Spherical semivariance model illustration

Circular model



$$\gamma(h) = c_0 + c\left(1 - \frac{2}{\pi}\cos^{-1}\left(\frac{h}{\alpha}\right) + \sqrt{1 - \frac{h^2}{\alpha^2}}\right) \quad 0 < h$$
$$\gamma(h) = c_0 + c \quad h > \alpha \tag{3}$$
$$\gamma(0) = 0$$

Fig. 4. Circular semivariance model illustration

Exponential model

$$\gamma(h) = c_0 + c\,(1 - \exp(\frac{-h}{r})) \quad h > 0$$
$$\gamma(0) = 0 \tag{4}$$

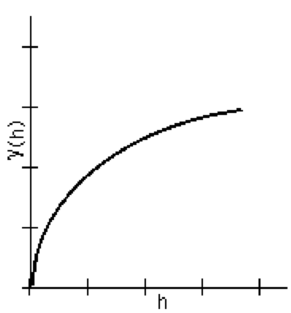


Fig. 5. Exponential semivariance model illustration

Mean Error (ME) and Mean Square Error (MSE)

Semivariogram models check the validity of the models and compare values estimated from the Semivariogram model with actual values (36). Differences between estimated and experimental values are summarized using mean error (ME) and mean square error (MSE) as follows:

$$ME = \sum_{i=1}^{n}(Z^* - Z) / n \tag{5}$$

$$MSE = \sum_{i=1}^{n}(Z^* - Z)^2 / n \tag{6}$$

Where Z* are the prediction values, Z are the mean values and n is the total number of prediction for each validation case.

RESULTS AND DISCUUSION

In order to conduct spatial investigation of suitable land for crop cultivation, a number of factors, such as saturation percentage (SP), electrical conductivity (EC), soil pH, sand%, silt%, clay%, nitrogen, phosphorus and potassium applied to the soil (ppm), should be assessed and measured (32). First of all, Kolmogorov-Smirnov Test (K-ST) was applied for testing the normal distribution of data and then variance of each factor was calculated in GIS software (23). The summary of the statistics of soil variable (Table 1) showed that the coefficient of variation for all of variables was low; the highest and lowest CV % was related to EC (5.6%) and pH (0.49%), respectively. In this study, CV values for selected soil properties were low, indicating the possibility of homogenous management on top soil. Descriptive statistic for soil parameters according to Table 1 Consist of: K soil ranging from80 to 640 (mg/kg), P soil rangingfrom2 to 38 (mg/kg) in 0-300 cm depth and N ranging from 0 to 0.2 (%). Most of texture soil is silt with the mean of 49.57 (%) of sand and clay. SP ranged from 32 to 64 (%) with the mean of 47.68. Mean and CV of soil EC ranged from 5.6 to 3.27 (ds/m). Mean soil pH in 0 – 300 cm depth was 7.67 (- log [H^+]).

Table 1. Descriptive statistics for variables for a depth of 0 -300 cm.

Variable	Unit	Mean	Min	Max	CV %
pH	**(-log[H^+])**	**7.67**	**7**	**8.5**	**0.49**
EC	**(dS m^{-1})**	**3.27**	**0**	**10**	**5.6**
SP	**(%)**	**47.67**	**32**	**64**	**0.89**
Sand	**(%)**	**20.37**	**0**	**48**	**1.12**
Silt	**(%)**	**49.57**	**30**	**70**	**1.16**
Clay	**(%)**	**30**	**16**	**44**	**1.14**
P	**(mg /kg)**	**14.38**	**2**	**38**	**3.1**
K	**(mg/ kg)**	**283.09**	**80**	**640**	**1.20**
N	**(%)**	**0.1**	**0**	**0.2**	**2.1**

In the analysis, the nugget value represents the random variation usually derived from the inaccuracy of measurements that cannot be detected in the sample range (33). The sill value is the upper limit of the fitted Semivariogram model (39). The ratio of nugget to sill indicates the spatial dependency of the soil properties. The range of the Semivariogram represents the average distance at which the semivariogram reaches the peak value (29).

According to Table 2, the ranges of spatial dependences gave a large variation (from 19.1 meter for pH up to 134 meter for EC). The range values showed considerable variability among the parameters. There were great differences between ranges of the different soil variables, as had been already reported in several studies. Weitz et al. (42) found that most of the soil properties had variable range between 30 and 100 m. In addition, Cambardella et al. (5) reported the measure of 80 m for total organic N at a farm in Iowa, USA. Doberman (9) fitted the spherical models to variograms ranging between 80 to 140 m.

According to spatial ratio parameters of SP (spherical model), EC and sand% (exponential model) were lower than 25% and thus, were strongly spatially dependent whereas spatial ratio in pH, N, K (spherical model) and P, silt, clay (exponential model) were between 25 to 75% that were moderately spatially dependent (10,11).

Table 2. Nugget, Sill, Range and Partial Sill of the fitted Semivariogram models for ordinary kriging in the study area

Geostatistical procedures	Model	Nugget	Sill	Range	Partial Sill	Spatial Ratio (%)	Spatial class	ME	MSE
pH	**Circular**	**0.0426**	**0.071**	**40.7**	**0.0284**	**37.50**	**Moderate**	**-0.00029**	**-0.0014**
(-log[H^+])	**Spherical**	**0.0324**	**0.064**	**19.1**	**0.0316**	**33.61**	**Moderate**	**0.00024**	**0.00111**
	Exponential	**0.0257**	**0.067**	**39.1**	**0.0413**	**27.72**	**Moderate**	**0.000406**	**0.0015**
EC†	**Circular**	**0.043**	**0.474**	**51**	**0.431**	**8.32**	**Strong**	**-0.123**	**-0.0141**
	Spherical	**0.0415**	**0.431**	**56**	**0.389**	**8.78**	**Strong**	**-0.118**	**-0.013**
(dS m^{-1})	**Exponential**	**0.0435**	**0.442**	**55**	**0.398**	**8.96**	**Strong**	**-0.098**	**-0.0111**
	Circular	**0.406**	**7.6**	**39**	**7.194**	**5.07**	**Strong**	**0.0173**	**0.00117**
SP (%)	**Spherical**	**0.39**	**6.3**	**51**	**5.91**	**5.83**	**Strong**	**0.0149**	**0.00079**
	Exponential	**0.31**	**5.4**	**36**	**5.09**	**5.43**	**Strong**	**0.023**	**0.00171**
	Circular	**0.003**	**0.013**	**134**	**0.01**	**18.75**	**Strong**	**-0.00046**	**-0.0023**
Sand (%)	**Spherical**	**0.0041**	**0.011**	**98**	**0.0069**	**27.15**	**Moderate**	**-0.0095**	**-0.00456**
	Exponential	**0.0038**	**0.017**	**143**	**0.0132**	**18.27**	**Strong**	**0.0007**	**0.00055**
	Circular	**0.25**	**0.58**	**20.6**	**0.33**	**30.12**	**Moderate**	**0.097**	**0.0157**
Silt (%)	**Spherical**	**0.254**	**0.59**	**21**	**0.336**	**30.09**	**Moderate**	**0.0918**	**0.0147**
	Exponential	**0.22**	**0.51**	**20**	**0.29**	**30.14**	**Moderate**	**0.085**	**0.014**
	Circular	**0.45**	**0.51**	**40**	**0.06**	**46.88**	**Moderate**	**0.0253**	**0.0029**
Clay (%)	**Spherical**	**0.46**	**0.79**	**70.3**	**0.33**	**36.80**	**Moderate**	**0.026**	**0.0031**
	Exponential	**0.35**	**0.82**	**71**	**0.47**	**29.91**	**Moderate**	**0.0126**	**0.00083**
	Circular	**0.29**	**0.61**	**91**	**0.32**	**32.22**	**Moderate**	**-0.017**	**-0.0033**
P (mg kg^{-1})	**Spherical**	**0.28**	**0.59**	**87**	**0.31**	**32.18**	**Moderate**	**-0.0172**	**-0.0034**
	Exponential	**0.26**	**0.57**	**90**	**0.31**	**31.33**	**Moderate**	**-0.0078**	**-0.0016**
	Circular	**81.2**	**135**	**116**	**53.8**	**37.56**	**Moderate**	**0.0726**	**0.00031**
K (mg kg^{-1})	**Spherical**	**84.4**	**151**	**96**	**66.6**	**35.85**	**Moderate**	**0.042**	**0.000043**
	Exponential	**83.9**	**135**	**78**	**51.1**	**38.33**	**Moderate**	**-0.207**	**-0.0018**
	Circular	**0.00017**	**0.0002**	**96**	**0.00003**	**45.95**	**Moderate**	**-0.00034**	**-0.0087**
N (%)	**Spherical**	**0.00018**	**0.0003**	**58**	**0.00012**	**37.50**	**Moderate**	**-0.0002**	**-0.0025**
	Exponential	**0.00001**	**0.0001**	**101**	**0.00009**	**9.09**	**Strong**	**-0.00028**	**-0.0038**

†Electrical conductivity (EC), saturation percentage (SP), phosphorus applied (P), potassium applied (K), nitrogen applied (N), mean error (ME), and mean square error (MSE)

Our findings were similar to those of Ayoubi Studies et al. (1), who reported that the range of spatial dependency was found to be varying within soil parameters and N had the shortest range of spatial dependence (23.99m) and K had the longest (93.92m). Weindorf and Zhu (41) used Semivariogram model for spatial variability of soil properties that had similar results. A large range indicates that observed values of the soil variable are affected by other values of this variable over greater distances than soil parameters that have smaller ranges (22). In the study area, a range of more than 134 m for EC indicates that EC values influence the neighboring values of EC over greater distances than other soil parameters (Table2).

In order to prepare the interpretation map for each parameters, according to Table 2, among the three models (spherical, circular and exponential Semivariogram models), the best model had the lowest mean error (ME) and mean square error (MSE). The best model for soil pH, SP, K and N were spherical model whereas for other parameters (sand%, silt%, clay%, and EC), exponential model were thebest model.

We found that the maps obtained by ordinary kriging for soil properties in the east of Shiraz, Iran and EC and pH in north of the study area were better than other parts of the area (Fig. 6). The comparison of these maps can be useful in the interpretation of the results and provide soil map. Distribution maps of soil nutrients showed that they were not very identical, indicating that nutrient distributions within the field were influenced by fertilizing management. Except for the south parts of the case study, most of the study area had the same distribution of potassium (k) (160-480 mg/kg). It was observed that the amount of potassium was very low in the southern part of the area. According to Fig. 6, in the northern parts of the study area, the amount of clay (%) was more than other areas, the amount of sand (%) in the north of the case study was lower than the south of the study area and the amount of silt (%) in the center of the study area was more than the northern and southern parts of the study area. As a result, the soil texture in the north of the study area was heavier than other part of the case study. The amount of phosphor (mg/kg) was lower than other study areas. Using the ordinary kriging method in a GIS for creating continuous surfaces from soil data, Ayoubi et al. (1) reported the inclusion of eight parameters including pH, EC, sand, silt, clay, P, $CaCO3$ and organic matter (OM) were moderately spatially dependent whereas saturation percentage (SP), bulk density, K, N, cation exchange capacity (CEC) and exchangeable sodium percentage (ESP) were strongly spatially dependent on the Sorkhankalateh district, in the Golestan province, Iran. Weindorf and Zhu (41) showed that only extractable P had weak spatial dependency while other properties had moderate or strong spatial dependency in Union County, northeastern New Mexico. Ewis Omran (13) showed that universal kriging can be considered as an accurate new method for interpolation soil properties and showed that the amount of EC, pH, and $CaCO3$ in soil had strongly spatially dependency on soil mapping of the area. Huo et al. (16) combined the geostatistics method with Moran’s I models for preparing soil mapping of heavy metals and showed that geostatistics analysis was a useful tool for forecasting soil mapping of heavy metals and aluminum and copper amount of soil had the highest and lowest spatial correlation, respectively, in semi-arid conditions of China. Also Kavianpoor et al. (19) showed that saturation moisture and percentage of sand had the highest and lowest spatial correlation, respectively, in the Nesho, Mountainous Rangelands, Mazandaran province, Iran.

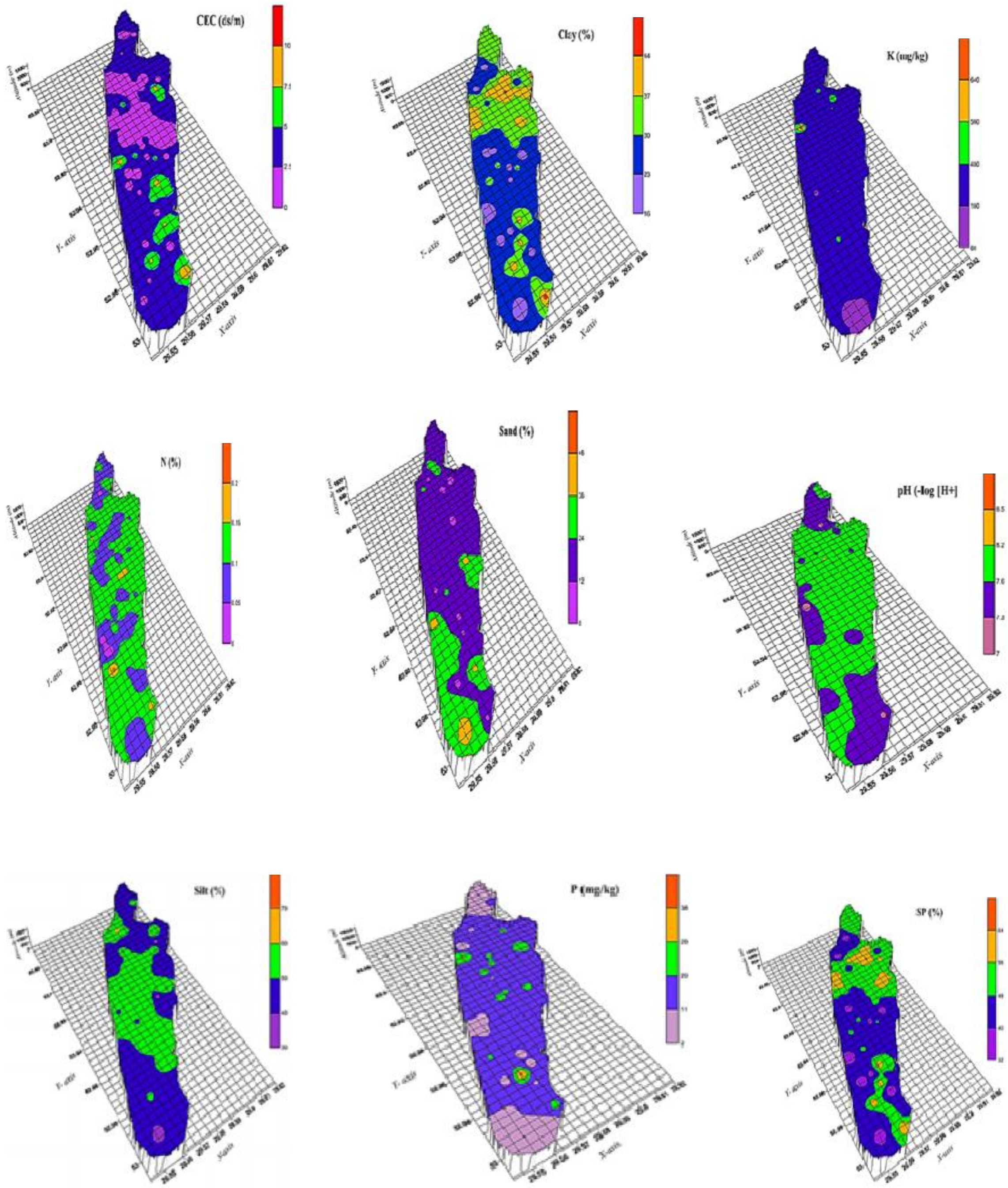


Fig. 6. Maps of soil properties prepared by ordinary kriging in the study area

CONCLUSIONS

The predicted map (Fig. 6) can be helpful to the farmers for soil management and design land management, especially for wheat. Semiovariogram models present alternative methods to conventional statistics for the estimation of soil parameters and their associated variability. In this study, the range of the Semivariogram had more widespread spatial structure. Hence, it can be used to estimate the amount of regional variable at unknown points. The ranges of some soil properties, including pH, K, N, silt, clay and P content, were higher and more widespread than other soil characteristics. The ranges were 19.1 - 134 m, showing the spatial pattern variations among soil parameters in the study area. The results of this study can be used to make recommendations for the better management and modeling of soil and plant relationships in future studies. Our results showed that the spatial distribution of soil properties might vary even within a similar agricultural management. Findings of this study can be of great help to those in charge of agricultural region to know how an area should be undertaken. Our findings showed the spatial structure found in the soil properties at the field scale in the study area. Understanding soil properties with their spatial dependency is of crucial importance for understanding the behavior of soil and hence providing better soil mangenets.

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استفاده از مدل های زمین آمار برای بررسی تغییرات مکانی برخی از ویژگی های خاک در شرق شیراز، ایران

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چکیده- ویژگی های مکانی خاک به منظور مدیریت خاک و افزایش محصول، مفید و حیاتی می باشد. تکنیک زمین آمار یکی از روش های تعیین ویژگی های مکانی خاک می باشد. هدف از این مطالعه بررسی مکانی ویژگی های فیزیکی و شیمیایی خاک برای گیاه گندم در شرق شیراز در ایران می باشد. برای این منظور، از ۸۰ نمونه خاک به طور تصادفی استفاده شد و فاکتورهایی مانند درصد اشباع، هدایت الکتریکی، pH، بافت خاک (درصد شن، ماسه، سیلت)، میزان نیتروژن ، فسفر و پتاسیم خاک، اندازه گیری شد. ویژگی های خاک بوسیله مدل های Semivariogram به طور آماری و مکانی مورد بررسی قرار گرفتند. نتایج نشان داد که بهترین مدل برای تهیه نقشه خاک در روش کریجینگ معمولی برای pH، درصد اشباع و پتاسیم در منطقه مورد مطالعه نمایی و برای دیگر فاکتورها بهترین مدل کروی می باشد. با استفاده از دامنه که یکی از پارامترهای Semivariogram می باشد، وابستگی هر یک از متغیرها نسبت به مکان بررسی گردید. pH، کمترین وابستگی مکانی با دامنه ۱۹/۱ متر و هدایت الکتریکی بیشترین وابستگی مکانی را با دامنه ۱۳۴ متر در منطقه مورد مطالعه نشان دادند. بنابراین نتایج نشان داد که استفاده از مدل های Semivariogram به منظور بررسی ویژگی های خاک و تعیین وابستگی مکانی متغییرها و تهیه نقشه خاک به منظور راهبرد مدیریت گیاهان زراعی مفید می باشد.

واژه های کلیدی: زمین آمار، کریجینگ معمولی، مدیریت مزرعه، ویژگی های خاک

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**به ترتیب استادیار ، استادیار و استادیار

**مکاتبه کننده