



Spatial variability of Soil fertility using soil chemical data, Atrush area, Duhok, Kurdistan region, Iraq

Lida I.¹, Omar A.O. Rekani¹, Vahil I. H. Barwari¹, Sipal M. Taher¹

1 Department of Soil and Water Sciences, Faculty of Agriculture and Forestry, University of Duhok, Duhok, Kurdistan Region–Iraq.

Corresponding author's email address: lida.issazadeh@uod.ac

Article info

Original:
13 October 2015
Revised:
10 May 2016
Accepted:
5 June 2016
Published online:
20 September 2016

Key Words:

Geostatistics, Semi-variogram, Soil properties, spatial variability

Abstract

One of the basic factors in sustainable crop production is enhancing soil quality based on the soil fertility and returning absorbed nutrition by plants to the soil. In this spatial research variability of soil properties in Atrush area in Duhok province, Iraq was conducted based on the 15 soil samples with randomized method were taken from different locations. Statistical analysis by SPSS and spatial distribution and interpolation of soil properties by GS⁺ software was done. Results showed all studied soil parameters such as pH, EC, %OM, percent of sand, silt and clay, %total N, available P and K had normal distribution. Strong spatial dependence related to the percent of organic matter, sand and clay percent, percent of total nitrogen, available phosphorus and potassium while pH, EC, and percent of silt showed moderate spatial dependence. The variogram model were spherical for pH, EC, %OM, %clay and % total nitrogen while for sand percent and available P were linear and for available K and percent of silt were exponential. Spatial interpolation accuracy and precision by MAE, MBE and RMSE showed Kriging prediction maps for pH, EC, %OM, %N, and available K had most accurate predictions with the lowest error, therefore, it can provide useful information about urban planning and environmental management.

Introduction

Spatial variability of soil properties is affected by parent materials, landforms and soil management. Soil evaluation studies and its physical, chemical and biological properties are conducted based on the normal distribution of data [1]. In some researchers by Dahiya *et al.* [2], some soil variables such as bulk density, texture, electrical conductivity, and soil nutrients have a normal distribution, but infiltration and exchanged cations have logarithmic distribution [3]. All soil variables distribution is studied by the physiographic condition in the research area [4].

Soil properties have spatial and temporal distribution from small to large scale that is affected by intrinsic and external characteristics [5],[6]. To obtain optimum agriculture practices, it is necessary to assess and evaluate spatial distribution of soil properties [7].

Muhammadi [8] investigated on spatial variability on some soil properties such as EC, percent of saturated water, SAR, and percent of lime by using geostatistics predictors included kriging, co-kriging and linear regression. Results showed between applied methods; Kriging method was the best model to predict spatial data. [9] studied on some soil chemical properties and showed soil properties have high spatial variability. The most variability coefficient related to available phosphorus and the lowest to the pH parameter. Statistical

analysis showed all soil properties had spatial dependence and strong spatial dependence related to pH, and the rest of soil parameters had moderate spatial dependence. Young *et al.*[10]reported spatial variability of soil properties relates to scale and by decreasing the scale of variable resources to the small area, soil variables can be affected by zonal scale. Wang *et al.* [11] investigated spatial variability on total soil nitrogen and phosphorus and percent of organic matter under different land management in small watershed. They showed total soil nitrogen had moderate and weak spatial dependence in agricultural and pasture area respectively, and soil total phosphorus had strong spatial dependence in agriculture land while in pasture area had moderate spatial dependence. Soil organic carbon had moderate spatial dependence and statistical properties of %OC related to different soil and land management with topography. Ghasemi *et al.* [12] studied on spatial variability in some chemical soil properties in the north part of Khuzestan plain with 21000 ha area with systematic soil sampling. Kriging predictor Maps showed soil salinity was increased from the north to the south of plain while the shortage of soil phosphorus was reported.

Materials and Methods

A. Study area

The study area is located in Atrush, near Duhok province, in Kurdistan Region of Iraq (Fig. 1). Geographically, this area is enclosed between latitude 36°50'11" N and longitude 43°20'08" E. It has a mountainous area with elevations ranging from 800 to 1200 meters. The climate is semi-arid with 962 mm average annual rainfall during the preceding ten years. However, the topography has a great effect on rainfall distribution. The region is typified by cold and snowy winters, (especially in the elevated mountains) and warm and dry summers. Summer temperatures can be very high with a maximum recorded temperature of 33.4 °C in July, and minimum winter temperatures reach 4.3 °C in January based on data recorded in Sarsink sub-district meteorological station. The study area consists of uplifted mountains with compacted vegetation cover and rock exposure. Atrush vegetation is natural vegetation, and it is composed of a variety of trees scattered over the expanse of grassland. The main geomorphology of Atrush region is defined largely by its lithology of limestone, dolomite, and depositions of soluble salts. The soil samples were collected from different farmlands using random sampling method. Fifteen soil samples were taken at a depth 0-30 cm using auger and trowel.

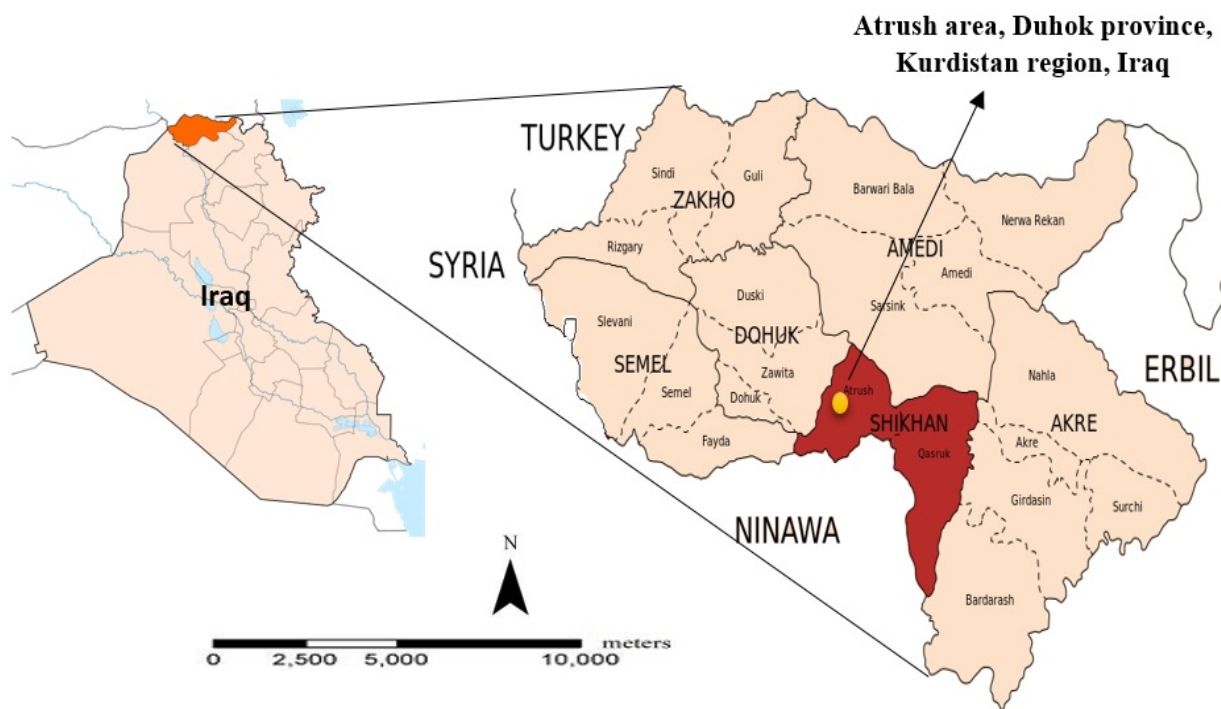


Figure-1: Physical map of study area

B. Laboratory analysis

After transporting soil samples to the laboratory, they were air dried then the sieved soil through a 2 mm sieves was applied for determining some soil physical and chemical properties. Soil texture (particle-size distribution) was determined using hydrometer method [13]. Soil pH was determined from soil suspension (1:2 soil-water ratio) using glass electrode pH meter, EC was determined using conductivity meter at 25°C in 1:2 soil-water ratio. Organic carbon was determined [14] and the values were multiplied by 1.73 to get organic matter. Total nitrogen was obtained using the Macro Kjeldahl digestion–distillation method (1965) and available P was determined using Olsen method [15]. Potassium in the extract was determined using flame photometer.

C. Statistical analysis

Descriptive analysis includes mean, median, standard deviation, skewness, and kurtosis, also normal distribution properties was computed by SPSS program. The logarithmic method was used if the data did not have a normal distribution.

D. Spatial distribution analysis

Geostatistics is a method of interpolation that predict unknown values from data observed at known locations, and it minimizes the error of estimated data that are estimated by the spatial distribution of the predicted data. The first step to apply geostatistic method is making a spatial correlation between applied data for each parameter in semi-variogram. The plot of the semivariance versus the lag h is called semi-variogram. When semi-variogram reaches to distinct level, values of properties will be spatially correlated. According to semi-variogram calculation, it is determined by distinct lag distance as follows:

$$\hat{\gamma}(h) = 1/2N(h) \sum_{a=1}^{N(h)} [z(u_a) - z(u_a+h)]^2 \quad (1)$$

Where:

$\hat{\gamma}(h)$ is the average sample semi variance to the distance h ,

$N(h)$ is the number of sample pair of points separated by the distance h and

$Z(u_a)$ is the value of variable in the point of sampling u_a .

Semi-variogram has three parameters include nugget, range, and sill. To calculate these parameters, it is necessary all data have a normal distribution, if not, data should be normalized by converting data to another form such as logarithmic or root square.

Kinds of theoretical models such as circle, linear, exponential were applied on studied variables. The model that gave a minimum standard error is chosen for further analysis. After fitted variogram plot, the kriging interpolation method is used. Kriging algorithms are described as a best linear unbiased estimator (BLUE), which is a process of a theoretical weighted moving average:

$$Y_{st}^*(X_0) = \sum_{i=1}^n \lambda_i Y_{st}(x_i) \quad (2)$$

Where

Y_{st}^* : is the estimated kriged value of Y_{st} . At the point x_0 and λ_i refers to weighing factors. The kriging variances need to be minimized. To ensure that the estimate is unbiased, the weights need to sum to one:

$$\sum_{i=1}^n \lambda_i = 1 \quad (3)$$

Thenspatial interpolation accuracy and precision were evaluated through cross-validation technique. Most important criteria include MAE (mean absolute error), MBE (mean bias error) and RMSE (root mean square error). When MAE and MBE are equal to zero or near to the nugget, it representsaclose simulation of reality and by receding to zero, kriging prediction will have high precision and less error. Also, the smallest RMSE indicate the most accurate predictions. Calculation of MAE, MBE and RMSE are as follows:

$$MBE = \frac{\sum_{i=1}^n (R_s - R_0)}{n} \tag{5}$$

$$MAE = \frac{\sum_{i=1}^n |R_s - R_0|}{n} \tag{6}$$

$$RMSE = \sqrt{1/n \sum_{i=1}^n (R_s - R_0)^2} \tag{7}$$

Where, Rs: Estimated data, R₀: Observed data, n: Number of data.

The GS⁺ Geostatistical Software Package (Gamma Design Software, version 5.1.1)was used for performing semivariance, kriging and cross-validation analyses.

Results and discussion

A. Descriptive statistics:

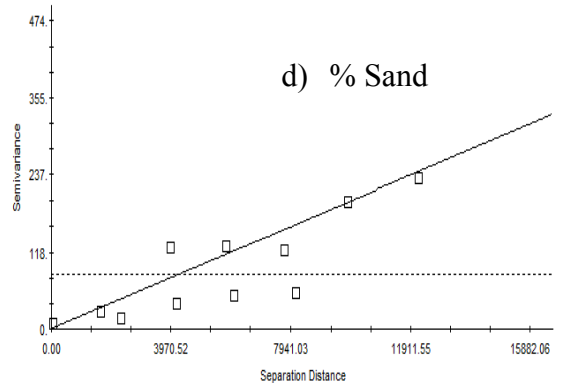
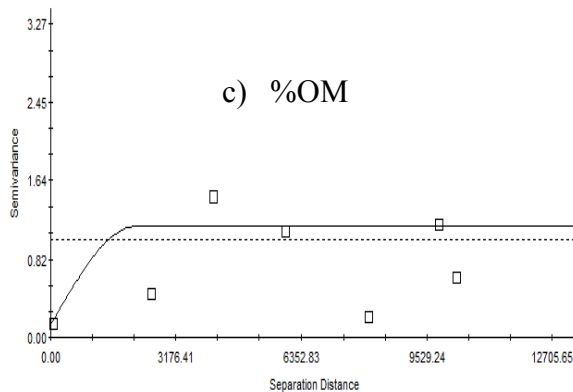
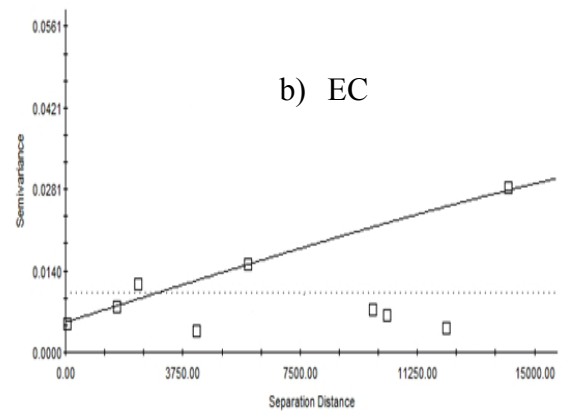
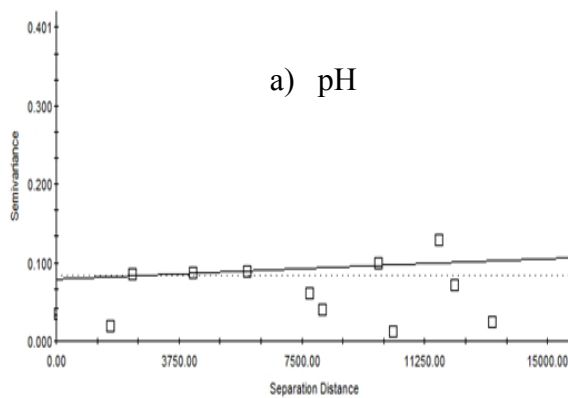
The results of descriptive analysis of soil variables and test of normality based on Kolmogorov-Smirnov test are shown in Table 1. To analyze test of normality kurtosis and skewness should be between 2 and -2 and significance difference in normality test should be more than 0.05. Also, ifthemean of data is close to median amount, it is indicated the parameter has normal distribution [16]. According tothetest of normality, all soil properties in Atrush area hadanormal distribution. Soil pH ranged from neutral (6.84) to alkaline (8.04) with a mean value of 7.28, which is indicated the soils with high pH are inherited from the CaCO₃ parent materials. The ranges of EC between 0.20 to 0.54 dS/m shows the soils in Atrush area are non-saline. The mean of soil organic matter 4.28%, which is ranged from 2.02% to 6.12% in natural forest area due to the vegetal materials accumulation.The amount of clay between 23 to 47.5% and sand content between 13 to 45% shows the soils have loam and clay loam texture. Percent of available soil nitrogen is significantly different and varied from 0.14 to 0.51% and classified from very low to very high rate. Mean available P of the soil was 7.73 ppm and mean soluble K was 11.38 ppm, and both of parameters hadalow rate.

Table 1. Descriptive analysis and test of normality of soil properties in studied area

<i>Variable</i>	<i>Mean</i>	<i>Median</i>	<i>Max</i>	<i>Min</i>	<i>Std. Deviation</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Normality sig.</i>
pH	7.28	7.30	8.04	6.84	0.29	1.01	2.00	0.84
EC (dS/m)	0.41	0.43	0.54	0.20	0.10	- 0. 69	- 0.31	0.70
%OM	4.28	4.43	6.12	2.02	1.01	- 0.70	1.29	0.71
%Sand	29.36	27.50	45.00	13.00	9.16	0.28	- 0.51	0.42
%Silt	33.80	33.00	43.00	25.00	5.89	0.21	- 0.98	0.21
%Clay	36.36	38.00	47.50	23.00	8.85	- 0.30	- 1.64	0.054
N (%)	0.33	0.37	0.51	0.14	0.12	- 0.22	- 1.23	0.63
P (ppm)	7.73	7.32	9.63	6.51	1.11	0.82	- 0.94	0.45
K(ppm)	11.38	11.41	15.99	5.85	2.61	- 0.26	-0.21	0.93

B. Semi-variogram analysis:

The fitted semi-variograms model presented in fig. 2(a)-(i). The minimum and maximum numbers of pairs in eachlag to calculate semivariance were 4 and 20 respectively. Parameters derived from the geostatistical analysis (standardized variables) for each soil parameters was shown in Table 2. To assess spatial dependence corresponding to each standardized variable the proportion of nugget semivariance/total semivariance ($C_0/C+C_0$) was used. This ratio expressed as a percentage, was used to classify spatial dependence [16], a ratio less than 25% indicated strong spatial dependence, between 25% and 75% indicated moderate spatial dependence and more than 75% indicated weak spatial dependence (Table 2). Under that proportion pH (nugget semivariance = 58%), EC (nugget semivariance = 45%) and percent of silt (nugget semivariance = 51%) showed moderate spatial dependence. On the other hand, percent of organic matter (nugget semivariance = 11%), clay percent (nugget semivariance = 9%), sand percent (nugget semivariance = 0%), total nitrogen percent (nugget semivariance = 10%), available phosphorus (nugget semivariance = 0%) and available potassium (nugget semivariance = 0%) presented strong spatial dependence. Cambardella *et al.* [17] showed strong spatial dependence maybe affected by intrinsic resources of soil, and weak spatial dependence could be controlled by non-intrinsic changes in soil. It could be concluded that variability of soil and plant production is related to soil formation. In this study, based on the spatial pattern for each soil parameters, different ranges of spatial dependence were obtained. Except total percent of nitrogen, all studied soil parameters correlation larger than 20 km. The different ranges of spatial correlation between soil properties relate to different response to many environmental factors such as erosion and sediment factors, slope, parent material and human activity [18]. On the other hand, it's necessary to use different semi-variogram models to describe the semi-variograms. Spatial patterns of soil pH, EC, %OM, %clay and % total nitrogen, were described by the spherical model (Fig. 2).



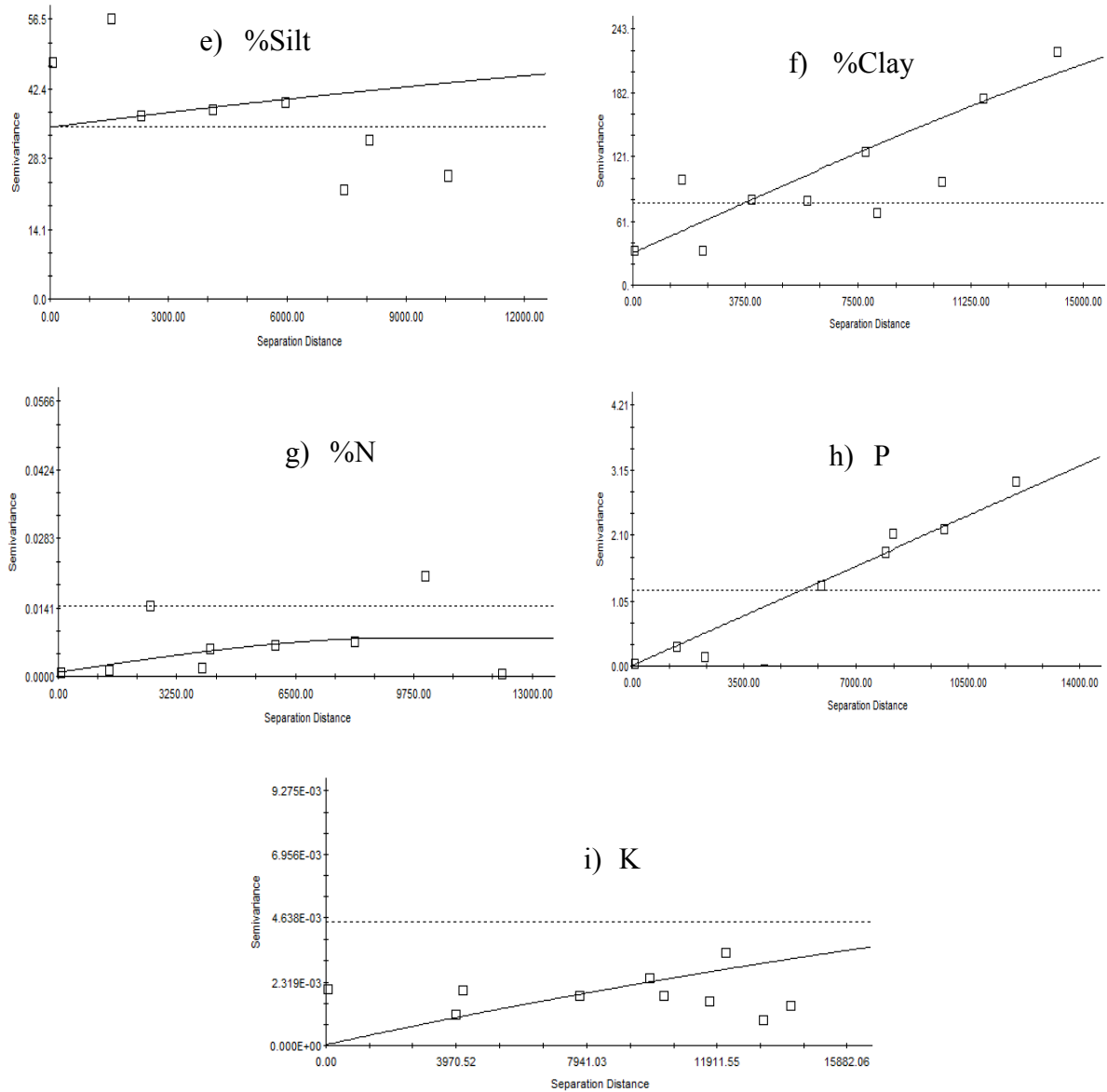
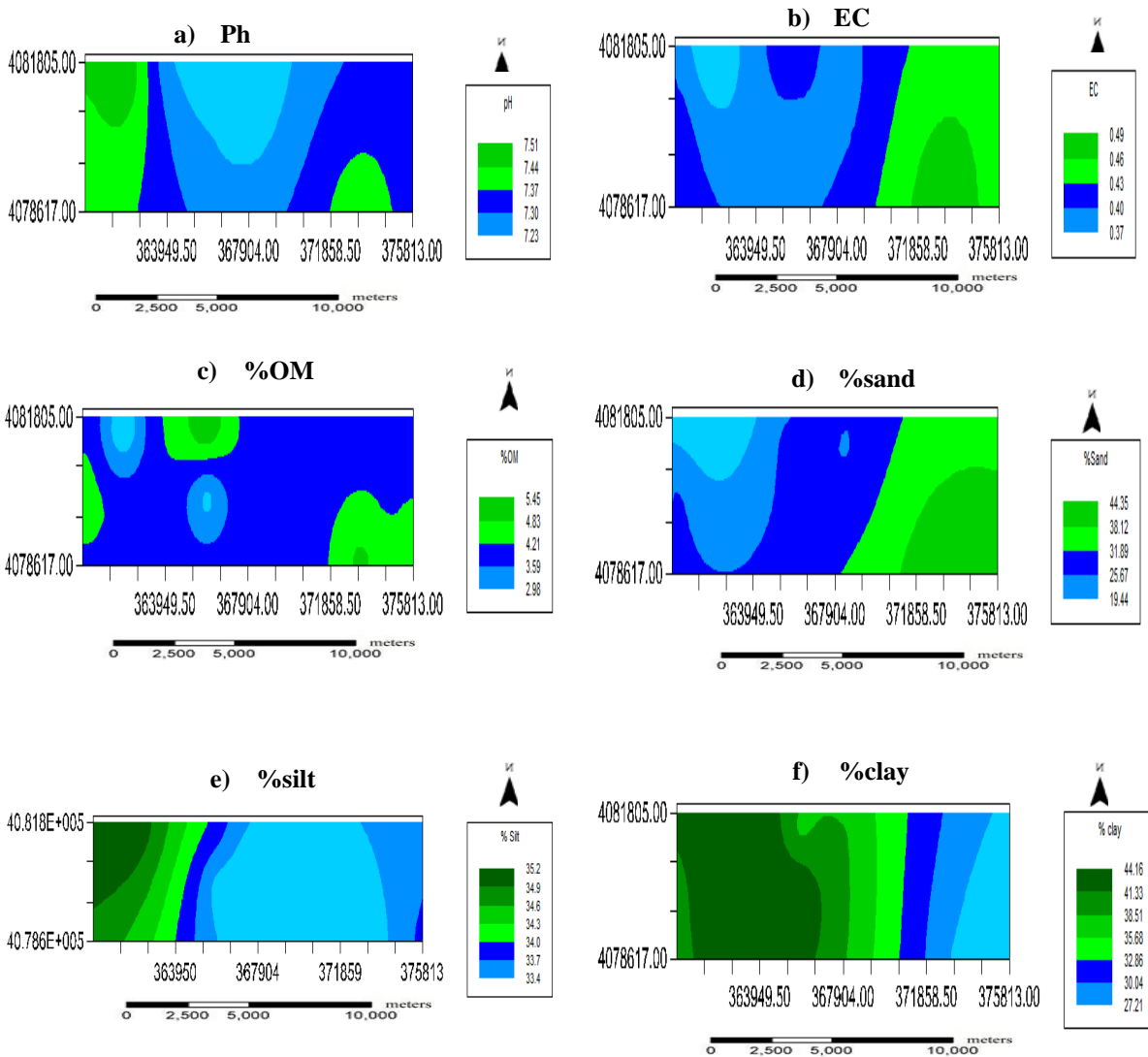


Figure- 2: Semi-variogram and spatial models for each soil properties

Table 2. Models and results of semi-variogram for soil chemical properties in study area

Parameter	Best model	Range (km)	Sill (m) (C+C ₀)	Nugget (C ₀)	Proportion C ₀ /C+C ₀	Spatial dependence
pH	spherical	41	0.12	0.07	0.58	Moderate
EC (dS/m)	Spherical	30	0.02	0.009	0.45	Moderate
%OM	Spherical	21	1.16	0.13	0.11	Strong
%Sand	Linear	25	510	1	0.00	Strong
%Silt	Exponential	31	67.21	34.60	0.51	Moderate
%Clay	Spherical	32	307	30	0.09	Strong
N (%)	Spherical	9.5	0.008	0.0008	0.10	Strong
P (ppm)	Linear	20	4.67	0.01	0.00	Strong
K(ppm)	Exponential	41	0.01	0.00	0.00	Strong

Fig. 3 (a)-(i) presented prediction kriging maps for each individual spatial pattern of soil properties. The selected cell size was 2*2 m to divide study area into a grid system and 16 neighbors within a radius equal to the range of the semi-variogram for kriging interpolation. From the spatial distribution of pH and percent of organic matter values, they distributed in high amount in west and south-east, low values were located in the center. The high amount of EC and percent of total nitrogen location were in the east and low values in the west. Low values of percent of silt and clay in the east and high amounts location were in the west while the distribution of sand was vice versa. Spatial distribution of phosphorus with high amount was in the center and east and low values in the west. The comparison between the amount of available P and pH indicated locations with lower pH had much more available P. Potassium distribution with high values in study area approximately was uniform.



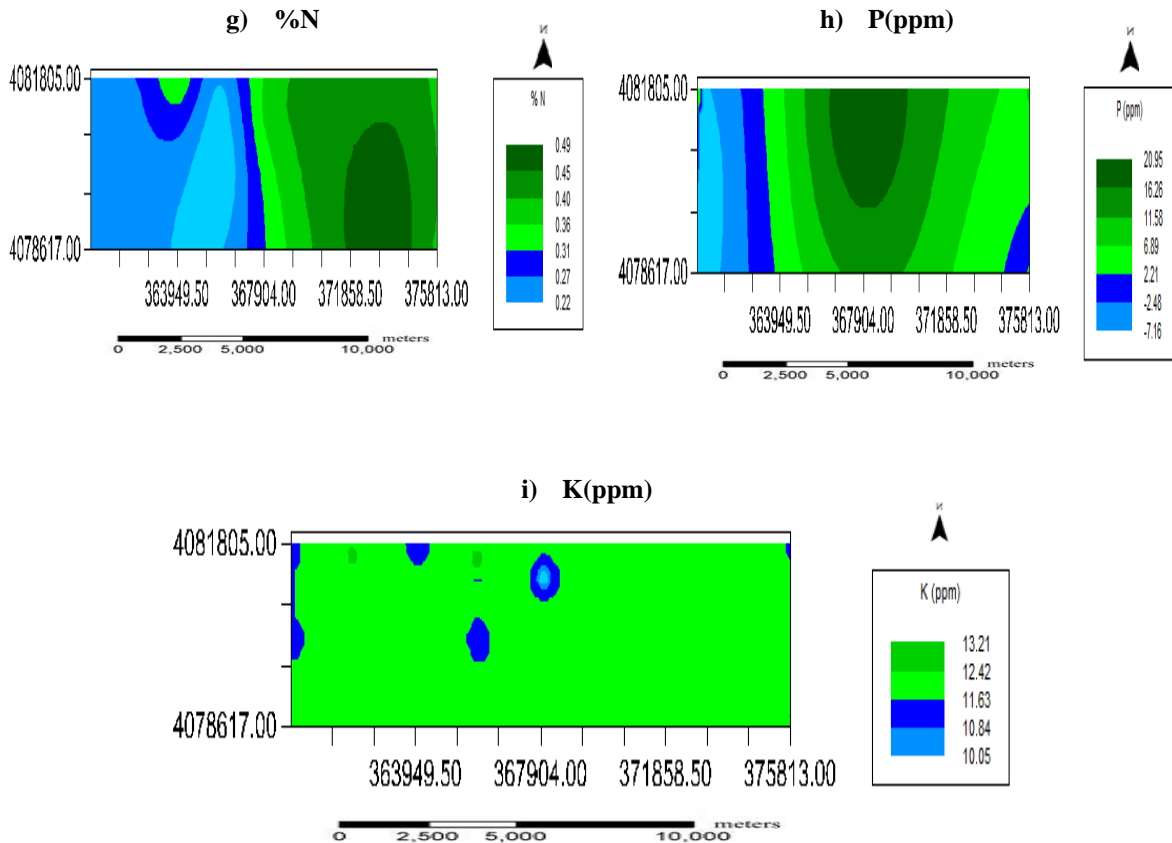


Figure-2: Kriging prediction maps for each soil properties

Kriging cross-validation results are shown in Table 3. Based on MAE, MBE and RMSE, pH, EC, %OM, %N and available K had most accurate predictions with the lowest error. In the other hand, the lowest precision to predict values in un-sampled points with high amount of MAE and RMSE relates to the percent of sand, silt and clay, also available phosphorus.

Table 3. Cross-validation statistics for soil chemical properties in study area

Parameter	MBE	MAE	RMSE
pH	0.00	0.00	0.29
EC (dS/m)	0.00	0.09	0.11
%OM	0.00	0.74	1.04
%Sand	0.81	4.33	10.19
%Silt	-0.04	5.30	6.31
%Clay	-0.26	5.29	6.61
N (%)	0.00	0.06	0.08
P (ppm)	-0.10	4.34	4.45
K(ppm)	-0.01	1.76	2.30

Conclusion

All soil parameters in the study area had a normal distribution. In this research, spatial dependence in pH, EC and percent of silt showed moderate spatial dependence and percent of organic matter, clay percent, sand percent, total nitrogen percent, available phosphorus, available potassium had strong spatial dependence. The best-fitted model for soil pH, EC, %OM, %clay, and % total nitrogen were described by the spherical model, whereas available K and %silt were an exponential and linear model for available P and percent of sand. The kriging prediction maps were successfully applied for most soil properties such as pH, EC, %OM, %N, and available K. It can be concluded that geostatistics method is an important tool to study and investigate spatial variability of soil properties.

References

- [1] Backett PHT and Webster R. "Soil variability: A review". *Soil Fert* Vol.34, pp 1-15, (1971).
- [2] Dahiya IS, Richter J, and Malik RS. "Soil spatial variability:A review". *Int J Trop Agric* Vol.11, pp 1-102, (1984).
- [3] Yost RS and Fox RL."Partitioning variation in soil chemical properties of some Andepts using soil taxonomy". *Soil SciSoc Am J* Vol. 45, pp 373-377, (1981).
- [4] Jafarzadeh AA, Dawatgar N and Hakaimian M. "Investigation normality of selected soil variables in different physiographic units in Khazar Sea".*Tabriz agriculture journal*.Vol 8, pp. 147-170. (1998).
- [5] QuineTA, and Zhang Y. "An investigation of spatial variation in soil erosion, soil properties and crop production within an agricultural field in Devon, UKJ". *Soil and Water Cons* Vol. 57, pp 50- 60, (2002).
- [6] Yemefack M, RossiterDG and yomgang RN."Multi-scale characterization of soil variability within an agricultural landscape mosaic system in southern Cameroon".*Geoderma* Vol.125, pp 117- 143, (2005).
- [7] Sun Bo, Shengiu Zhou, Qiguo Zhao. "Evaluation of spatial and temporal changes of soil quality based on geostatistical analysis in the region of subtropical China". *Geoderma* Vol.115, pp 85-99, (2003).
- [8] Mohammadi J. "Evaluation and mapping of soil salinity hazard in Ramhormoz area (Khuzestan) using disjunctive kriging". *Journal of Agricultural Research* Vol. 25, pp 45-57, (2000).
- [9] Cetin M and Kirda C. "Spatial and temporal changes of soil salinity in a cotton field irrigated with low-quality water". *J Hydrol* Vol. 272, pp 238-249, (2003).
- [10] Young FJ, Hammer RD and Larsen D. "Frequency distribution of soil properties on a loessmantled Missouri watershed". *Soil SciSoc Am J* Vol. 63, pp 178-185, (1999).
- [11] Wang YQ, Zhang XC, Zhang JL and Shun-Ji LI. "Spatial variability of soil organic carbon in a watershed on the loess Plateau".*Pedosphere* Vol.19, pp 486-495, (2009).
- [12] Ghasemi VR, Shahbazi K, MohammadiJ and Mashayekhi HM. "Spatial variability of some soil fertility properties in the north part of Khuzestan plain". 8th soil science congress, Rasht, Iran. (2003).
- [13] Bouyoucos, G. J. "Hydrometer method improved for making particle size analyses of soils". *Agronomy Journal*, Vol. 54, pp 464-465, (1962).
- [14] Walkley A, Black IJ. "An examination of the Degtjaref method for determining organic carbon in soils: effect of variations in digestion conditions and of inorganic soil constituents". *Soil Sci*. Vol. 63, pp 251–263, (1934).
- [15] Olsen SR and Sommers LE. Phosphorous, Al, Miller RH and Keeney DR (Eds). "Methods of Soil Analysis. Part 2", *Soil SciSoc of Am*. Madison, WI , pp 403-427, (1986).
- [16] Godwin, R. J., and Miller, P. "A review of the technologies for mapping within- field variability". *Biosystems Engineering*, Vol. 84, pp 393-407, (2003).
- [17] Cambardella CA, Moorman TB, Novak JM, Parkin TB, Karlen DL, Turco RF and Konopka AE."Field-scale variability of soil properties in central Iowa soils". *Soil Sci. Soc Am J* Vol. 58, pp 1501-1511, (1994).
- [18] Tesfahunegn G.B., L. Tamene, P.L.G. Vlek. "Catchment-scale spatial variability of soil properties and implications on site-specific soil management in northern Ethiopia".*Soil Till. Res*. Vol.117, pp 124-139. (2011).

