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Determination of Cd, Zn, K, pH, TNV, Organic Material and Electrical Conductivity (EC) Distribution in Agricultural Soils using Geostatistics and GIS (Case Study: South-Western of Natanz- Iran)

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***Abstract*—**Soil chemical and physical properties have important roles in compartment of the environment and agricultural sustainability and human health. The objectives of this research is determination of spatial distribution patterns of Cd, Zn, K, pH, TNV, organic material and electrical conductivity (EC) in agricultural soils of Natanz region in Esfehan province. In this study geostatistic and non-geostatistic methods were used for prediction of spatial distribution of these parameters. 64 composite soils samples were taken at 0-20 cm depth. The study area is located in south of NATANZ agricultural lands with area of 21660 hectares. Spatial distribution of Cd, Zn, K, pH, TNV, organic material and electrical conductivity (EC) was determined using geostatistic and geographic information system. Results showed that Cd, pH, TNV and K data has normal distribution and Zn, OC and EC data had not normal distribution. Kriging, Inverse Distance Weighting (IDW), Local Polynomial Interpolation (LPI) and Redial Basis functions (RBF) methods were used to interpolation. Trend analysis showed that organic carbon in north-south and east to west did not have trend while K and TNV had second degree trend. We used some error measurements include, mean absolute error(MAE), mean squared error (MSE) and mean biased error(MBE). Ordinary kriging(exponential model), LPI(Local polynomial interpolation), RBF(radial basis functions) and IDW methods have been chosen as the best methods to interpolating of the soil parameters. Prediction maps by disjunctive kriging was shown that in whole study area was intensive shortage of organic matter and more than 63.4 percent of study area had shortage of K amount.

***Keywords*—**Electrical conductivity, Geostatistics, Geographical Information System, TNV

I. Introduction

SOIL management systems and environments play an important role in sustainable agriculture. Management systems such as soil tillage, fertilization and irrigation systems have numerous effects on the soil physical and chemical properties. Soil quality and its effects on the ecosystem have been studied by some researchers [8]. Soil chemical and physical properties are severely affected by inherent soil factors (pedogenic factors) and external factors (soil management, fertilization and tillage) [1]. To understand the effects of the soil properties and soil management on land use changes in ecosystems, quality and quantity should be shown. During the last decades, Geostaistical methods are intensively used to estimate spatial variability and mapping distribution patterns of soil properties [2,5]. Geographic Information System (GIS) to collect, store, and analyze data and imagery can be for scientific research, resource management, environmental impact assessment, urban management, Cartography and used to plan roads. GIS-based models have been used for other aspects of as soil studies, such as environmental studies, hydrology and land degradation [9] environmental assessment risks [4]. The objective of this study was to determine spatial distribution patterns of Cd, Zn, K, pH, TNV organic material, and electrical conductivity (EC), in Esfehan province-Natanz agricultural soils using geostatistics and GIS.

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II. Materials And Methods

The Natanz region extends for about 1095 km^2 in central of Iran. The study area is bounded by longitude 51°55′-52°26′ East and latitude 33˚ 31′ - 33˚ 49′ North, encompassing an area of 731 km^2. The region is characterized by small variability in lithology, pedological features and large variability in land use. The climate is typically Semiarid, with a maximum and minimum annual temperature of 38.5 and -6˚C respectively. An average annual rainfall is 142mm. 65 component soil samples, consisting of five subsamples, were taken from the upper 0–30-cm layer. The locations of all sample sites were recorded using a global position system (GPS). All samples were air-dried at room temperature (20–22 °C). The prepared soil samples were then stored in polyethylene bottles for analysis. Soil samples were hand-sieved through a 2-mm screen to remove roots and other debris (discarded). Soil organic carbon (SOC) was measured by the dichromate oxidation method of Walkey and Black [7]. Cd and Zn were analysed using a strong acid digestion method [6] .In addition, Spatial distribution for Cd, Zn, organic carbon, pH, electrical conductivity (EC), in each dune site were analyzed using geostatistical techniques. Geostatistical techniques evaluate the autocorrelation commonly observed in spatial data, where data values from locations close to each other are more similar than data values from locations far apart [3]. Spatial autocorrelation analysis provides a quantitative estimate of the spatial correlation between the two samples as a function of their separation distance [3]. This spatial analysis used the semivariance estimated by:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \qquad (1)$$

Where c (h) is the semivariogram expressed as a function of the magnitude of the lag distance or separation vector h, N. (h) is the number of observation pairs separated by distance h, and $z(x_i)$ is the regionalized variable at location xi. The experimental variogram is calculated for several lag distances. The experimental semivariogram, γ (h) is fitted to a theoretical model such as Spherical, Exponential, Gaussian and Linear to determine three parameters, such as the nugget (c_0), the sill (c) and the range (A_0). These models are defined as follow [3]:

Exponential model:

$$\gamma(h) = c_0 + c\left[1 - \exp\left(-3\frac{h}{A_0}\right)\right] \qquad (2)$$

Gaussian model:

$$\gamma(h) = c_0 + c\left[1 - \exp\left(\frac{3h}{A_0}\right)^2\right] \qquad (3)$$

Using different interpolation parameters mean bias error (MBE), mean absolute error (MAE) and the root mean square error (RMSE) were evaluated. Distribution maps were generate using the best selected models.

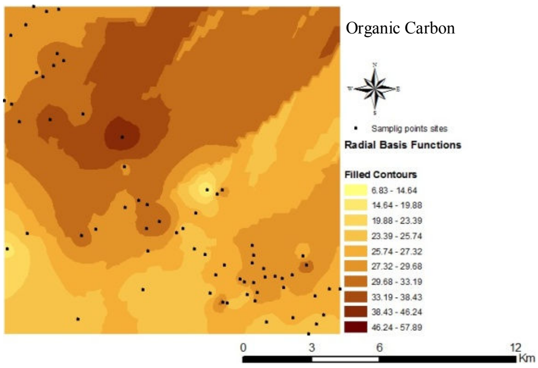
III. Result And Discussions

The distribution of the variables in soils should be normal in geostatistics. Row data often are abnormal and then impair the semivariance structure and the kriging results. Therefore, data transformation is necessary to normalize such data sets. The statistical parameters and skewness and kurtosis for all of the raw data describing the heavy metals were high, and these data did not pass the Kolmogorov– Smirnov (K–S) test for normality ($p > 0.05$). Log transformation resulted in smaller skewness, and kurtosis values for all soils parameters, P passed the lognormal test but OC, N, SP, Zn and Cd was not passed.

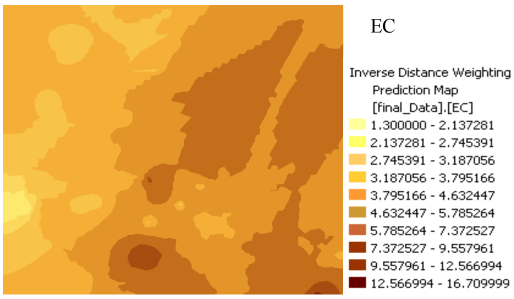
Table I gives the summary statistics of the data sets for soils parameters. It is shown that the kurtosis and skewness values for pH, EC, TNV and OC were low, however, that for Zn, OC and EC were high and these three parameters were not normally distributed. The kurtosis and skewness values for Zn, OC and EC decreased after the raw data sets were logarithmically transformed. The highest coefficients of variation was 49.25%, 51.51%, 65.62% and 51.68% in Zn, OC, EC and K respectively, suggesting that Zn, OC, EC and K had greater variation among the soils.For the evaluation of the degree simulation quality and the model–experiment comparison of different model approaches, cross-validation indicators and additional model parameters can be used. For comparing these models, we used cross validation by the statistical parameters mean absolute error (MAE), mean bias error (MBE) and root mean square error (RMSE). To make distribution maps out of sampled data, some geostatistis and non geostatistics spatial interpolation techniques were used, including Inverse Distance Weighting (IDW), Global/Local Polynomial Interpolation (G/LPI), Radial Basis Functions (RBF) and kriging. Table 2 shows the best interpolation method for each soil parameters. Ordinary kriging was selected for OC and Cd with 0.33 and 1.58 respectively for MAE. N and Zn interpolated with IDW and finally P and SP interpolated with LPI and RBF respectively.Semivariograms showed that soil OC and Cd were all fitted for Gaussian model, while pH fitted with spherical model. The Nug/Sill ratios of these parameters were between 41.54% and 36.54%. After choosing the best method of interpolation for the distribution of organic carbon, K, TNV, EC, pH, Zn and Cd final prediction maps were drawn.Final distribution maps show that average organic matter content in study area is very low (less than 0.5%). The lack of organic matter and soil humus needed because the soil had neglected the needs of farmers. K analysis data and distribution map showed that less than half a percent of the total area of the study area (145 ha) has K deficiency. Interpolation maps showed that in north-eastern and south-eastern parts of the study area has higher amounts of EC. Results showed that the amount of pH in the study area in south and central study area is a severe shortage. Prediction maps by disjunctive kriging was shown that in whole study area was intensive shortage of organic matter and more than 62.4 percent of study area had shortage of K amount.

TABLE II
Soil Statistical Parameter Interpolation Method With Errors In Agricultura

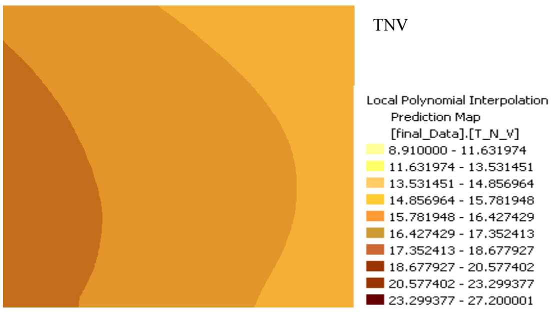
Soil parameter	Interpolation method	RMSE	MBE	MAE
Cd	Ordinary Kriging	0.18	0.29	0.42
Zn	IDW	3.58	0.68	1.58
OC	Ordinary Kriging	0.14	-0.055	0.33
TNV	LPI	3.97	0.008	3.06
EC	IDW	3.24	0.011	2.36
pH	Ordinary Kriging	0.316	0.005	0.243
K	RBF	150.6	2.23	109.75



(A)



(B)



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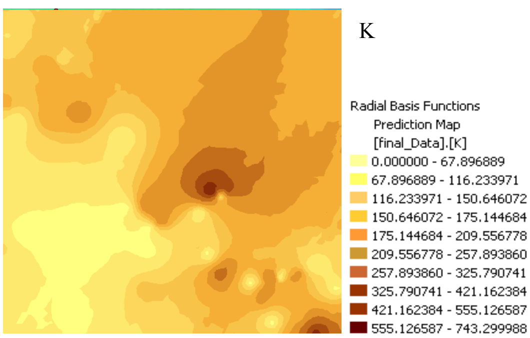

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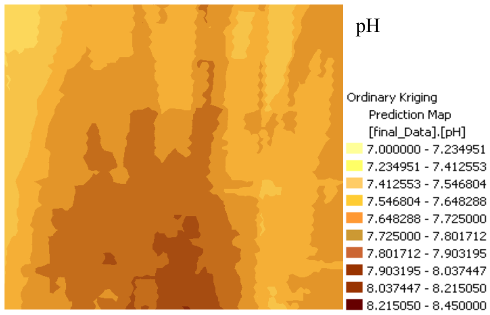

(E)

Fig. 1 Prediction maps of organic carbon, pH, TNV, EC and K

REFERENCES

[1] Cambardella CA, Karlen DL. Spatial analysis of soil fertility parameters. *Precision Agriculture*, 1999. 1: 5-14.

[2] Dercon G, Deckers J, Govers G, Poesen J, Sanchez H, Vanegas R, Ramirez M, Loaiza G. Spatial variability in soil properties on slow-forming terraces in the Andes region of Ecuador. *Soil & Tillage Research*, 2003, 72: 31-41.

[3] Isaaks, E., & Srivastava, R. (1989). Applied geostatistics (p. 561). New York: Oxford University Press.

[4] Kolat, C., Doyuran, V., Ayday, C., Su¨ zen, M.L.. Preparation of a geotechnical microzonation model using Geographical Information Systems based on Multicriteria Decision Analysis. *Engineering Geology*, 2006, 87:241–255.

[5] Lark RM. Optimized spatial sampling of soil for estimation of the variogram by maximum likelihood. *Geoderma,*(2002, 105: 49-80.

[6] Li XD, Lee SL, Wong SC, Shi WZ, Thornton I. The study of metal contamination in urban soils of Hong Kong using a GIS-based approach. *Environmental Pollution,* 2004, 129:113– 24.

[7] Nelson, D., & Sommers, L. Total carbon, organic carbon and organic matter. In A. L. Page, et al. (Eds.), Methods of soil analysis, part 2, no. 9 (2nd ed., pp. 539–577). 1982. Madison: ASA Publication.

[8] Paz-Gonzalez A, Vieira SR, Taboada Castro MaT. The effect of cultivation on the spatial variability of selected properties of an umbric horizon. *Geoderma*, 2000, 97: 273-292.

[9] Wang, X., Qin, Y. Spatial distribution of metals in urban topsoils of Xuzhou (China): controlling factors and environmental implications. *Environmental Geology*. 2006, 49:905–914.

TABLE I
SOIL STATISTICAL PARAMETER IN AGRICULTURAL SOILS

Soil parameters	Cd	Zn	OC	pH	EC	TNV	K
Mean	0.32	189	0.3316	7.741	5.355	16.785	240.315
Std. Deviation	0.37	78.23	0.176	0.317	3.510	3.772	124.197
Skewness	6.24	3.56	-0.034	-0.338	1.776	0.211	1.887
Kurtosis	14.25	11.65	-0.840	0.173	3.403	-0.014	4.680
Range	0.34	288	0.70	1.45	16.58	18.29	643.30
Minimum	0.14	17	0.01	7.00	1.30	8.91	100.00
Maximum	0.48	305	0.71	8.45	17.88	27.20	743.30
CV%	14.36	49.25	51.51	4.09	65.62	22.47	51.68
KS	0.62	0.023	0.046	0.855	0.017	0.951	0.651