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Simulation of Organic Matter Variability on a Sugarbeet Field Using the Computer Based Geostatistical Methods

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***Abstract*—**Computer based geostatistical methods can offer effective data analysis possibilities for agricultural areas by using vectorial data and their objective informations. These methods will help to detect the spatial changes on different locations of the large agricultural lands, which will lead to effective fertilization for optimal yield with reduced environmental pollution. In this study, topsoil (0-20 cm) and subsoil (20-40 cm) samples were taken from a sugar beet field by 20 x 20 m grids. Plant samples were also collected from the same plots. Some physical and chemical analyses for these samples were made by routine methods. According to derived variation coefficients, topsoil organic matter (OM) distribution was more than subsoil OM distribution. The highest C.V. value of 17.79% was found for topsoil OM. The data were analyzed comparatively according to kriging methods which are also used widely in geostatistic. Several interpolation methods (Ordinary, Simple and Universal) and semivariogram models (Spherical, Exponential and Gaussian) were tested in order to choose the suitable methods. Average standard deviations of values estimated by simple kriging interpolation method were less than average standard deviations (topsoil OM ± 0.48, N ± 0.37, subsoil OM ± 0.18) of measured values. The most suitable interpolation method was simple kriging method and exponantial semivariogram model for topsoil, whereas the best optimal interpolation method was simple kriging method and spherical semivariogram model for subsoil. The results also showed that these computer based geostatistical methods should be tested and calibrated for different experimental conditions and semivariogram models.

***Keywords*—**Geostatistic, kriging, organic matter, sugarbeet.

I. Introduction

SOIL organic matter is the most significant source of total soil nitrogen. Under normal circumstances organic nitrogen compounds, being exposed to weathering, turns into beneficial nitrates for plants. However, soil organic matter in agricultural areas or densely cultivated lands is quite changeable. For instance, due to dense cultivation or the method of cultivation, soil's organic matter is rapidly exposed to losses [1]. On the other hand, the same soil structure can show great differences in terms of its soil organic matter depending on soil development on lands which have the same soil structure, topography and drainage. All in all serial or even on farm scale it has been known for a long time that soil characteristics vary critically according to distance [2].

It has been emphasized that quantitatively important yield variation might occur over distances as short as 10 m, however, only some factors such as soil structure, water status, pH, nutrient levels, weeds, pests and diseases can be controlled but not the others such as soil texture, weather, topography [3]. For instance, homogeneous fertilization program based on mixed soil sampling may cause loss of plant nutrients, pollution of natural resources and economic losses. It is quite a necessity to employ technological developments in agricultural lands so as to perform a more economical and profitable agriculture management. Especially, use of advance technologies and detecting of changes for different locations on the land are important steps in precision farming and effective fertilization for both crop yield and quality [4, 5, 6].

Researchers have abstained from using geostatistical methods for a long time due to the complexity and difficulty in measurements. Recently, these handicaps were greatly eliminated by commonly using of micro-computers and availability of package software of these methods [7, 8]. However, the models based on computer programs should be evaluated and correlated depending on varied experimental conditions. Contrary to traditional statistics, geostatistical approach assumes that there exists a correlation between data obtained from two separate points on land. In evaluating spatial change by geostatistical approach, heterogeneity based on distance can be measured by using the relation between observations related to the structure of any soil on different points close to one another. By making use of observed values, through kriging method and semivariogram model that best fit to the data values of non-sampled points can be estimated. As a matter of fact, these geostatistical methods can be tested for environmental aspect or spatial analysis can also be made for many varied conditions [9, 10, 11].

Via these computer based applications for agricultural areas, it is possible to fertilize the land in a more healthy and moderate way. In that way it will be possible to add required

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nutrients of a plant, and also fertilizer loss will be prevented in areas which do not give economic responses to fertilization. It will be rewarding to extend geostatistical methods and calibrate these methods according to different regions and conditions to minimize the difficulties stemmed from dense sampling and analyses occurred during precision fertilization applications.

II. Materials and Methods

Geostatistical analyses of research data were studied by Geostatiscial analyst module of ArcMap 9.1 GIS software by ESRI [12]. The processes of definitive statistical information of the chemical properties of soil samples and sorting of the excess values were done by SPSS 11.5 statistics program. Also 3D analyst module has been used for three dimensional mapping of research data. In this study, topsoil (0-20 cm) and subsoil (20-40 cm) samples on a sugarbeet field in Turhal-Tokat region, Turkey were collected based on 20 x 20 m grids. Plant samples were also collected from the same plots. The soil and plant samples were prepared for analysis. Some physical and chemical analyses were made by routine methods. Experimental data concerning with measured values were subjected to the statistical analysis using StatMost package program [13]. In the soil samples, available phosphorus analysis was made by the method of [14]. Determinations were also made for saturation percent [15], $CaCO_3$ [16], pH [17], electrical conductivity (E.C.) [15] and organic matter contents [18] for both topsoil and subsoil samples. For the plant samples, nitrogen analysis were made by the method of [19]. In the experimental topsoils; saturation percent was 54.19 %. Average value of $CaCO_3$ was 77.6 kg^{-1}, pH was 8.13, available soil phosphorus was 17.84 kg P_2O_5 da^{-1} and EC was 441 µmhos cm^{-1}. In the subsoils; saturation percent was 58.11%. Average value of $CaCO_3$ was 83.5 g kg^{-1}, pH was 8.11, available soil phosphorus was 7.85 kg P_2O_5 da^{-1} and EC was 522 µmhos cm^{-1}.

Topsoil organic matter (OM), subsoil OM and plant nitrogen (N) data were analyzed through kriging analysis using geostatistical interpolation method. To achieve cross-validation, distribution percentages were formed by using all kriging interpolation methods (Ordinary, Simple, Universal) and some suitable semivariogram models. Each thematic map is generated by the use of kriging. An isotropik variogram was computed for each measured variable and then a suitable model was fitted to the variogram in order to create a continuous surface. Several interpolation methods (ordinary, simple, and universal) and models (Spherical, Exponential, and Gaussian) were tested in order to choose the suitable methods and the appropriate models. The semivariogram is defined as: $\gamma(\mathbf{s}_i,\mathbf{s}_j) = \frac{1}{2} \operatorname{var}(Z(\mathbf{s}_i) - Z(\mathbf{s}_j))$, where *var* is the variance.

If two locations, s_i and s_j, are close to each other in terms of the distance measure of $d(s_i, s_j)$, then you expect them to be similar, so the difference in their values, $Z(\mathbf{s}_i) - Z(\mathbf{s}_j)$, will be small. As s_i and s_j get farther apart, they become less similar, so the difference in their values, $Z(\mathbf{s}_i) - Z(\mathbf{s}_j)$, will become larger. Theoretically when h=0, the variogram value is equal to zero [$\gamma(0) = 0$]. In addition to this, there is a limit distance value at which the change with respect to distance can be determined from data. In variogram, this arises as nugget variance “Co”. The spatial variability variogram stops its increase after a certain distance and the peak variance (sill) starts having values around “Co+ C”. The distance at which the variogram reaches the sill value is named as the effect area or range (structural distance) “a”. Values don’t have any affect on each other for distances greater than the structural distance; that is the relationship with distance is over. The model selection criteria was the value of Root Mean Square Prediction Error.

III. Results and Discussion

The definitive statistical information for the sample point data have been given in Table I. The coefficient of variance (C.V.), kurtosis and skewness values revealed that a great spatial variability occurred in organic matter content for both topsoil and subsoil. According to derived variation coefficients, top soil OM distribution was more than subsoil OM distribution. Accordingly the highest variation (17.79%) was found for topsoil OM value, whereas the lower C.V. value of 13.07% was found for subsoil. On the other hand, the lowest coefficient of variation was observed for N values. The variation coefficient for plant N content was found to be 8.9%. Asymmetry caused by outliers has a more serious effect on the form of the variogram [20]. That is why the outlier values in the data sets have been analyzed by box-plot method and only two values were deleted in the plant N data, and 23 sample values were used.

TABLE I
Site Specific Soil Organic Matter (%) and Plant N Values (%) for Sugarbeet Area

Parameters	Min	Max	Mean	C.V %	Kurtosis	Skewness
Topsoil OM	1.84	3.86	2.77	17.79	2.569	0.069
Subsoil OM	1.12	1.76	1.39	13.07	1.935	0.163
Plant N	3.50	5.16	4.30	8.90	3.302	0.345

Topsoil OM, subsoil OM and plant N data are analyzed through computer based geostatistical kriging analysis methods and some semivariogram models. To achieve cross-validation, distribution percentages were formed by using all kriging methods and suitable semivariogram model [21]. The two and three dimensional distribution maps obtained for the related elements as a result of the interpolation made by using the chosen kriging method and the semivariogram model for points the values of which are unknown have been given in Fig. 3.

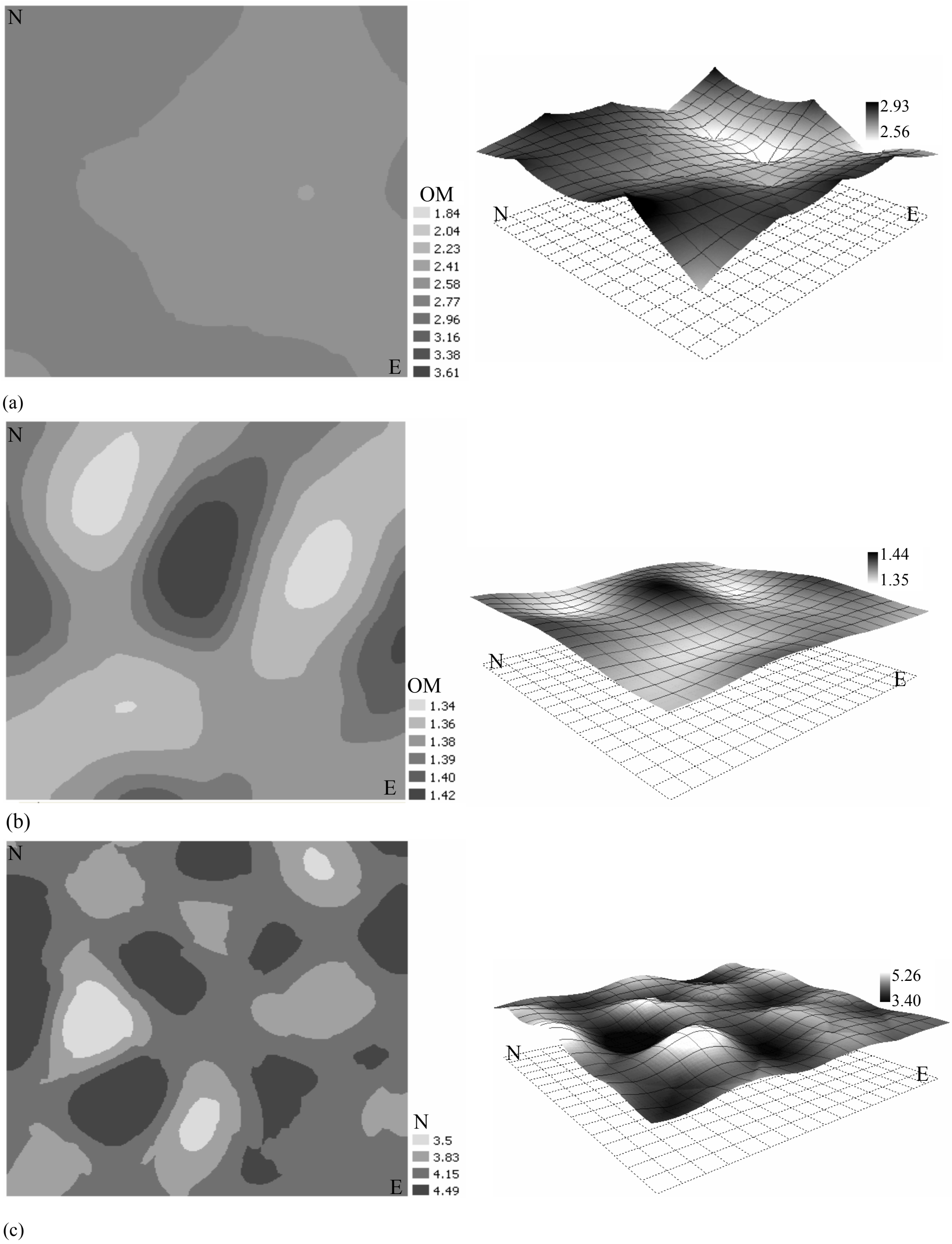

Fig. 1 Kriging maps showing distribution of topsoil OM (%) 2D and 3D (a), subsoil OM (%) 2D and 3D (b) and Plant N (%) 2D and 3D (c)

From the prediction surfaces for each element obtained by using optimal parameters, the geostatistical method and semivariogram models which give results with the lowest mean-square error have been obtained (Table II). The results of the analysis revealed that the most appropriate geostatistical interpolation method for the experimental data was simple kriging. Average standard deviations of values estimated by simple kriging interpolation method (Topsoil OM ± 0.05, N ± 0.27, Subsoil OM ± 0.02) were less than average standard deviations of measured values (Topsoil OM ± 0.48, N ± 0.37, Subsoil OM ± 0.18). For this study, simple kriging method and exponantial semivariogram model for topsoil OM, simple kriging method and spherical semivariogram model for subsoil OM was determined as the best optimal interpolation method (Table II). The characteristic properties of the semivariogram models were also presented in Table III.

TABLE II
THEORICAL MODELS TESTING FOR SOIL PROPERTIES AND RMS ERRORS

Element	Model	Ordinary Kriging (RMS)	Simple Kriging (RMS)
OM_{top}	Spherical	0.5278	0.5012
	Exponential	0.5255	0.4984
	Guassian	0.5274	0.5039
OM_{sub}	Spherical	0.1944	0.1770
	Exponential	0.1851	0.1786
	Guassian	0.1830	0.1792
N	Spherical	0.4087	0.3666
	Exponential	0.4099	0.3682
	Guassian	0.4127	0.3699

TABLE III
SEMIVARIOGRAM MODELS AND PARAMETERS FOR MODELS

Parameters	SD*. Model	Nugget C_0	Sill C_0+C	Nugget/Sill %	Range m
OM_{top}	M. Exponential	0.129	0.254	50	103
OM_{sub}	W. Spherical	0.030	0.033	90	52
Plant N	W.Spherical	0.134	0.148	90	104

* Spatial distribution (S-strong spatial dependence (< 25 %); M-modarate spatial dependence (26-75 %); W-Weak spatial dependence (> 75 %); Pure nugget-no spatial correlation (100 %) and their spatial distribution model.

In geostatistical aspect, spatial dependence is defined as the percentage ratio of nugget semivariance to the sill semivariance. In this study while the medium spatial dependency was being determined for top soil OM, weak spatial dependency was observed for sub soil OM and plant N values. The range of the chosen semivariogram was determined to be 103 m for topsoil OM, 52 m for subsoil OM and 104 m for plant N levels.

IV. CONCLUSION

Computer based geostatistical methods which can also be employed in the ambiance of Geographical Information System offer effective analysis possibilities by using vectorial data and their objective information. In this study, topsoil, subsoil and plant samples were taken from a sugar beet field. According to derived variation coefficients, the highest variation was observed for top soil OM value. For this study, the experimental data concerning with topsoil OM, subsoil OM and plant N levels were analyzed by using computer based geostatistical interpolation methods. The data were analyzed comparatively according to kriging methods, which are also used widely in geostatistic, and suitable semivariogram models. Average standard deviations of values estimated by simple kriging interpolation method were less than average standard deviations of measured values. As a result, it has been found that the most suitable interpolation method for topsoil was simple kriging method and exponantial semivariogram model, whereas the best optimal interpolation method for subsoil was simple kriging method and spherical semivariogram model. The results also showed that these computer based geostatistical methods should be tested and calibrated for different experimental conditions and semivariogram models.

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