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تطبيق تقنيات الجيوإحصائية لتحديد التركيب الكيميائي للتربة السطحية والتربة الجوفية

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الخلاصـة

تستخدم تقنيات الجيوإحصائية عادة من أجل تحويل القياسات الميدانية إلى سطح مستمر. والهدف من هذه الدراسة إظهار الاستعمال الأمثل لهذه التقنيات في زيادة متغيرات التربة السطحية والتربة الجوفية في تجمع زراعي. وقد أُجريت هذ الدراسة على حوض لتجميع المياه في مدينة توقات بتركيا في سنة 2011م. وكمثال على ذلك فقد تم فحص الاختلاف المكاني لدرجة الحموضة، ولتركيز اثنين من المعادن الثقيلة المهمة، هما الحديد والنحاس. وأُخِذَتْ عينات من التربة، ثم جرى تحليلها ضمن عمقين (30-0 سم) و(60-30 سم). وبعد التحقق من الحالة الطبيعية والمتغيرات الثابتة والمتطرفة، أُجريت تجارب الخواص العادية لكل من طريقة كريغنغ وكريغنغ الثنائي، للاستدلال على التوزع المكاني للمتغيرات المختارة، وذلك باستعمال مجموعة بيانات التدريب التي تحتوي على ١١٥ عينة، واختبار مجموعة البيانات التي تضم ٢٧ عينة. وقد جرت مقارنة الطريقة المقترحة وهي طريقة كريغنغ الثنائي (co-kriging)، وفيها يُستعمل متغيران اثنان أو أكثر، مع طريقة كريغنغ (kriging) التي يستخدم فيها متغير واحد. وقد أظهرت النتائج أن لهذا التغير دقة إحصائية أكبر من طريقة كريغنغ التقليدية.

Application of geostatistical techniques in mapping topsoil and subsoil chemical composition

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ABSTRACT

Geostatistical techniques are commonly used for converting field measurements into continuous surface.The objective of this study was to show the better use of them in the interpolations of the topsoil and subsoil variables in an agricultural catchment.This study was conducted in a watershed basin in Tokat, Turkey in 2011. As an example, the spatial variability of pH, and two important heavy metal concentrations, Fe and Cu were examined. The soil samples were taken and analyzed at two depths (0-30 and 30-60 cm). After checking normality, stationary and outliers, the ordinary kriging and isotropic cokriging methods were conducted to infer the spatial distribution of variables selected by using training data set that contains 115 sample points and test data set that contain 27 sample points.The proposed method (cokriging), in which two or more variables are used, were compared with the method (kriging) in which one variable is used. The results showed that the approach, had higher accuracy statistics than the conventional kriging mapping method.

Keywords: Co-kriging; geostatistics; GIS; kriging; spatial variability

INTRODUCTION

Geostatistical analysis is the method commonly used by different disciplines in GIS environment to interpolate field data, especially the point samples into a continuous form such as grid or raster data formats.

It is well known that micronutrients such as Iron (Fe) and Copper (Cu) are essential elements for plant growth and yield (Soon & Bates, 1982). The concentration of heavy metals in soil solution plays a critical role in controlling the availability of ions to plants (Lorenz *et al.,* 1994). The solubility and therefore the bioavailability of heavy-metal ions vary widely since many factors influence their concentration in soil solution. pH is one of the most important factors affecting metal availability in soil (Anderson & Christensen, 1988). The variability of soil properties within catchments is often described by a classical method, which assumes that variation is randomly distributed within mapping units. Soil variability is the outcome of many processes acting and interacting across a continuum of spatial and temporal scales and is inherently scale dependent (Parkin, 1993).

Geostatistics provides a tool for improving sampling design by utilizing the spatial dependence of soil properties within a sampling region and is useful to illustrate spatial inter-relationship of collected data and it reduces error, biasedness and increases accuracy of estimations for kriging (Myers, 1997). Geostatistical analyses have been used to estimate spatial variability of soil physical properties (Lascano & Hatfield, 1992), soil biochemical properties (Bonmati*et al.,* 1991;Sutherland*et al*., 1991) and soil microbiological process (Aiken*et al.,* 1991; Rochette*et al.,* 1991). Kriging methods for constructing prediction surface maps by using field measurements are widely used geostatistical techniques, which are used by different disciplines of science such as geomatic, agriculture, geology, and public health. Spatial variability patterns of soil properties withinan agricultural field or a pasture are useful tools for making effective management practices, defining relations among soil properties, and also for evaluating disruptive factors affecting these properties (Aksakal*et al.,* 2011). As has been known, precision agriculture within GIS requires higher standards for the accuracy of spatial data. In classical statistics, parameters such as standard deviation, coefficient of variation, and standard error from the mean are frequently used to characterize spatial variability of a given property.

The aim of this study, by using the combination of the GIS and geostatistical analysis, was to determinethe best prediction method for pH, Fe and Cu of topsoil (TS) and subsoil (SS), to create thematic maps, and then to analyze spatial variability of these soil variables in the study area. In addition, to develop a database for monitoring the variability of these soil properties for future use in the catchment of Çelikli, Tokat, Turkey is another objective of this study.

MATERIALS

This study was conducted in 2011 in anagricultural basin, named Çelikli. It is located in Tokat city, which is in the North Central Anatolia of the Middle Black Sea region (Figure1).

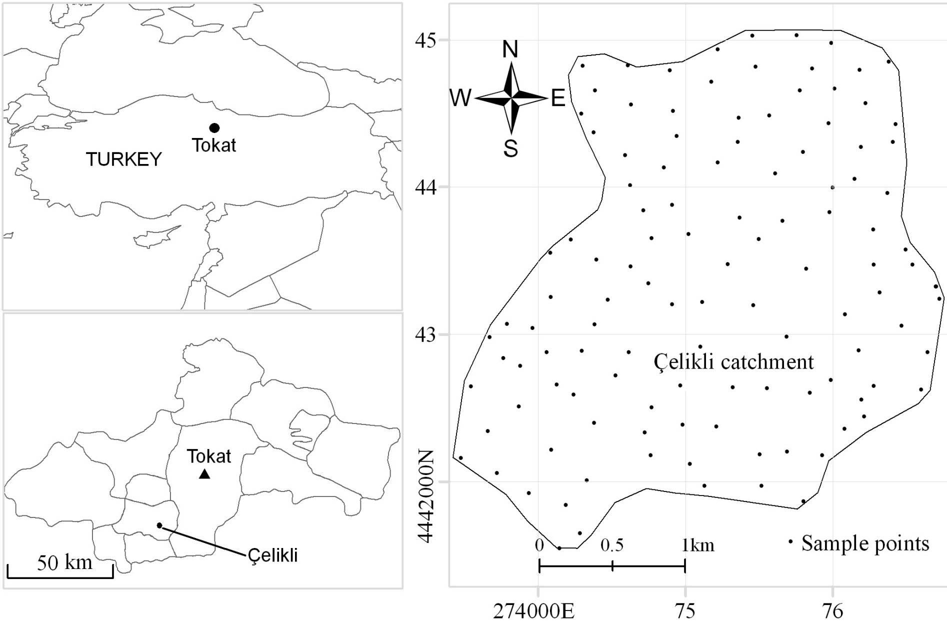

Fig. 1. Location of the study area with soil sampling points

The catchment is 7.5 ha, and has an average altitude of 1300 m. The soils are Entisols, Mollisols, and Alfisols, which are moderate-to-well drained soils with slope of 1.5° to 6.5°. The land covertypes in the catchment are farmland, grassland, and forestland. The major land use is farmland, covered 68% of the catchment. The mean annual temperature is 8°C, and the annual precipitation mean is 536mm. Table 1 shows some general charactetistics of TS and SS in the study area in detail. Average values of $CaCO_3$ are 7.85% and 8.55% for topsoil and subsoil respectively. The clay content of the TS has changed between 4.08%- 47.88%, and the CV level has become 30%. On the other hand, the clay content of the SS has changed between 10.73% and 53.39%. The CV level has become 28%.

Table 1. Descriptive statistics of sample points for TS and SS variables

Topsoil					
Variable	Minimum	Maximum	Mean	SD	CV%
$CaCO_3$(%)	1.94	47.14	7.85	7.13	91
Sand(%)	28.27	74.84	46.54	9.58	21
Silt(%)	12.91	33.20	23.45	3.94	17
Clay(%)	4.08	47.88	30.01	9.07	30
OM(%)	0.41	4.33	1.61	0.65	40
pH	6.37	8.63	7.460	0.480	6.43
Fe(ppm)	2.202	20.572	9.533	4.234	44.41
Cu(ppm)	0.460	5.026	1.936	0.887	45.81

		Subsoil			
$CaCO_3$(%)	1.55	50.7	8.55	7.66	90
Sand(%)	26.72	76.39	44.62	9.96	22
Silt(%)	12.86	30.19	21.82	3.48	16
Clay(%)	10.73	53.39	32.54	9.01	28
OM(%)	0.15	2.31	1.11	0.46	41
pH	6.37	8.30	7.55	0.42	5.56
Fe(ppm)	2.570	20.496	8.699	3.852	44.28
Cu(ppm)	0.168	3.828	1.734	0.824	47.52

OM=organic matter; SD=Standard deviation; CV% = Coefficient of variability, (Wilding, 1985) described a classification scheme for identifying the extent of variability for soil properties based on their CV% values, in which CV% values of 0 - 15, 16 - 35 and > 36% indicate low (least), moderate and high variability, respectively.

As can be seen in the Table 1, the clay content of the TS has a higher variability. The variability in the subsoilhas resulted from the formation of the soil of the study area from different main materials. Monoculture farming is being practiced in the study area, and microelement fertalization is not applied. The differences in the main materials and the high level of variability of the clay content of the SS have not caused a significant effect in the Fe content of the TS and SS; however, they resulted in more variations in the Cu contents of the SS. The Cu content in Çelikli catcment soils ranges from 0.4 to 5ppm. The critical level required for normal crop production is around 0.5ppm. Soils with Cu concentrations in excess of 20 ppm may occur in areas, where copper fungicides or poultry and swine wastes have been applied (Tucker, 1999). The mean value (9.11ppm) of Fe content in the soil samples was higher than the sufficent value (2ppm) (Chen & Barak, 1982).

Simple correlation coefficients between general characterictics and pH, Fe and Cu contents of TS and SS in the study area were shown in table 2.

Table 2. Spearman's correlations(r) between soil characteristics and pH, Fe and Cu

	Sand	Silt	Clay	Organic Matter
		Topsoil		
pH	-0.07	0.07	0.04	-0.25
Fe	0.00	0.00	0.00	0.24
Cu	-0.18	0.11	0.14	-0.01
		Subsoil		
pH	0.11	-0.02	-0.11	-0.35
Fe	-0.24	-0.15	0.31	0.25
Cu	0.00	-0.28	0.11	-0.05

ArcMAP 10.0 GIS software package supplied with geostatistical analyst module was used to establish GIS database, to determine descriptive statistics, to visualize spatial analysis and to estimate prediction maps (ESRI,2010). The location of the sample points were recorded with a Global Positioning System (GPS).

METHODS

Soil sampling and analysis

Soil samples were randomly taken from 142 sites at TS (0-0.30m) and SS (0.30-0.60m), based on the similar type of slope, soil, and visual properties of the landscape in the catchment. Minimum sampling distance was 125m. After removing stones and large plant roots or debris by air-drying, each sample was thoroughly mixed and pulverized to pass through a 2-mm sieve and then stored in a plastic container prior to analysis. Soil pH was determined using 1:2.5 soil water suspension (adequate to wet the electrode) using a pH meter (IITA, 1982). The soil samples were then analyzed for soil pH in 1:2 soil: water suspension (McLean, 1982). Fe and Cu concentrations were measured with atomic absorption spectrophotometer, using standards made in the diethylene triamine penta acetic acid (DTPA) solution.

Geostatistical analysis

Geostatistical methods are optimal when data are normally distributed and stationary (mean and variance do not vary significantly in space). Significant deviations from normality and stationarity can cause problems, so it is always best to begin by looking at a histogram or similar plot to check for normality. Therefore, statistical parameters of mean, maximum, minimum, standard deviation, coefficient of variation, skewness, and kurtosis were calculated for pH, Fe and Cu contents for TS and SS. Estimation was performed using kriging and co-kriging for the three different soil variables. Estimation with co-kriging can be done with more than one covariable, but we have included only one soil variable as co-variable for simplicity. Comparison of the estimation results were done using prediction variances, calculated by cross validation and validation procedure.

The semivariogram

Spatial variability of any variableis described by a semivariogram. It is calculated as half of the average squared difference between paired data values. It is a graphical representation of spatial self-correlation by plotting the semi variance against several distance intervals. An estimator of the semivariogram is:

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

where, $\gamma(h)$ is the estimated semivariogram, $z(x_i)$ and $z(x_i+h)$ are the values of a variable separated by the lag h, and N(h) is the number of data pairs in the corresponding lag. Directional influences (anisotropy) for each dataset were checked by calculating the empirical semivariogram (Equation 1) for different directions (0^0, 45^0, 90^0 and 135^0). The anisotropy ratios were not significantly different from one another and no significant anisotropy could be seen. No data were detrended because none of them showed trends.

The semivariogram describing spatial dependence for one variable is called auto-semivariogram. A spatial relation between two or more variables at the same location is called as co-regionalised. The cross-dependence between two variables (z_1 and z_2) can be expressed by the cross-semivariogram with the estimator:

$$\gamma_{12}(h)=\frac{1}{2N(h)}\sum_{i=1}^{N(h)}\left[z_1(x_i)-z_1(x_i+h)\right]\left[z_2(x_i)-z_2(x_i+h)\right], \tag{2}$$

with definitions as in Equation 1.

The empirical semivariogram Equation (1) and Equation (2) are characterised by three parameters; the nugget variance, sill and range. The nugget variance is a discontinuity at lag zero (i.e. h=0) due to both measurement error and variation within the distance sampling interval. The range of influence indicates the distance, where observations are spatially uncorrelated, and the sill is the maximum constant variance at distances exceeding the range of influence.

A model can be usually fit to the empirical auto- and cross-semivariogram using, e.g. a spherical, exponential orgaussian equation. For a detailed description of models and parameters see e.g. Isaaks & Srivastava (1989).The spherical model was used to describe the spatial variability from Equations 1 and 2:

$$\gamma(h)=C_0+C\left\{\frac{3/|h|}{2r}-\frac{1}{2}\left(\frac{h}{r}\right)^3\right\}\text{For } 0<|\mathrm{h}|\leq \mathrm{r}$$

$$\gamma(h)=C_0+C\text{ for }|\mathrm{h}|>\mathrm{r} \tag{3}$$

$$\gamma(0)=0$$

where γ(h) is the semivariance and C_0 is the nugget variance. The maximum semivariance was defined as the sill (C_0 + C).

Prediction methods

The values of studied soil variables were used for predicting of values at unknown points by using the kriging interpolation methods. The interpolation methods used are explained shortly since discussions in detail about interpolation techniques could be found in books written by (Journel & Huijbregts, 1991; Isaaks & Srivastava, 1989; Burrough & McDonnel, 1998).

Kriging

Kriging is a spatial estimation procedure that provides the best linear unbiased estimator with minimum variance. The estimated value of a regionalised variable at location x_0 is a weighted average of available data:

$$\hat{Z}(x_0) = \sum_{i=1}^{N} \lambda_i z(x_i) \tag{4}$$

where N is the number of observations $z(x_i)$ and λ_i are the weights assigned to the sampling points. The kriging variance at location x_0 is:

$$\sigma^2(x_0) = \sum_{i=1}^{N} \lambda_i \gamma(x_0, x_i) + \psi \tag{5}$$

where $\gamma(x_0, x_i)$ are auto-semivariograms and ψ is a Lagrange multiplier.

Co-kriging

Co-kriging is an extension of kriging to situations where two (or more) variables are spatially intercorrelated. It is a weighted average of observed values of the primary variable z_1 and the co-variable z_2. The estimated value of the primary variable at location x_0 is:

$$\hat{Z}_1(x_0) = \sum_{i=1}^{N_1} \lambda_{1i} z_1(x_{1i}) + \sum_{j=1}^{N_2} \lambda_{2j} z_2(x_{2j}), \tag{6}$$

where N_1 and N_2 are the number of neighbours of z_1 and z_2 ; λ_{1i} and λ_{2j} are the weights associated to each sampling point. The co-kriging variance at location x_0 is given by:

$$\sigma^2(x_0) = \sum_{i=1}^{N} \lambda_{1i} \gamma_{11}(x_{10}, x_{1i}) + \sum_{j=1}^{N_2} \lambda_{2j} (x_{10}, x_{2j}) + \psi_1 \tag{7}$$

where $\gamma_{11}(x_{10}, x_{1i})$ and $\gamma_{22}(x_{10}, x_{2i})$ are auto-semivariograms and ψ_1 is the Lagrange multiplier.

Prediction variance

The prediction variance was calculated by cross-validation as the average squared difference between actual and predicted values. In the cross-validation procedure an observation $z(x_k)$ is deleted and then predicted $z_{-k}(x_k)$ by either kriging or co-kriging. This procedure is repeated for all observations (k=1 . . . N). The prediction variance σ_p^2 is calculated as (Weisberg, 1985):

$$\sigma_p^{\ 2} = \frac{1}{N} \sum_{k=1}^{N} \left[z(x_k) - \hat{z}_{-k}(x_k) \right]^2 \tag{8}$$

where N is the number of observations, $z(x_k)$ is the actual value at location xk and ẑ-k(x_k) is the predicted value at location x_k without $z(x_k)$.

Validation procedure

Validation allows us to evaluate our predictions using a known data that was not involved in creating the prediction model. To validate interpolation techniques, we examined the difference between the known data and the predicted data using the root mean squared error(RMSE) Equation (9) and the standardized root mean square error (SRMSE) Equation (10). Generally, the best model is the one that has the smallest RMSE and and SRMSE nearest to one.

$$RMSE = \sqrt{\left[\frac{1}{n}\sum_{i=1}^{n}\left[\hat{z}(x_i) - z(x_i)\right]^2\right]} \tag{9}$$

$$SRMSE = \sqrt{\left[\frac{1}{n}\sum_{i=1}^{n}\left[\hat{z}(x_i) - z(x_i)/\sigma(x_i)\right]^2\right]} \tag{10}$$

where $\hat{z}(x_i)$ is the predicted value, $z(x_i)$ the observed (known) value, n the number of values in the dataset and σ^2 isthe kriging variance for location x_i(Webster, 2001).

RESULTS

Correlation is a measure of the similarity of variables. Strong correlationis expected for same variable of TS and SS. In other words, it is expected that pH at TS will relate strongly with pH at SS. Similarly for Fe and cu. Therefore correlation coefficients were generated between pH, Fe and cu levels at TS and SS. Figure 2 shows that there are strong correlations between the variables studied of TS and SS as expected.

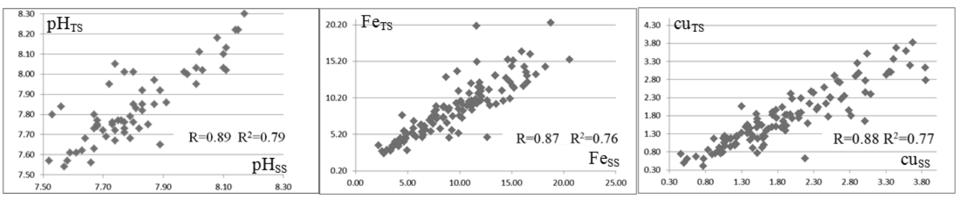

Fig. 2. Correlations between pH, Fe and cu of TS and those of SS respectively

At the study area, the correlation coefficient between the pH, Fe and Cu contents of the TS and SS are given in the Figure 2. According to this figure, the relationships mentioned are all positive and significant ($p<0.01$).

The spherical (Equation 3) model was mostly used to fit the empirical auto- and cross-semivariograms. By comparing the RMSE and SRMSE resulted from the semivariograms it is clear that the spherical model is the better in modelling of variables studied more accurately. The plots (Figure 3) below show semivariances versus 150m.lag. for six variables (pH, Fe, Cu for TS and SS respectively).

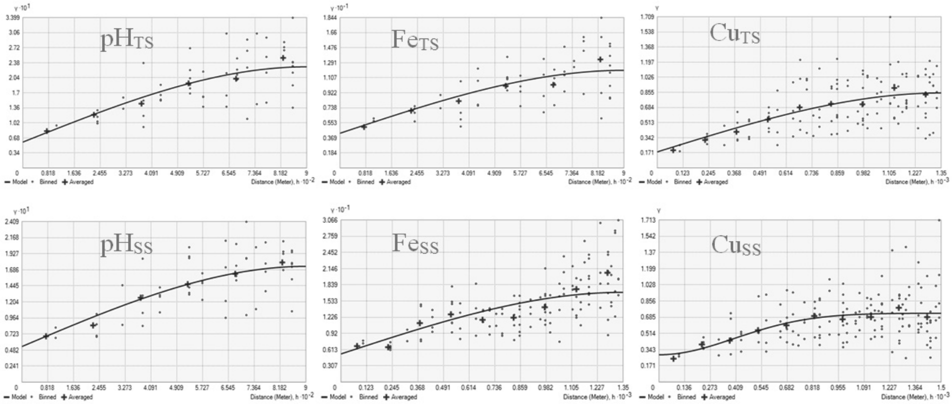

Fig. 3. Experimental and theoretical semivariograms computed on datasets studied

The RMSE amounts resulted from spherical, guassian and exponantial models are found in Table 2. The spherical model exhibits linear behavior. For the auto-semivariogram of Cu_{SS} the guassian model and for the cross-semivariogram of cu_{SS}-cu_{TS} were chosen exponantial, because they resulted in the minimum residual mean square error. Table 2 shows RMSE and SRMSE values for semivariograms of pH, Fe and Cu variables of TS and SS.

Table 2. Comparison between the semivariogram models based on RMSE and SRMSE

Variable	Model	SRMSE	SRMSE	Variable	Model	RMSE	SRMSE
Topsoil				Subsoil			
pH	Spherical	0.375	1.080	pH	Spherical	0.326	1.060
	Guassian	0.376	1.088		Guassian	0.328	1.075
	Exponantial	0.376	1.060		Exponantial	0.329	0.989
Fe	Spherical	2.923	0.885	Fe	Spherical	3.068	1.042
	Guassian	2.996	1.154		Guassian	3.116	1.058
	Exponantial	3.483	0.898		Exponantial	3.092	1.011
Cu	Spherical	0.657	1.092	Cu	Spherical	0.692	1.097
	Guassian	0.653	1.181		Guassian	0.686	1.102
	Exponantial	0.848	1.005		Exponantial	0.694	1.053

As there is no anisotropy evident in the directional semivariograms for variables studied, auto- and cross-semivariograms for all variables were assumed isotropic. The auto- and cross-semivariogram parameters for the soil variables are shown in Table 3. It shows the characteristics of variogram models that are fitted to data sets studied in catchment.

Table 3. Geostatistical parameters for soil reaction (pH), iron (Fe) and copper (Cu)

Variable	Depth	Model	Co	Co + C	r	NE%	SD
			Auto-Semivariograms				
pH_{TS}	0 - 30	Spherical	0.0720	0.2095	695	34.39	M
pH_{SS}	30 - 60	Spherical	0.0475	0.1615	594	29.46	M
Fe_{TS}	0 - 30	Spherical	5.1544	11.161	1108	46.18	M
Fe_{SS}	30 - 60	Spherical	5.3501	11.988	736	44.62	M
Cu_{TS}	0 - 30	Spherical	0.1240	0.8705	1325	14.25	S
Cu_{SS}	30 - 60	Gaussian	0.3390	0.7546	2963	44.93	M
PV-SV				cross –semivariograms			
pH_{TS} - pH_{SS}	0 - 30	Spherical	0.0652	0.2067	590	31.56	M
pH_{SS} - pH_{TS}	30 - 60	Spherical	0.0063	0.0217	587	29.13	M
Fe_{TS} - Fe_{SS}	0 - 30	Spherical	3.6942	10.624	649	34.77	M
Fe_{SS} - Fe_{TS}	30 - 60	Spherical	0.5645	1.1940	689	47.27	M
Cu_{TS} - Cu_{SS}	0 - 30	Spherical	0.0638	0.4114	1252	15.51	S
Cu_{SS} - Cu_{TS}	30 - 60	Exponential	0.1187	0.7267	1229	16.33	S

C = Structural variance; C_0 = nugget variance; r = range; NE% = $C_o/(C_o+C)$; SD = spatial dependency; S = strong (NE%<25% was highly space-dependent), M = moderately (between NE% = 25% and NE% = 50% moderately space-dependent), and W = weak (above NE%>75% weakly space-dependent), Cambardella*etal*. (1994). PV = Primary Variable, SV = Secondary variable

The semivariograms have been extended to 1,800 m, which is less than the shortest axis of the study area, as suggested by Rossi *et al*., 1992. They were divided in to 12 lag distance classes separated by an average of 150 m. Each lag distance class contained at least 30 pairs of points. Based on the results from the cross validation procedure, a search ellipse with a radius of 250 m was used in both kriging and co-kriging estimations, and a minimum of four and a maximum of eight data values within the search ellipse were included in the estimations. The spherical model, except for Cu content of SS, produced the satisfactory results for all variables studied. A Gaussian model provided a good fit to Cu for SS.

The range value of a variogram model shows the degree of spatial autocorrelation. Samples separated by distances closer than the range value are related spatially, and those separated by distances greater than the range value are not spatially related. The range values at auto-semivariograms showed considerable dissimilarity between same variable of topsoil and subsoil. Conversely, the range values at cross – semivariograms showed conciderable similarity for both topsoil and subsoil variables. For instance, at auto-semivariogram, pH has range values of 695m and 594m at topsoil and subsoil respectively. Same values at cross-semivariogram for pH variable are 590m and 587m for topsoil and subsoil respectively. This result indicates that same type of variables at topsoil and subsoil are related to one another.

The semivariance at h=0 nugget is called to nugget (Webster 2001). It represents variabilities that are undetectable at the scale of sampling. There are nuggets associated with all of the models. The nugget semivariance expressed as a percentage of the total semivariance enables comparision of the relative size of the nugget effect among soil properties (Trangmar*et al.*, 1985). This ratio was used to define distinct classes of spatial dependence for the soil variables. Except for Cu, all the variables studied exhibited moderate spatial dependency. There were strong spatial correlations for Cu in TS and SS.

For aquantitative comparison the prediction variances are presented in Table 4. As expected, the prediction variance decreased with co-kriging.

Table 4. Prediction variance andimprovement by co-kriging in %

	Prediction variance		Improvement by co-kriging
Variable	Kriging	Co-kriging	(%)
pH_{TS}	0.14	0.09	64
Cu_{TS}	0.41	0.06	14
Fe_{TS}	8.82	5.90	67
pH_{SS}	0.12	0.07	58
Cu_{SS}	0.42	0.18	43
Fe_{SS}	9.42	5.90	63

A comparison between kriging and co-kriging shows 14-64 % improvements with co-kriging.

Table 5. RMSE and improvement by co-kriging in %

	RMSE-SRMSE		Improvement by co-kriging
Variable	Kriging	Co-kriging	(%)
pH_{TS}	0.38 – 1.08	0.30 - 0.91	79
cu_{TS}	0.64 – 1.19	0.52 – 1.09	81
Fe_{TS}	2.97 – 1.05	2.43 – 0.96	82
pH_{SS}	0.35 – 1.13	0.27 - 0.96	77
cu_{SS}	0.65 – 1.03	0.43 -0.94	66
Fe_{SS}	3.07 – 1.02	2.43 – 0.95	79

For a quantitative comparison the RMSEs are presented in Table 5. The comparison between kriging and co-kriging shows 66-81 % improvements with co-kriging. The validation analysis revealed that the prediction errors were smaller than those by kriging.

Spatial distributions of pH are presented in Figure 4. It illustrates the spatial distribution of pH for TS and SS respectively. The maps showed that > 50% of the study area were slightly alkaline for both depths. At TS, pH were found moderately alkaline in 1.04 ha, slightly alkaline in 4.27 ha, neutral in 2.24 ha; and slightly asid in 0.01 ha, while at SS, it was moderately alkaline in 1.59 ha, slightly alkaline in 4.42 ha, neutral in 1.55 ha. Most crops grow best when the pH is at or near neutral, which is 7.0. In the study area, pH values were found around neutral so it is proper for crop productions.

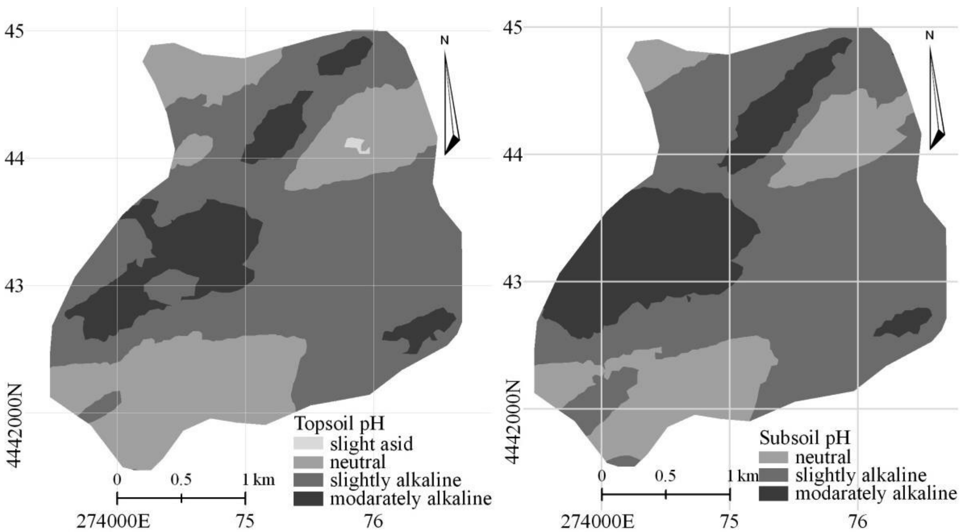

Fig. 4. Spatial variability maps of pH of TS and SS, respectively.

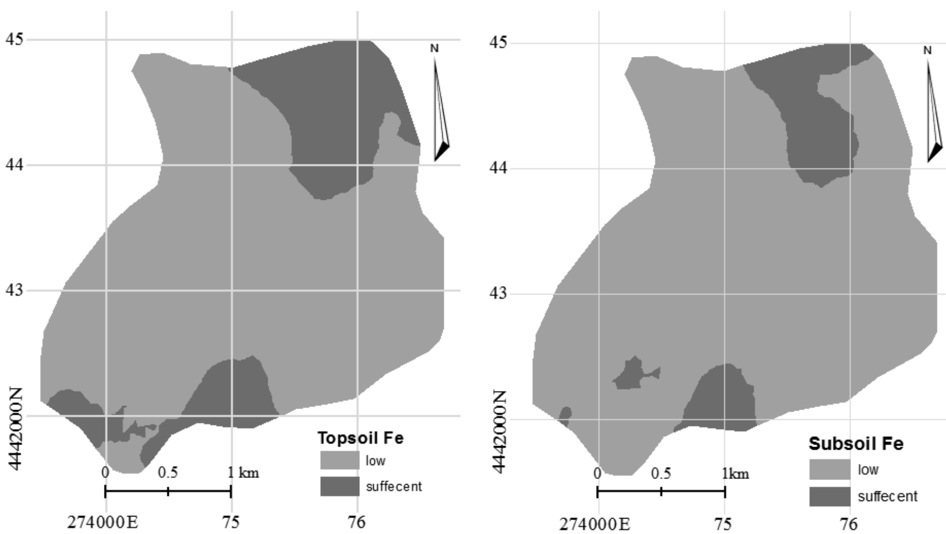

Fig. 5. Spatial variability maps of Fe of TS and SS, respectively.

Figure 5 illustrates the spatial distribution of Fe in TS and SS, respectively. Spatial distribution of Fe is divided in two main regions. The maps showed that Fe was generally low in both TS (5.97 ha) and SS (6.6 ha). Iron deficiency is one of the major limiting factors effecting crop yields, food quality, and human nutrition. The World Health Organization estimates that globally some two billion people are affected by iron deficiency and that some 750 million people suffer from iodine deficiency (WHO,2006**)**. In most of the catchment soils, iron added fertilizers should be used. However, there are some areas at the north and south region in which Fe is sufficient in TS and SS.

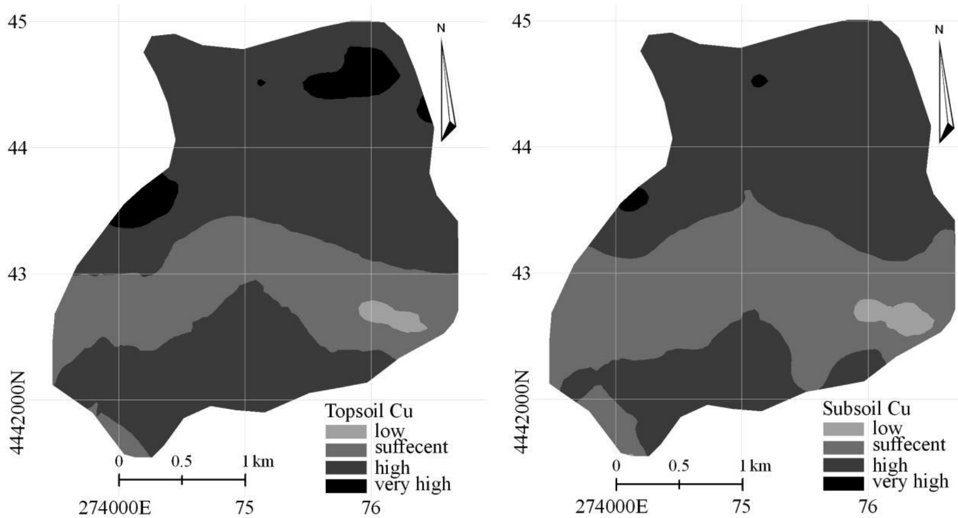

Fig. 6. Spatial variability maps of Cu of TS and SS, respectively.

Figure 6 illustrates the spatial distributions of Cu for TS and SS respectively. Maps for the Cu content showed that Cu contents of both TS and SS were changing high to very high while some Cu deficient areas exist. The study catchment is consisting of mostly cropland and, main crop is wheat. Wheat is probably the most sensitive cereal to Cu deficiency (McAndrew*et al.,* 1984). For that reason in the study area, Cu fertilization should be done only at the areas where Cu is insufficient.

The results of this study demonstrate the advantages of using GIS with geostatistical analysis. The isotopic co-kriging definitely improved the mapping of TS and SS, in case TS and SS was used as auxiliary variable for each other. Spatial distribution of pH, Fe and Cu content were compared by means of the coefficient of variation of classical statistics and semivariogram analysis of geostatistic in order to evaluate their variability in a catchment with sloping landscapes. The variables were evaluated separately in the TS and in the SS. As a result, in generally, as there would be significant correlations between same variables of TS and SS, when the number of observations is adequate, co-kriging technique seems to provide better fit in TS and SS content modeling in terms of realistic visualization of the results than ordinary kriging. The comparison of results shows 14-64 % improvement in prediction variance and 66-81 % improvements in validation with co-kriging. More studies can be carried out to make better estimation for soil nutrients by using different soil properties or other factors, which affect variable interested, as a secondary variable.

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