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Geostatistical Analysis of a Water Well Field for Determination of Land Management Constraints

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ABSTRACT

Soil spatial variability and heterogeneity is a tough but very important matter in the field-scale description of soil properties, such as soil electrical conductivity, soil saturated hydraulic conductivity, and soil salinity. Geostatistics is a useful tool to study spatial distribution of soil properties and optimum sampling strategies in field. Estimating soil salinity, EC and Ks is a vital issue in soil fertility and management. Geostatistical methods, kriging and cokriging, were applied to estimate spatial distributions of the variables that were collected from a large size water well field for the surface soil, rather than entire bore-hole profile of the soil. The results suggested that estimation can be improved using cokriging , rather than kriging. Comparing to kriging results, cokriging reduced the mean squared error and improved the estimation of EC by 2-100% depending on cross-correlated variables. Using the cokriging prediction maps of the soil properties, the soil can be managed cell by cell with prescribed appropriate management strategies such as irrigation and manure application to mitigate soil salinity in the region.

Key words: Geostatisctics, salinity, kriging, cokriging.

INTRODUCTION

Soil salinity, soil electrical conductivity and other soil fertility parameters are on a regular timely basis determined in field and laboratories for arid and semi arid areas in southern Turkey. Excessive soil salinity may result in a large amount of crop loss and eventually land degradation (Lesch et al., 1992). Inappropriate management of low saline and high saline areas due to their non-homogeneous distribution on the landscape is known as the same input of tillage, irrigation water, fertilizer and pesticide application, seed spreading on indiscriminately selected agricultural lands although no economic yield return is very well known in these areas (Halvorson and Rohades, 1976). From the same study, the salinity problem is observed to influence the soil in two principle ways. Soluble salts bring about a high ESP (content of exchangeable sodium) and high osmotic potential, which are collectively unfavorable physical conditions for a soil to be fertile for a plant species. The attempts were made to remediate high saline areas by biological methods and by pinpoint site specific irrigation of good quality of water, gypsum addition, and leaching (Szabolcs, 1989; Mankin et al., 1997). Maintaining upgrade data of soil salinity requires high cost of densely sampling of a soil. This adds to saline soil irrigation or reclamation costs to be more expensive. Therefore, geostatistics provides appropriate tools to reduce the cost of soil sampling and maintenance of management practices, such as irrigation system in a field. As a result, soils are mapped in terms of soil properties using some estimation techniques such as kriging and cokriging, numerical methods, and fuzzy set analyses. In this study, kriging and cokriging are used to map the pattern of the spatial distribution of a large water-well area growing cash crops of every kind, except citrus fruits. Kriging is used by Tabor et al. (1984, 1985) to determine spatial variability of nitrate in cotton plants and soil nitrate was correlated with nitrate content of cotton seedlings. Similarly, Yates et al. (1993) used kriging and cokriging in determination of salt affected soils, while Istok and Cooper (1988) applied kriging to study groundwater contamination. Zhang et al. (1995) applied kriging and cokriging to estimate trace elements of soils and plants and Yates and Warrick (1987) utilized cokriging to estimate soil water content with standby data of bare soil surface temperature and sand content. In this study, kriging and cokriging were applied to predict spatial variability of soil electrical conductivity (EC), hydraulic conductivity (Ks), Total Dissolved Solids (TDS), pH, and elevation and cokriging was compared to kriging in improvement of the estimation accuracy. The main goal is to determine soil constraints to agriculture in the studied basin.

MATERIALS and METHODS

Sampling and Analysis

A total of 49 water wells and soil profiles at the same location in the Harran Plain, Turkey, have been sampled for the purpose of monitoring salinity**.** Sampling scheme and locations are given in Figure 1. Soil pH, electrical conductivity (EC: µmhos/cm) and Total Dissolved Solids (TDS: mg/l) of water wells have been determined according to Richards (1954). Soil saturated hydraulic conductivity (Ks: cm/day) has been measured according to constant head method (Klute and Dirksen, 1986). Elevation at each location in the study area has been recorded using a GPS instrument.

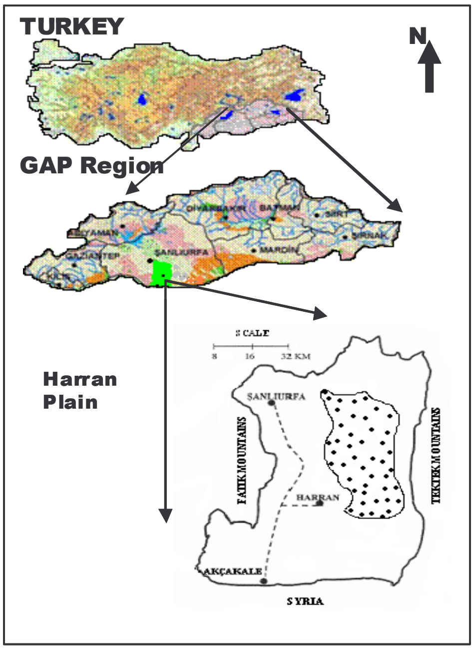

Figure 1. Study area and sampling locations.

Geostatistical Modeling

Kriging, as a linear spatial interpolation method, estimates the quantities of soil properties at unsampled locations by assigning weights to each neighbor location based on their distance from the location being estimated. Weights sum up to one. Kriging can be formulized as:

$$Z^*(x_0) = \sum_{i=1}^{n} w_i Z(x_i)$$

where $Z^*(x_o)$ is the kriging estimation at an unsampled location (x_o), n is the number of samples in a search neighborhood, w_i are the weights assigned to the ith observation $Z(x_i)$. Weights are determined using a semivariogram that measures spatial correlation and covariance structure between data points for each variable. It is computed using following equation (Journel & Huijbregts,1981):

$$\hat{\gamma}(h) = 0.5n\sum_{i=1}^{n}\left[Z(x_i + h) - Z(x_i)\right]^2$$

where $\hat{\gamma}(h)$ is the semivariance between two observation points, $Z(x_i)$ and $Z(x_i+h)$, separated by a distance h, and n is number of pairs at the distance h.

Cokriging (COK) uses a secondary variable, (Z_2), which is spatially cross correlated with the primary variable (Z_1). It is formulated as:

$$Z_{COK}{}^*(x_0) = \sum_{i=1}^{n1} w_i Z_1(x_i) + \sum_{j=1}^{n2} w_j Z_2(x_j)$$

where $Z^*_{COK}(x_o)$ is the cokriging estimate at an unsampled location (x_o), w_i and w_j are cokriging weights associated with the primary variable $Z_1(x_i)$ and the secondary variable $Z_2(x_j)$ at i^{th} and j^{th} locations, respectively, which are obtained based on the cross-semi variogram:

$$\hat{\gamma}_{Z_1Z_2}(h) = 0.5n\sum_{i=1}^{n}\left[Z_1(x_i+h)-Z_1(x_i)\right]\left[Z_2(x_j+h)-Z_2(x_j)\right]$$

RESULTS and DISCUSSION

Table 1. Descriptive statistics of the random variables.

Variable	Count	Max.	Min.	Mean	Stdev	Skewness	Kurtosis	1st Quart.	Median	3rd Quart.
EC (µmhos/cm)	49	3450	412	1071	654	1.92	6.48	693.8	885	1150
pH	49	8.85	7.95	8.3	0.47	0.74	1.55	8	8.38	8.85
Ks (cm/day)	49	6.63	0.39	1.571	1.4	1.58	6.136	1	4.03	2
Elevation	49	399	368	379.3	6.7	0.77	3.39	374.7	378	382.3
TDS (mg/l)	49	27.5	3.7	11.8	5.6	0.9	3.16	7.75	10	15

Table 1 shows descriptive statistics of the data set used in spatial analysis. It is clear that the soil EC has the highest variability than the rest of the variables. The soil EC proves the highest asymmetrical distribution with the highest skewness on comparison to the other variables. Similarly, the second highest skewed variable is Ks. All the variables are positively skewed. This pattern is the same for standard deviation which is the highest for EC and the lowest for soil pH. This statistics is strongly influenced by outliers in the data set. Since the data showed positive skewness, all mean values are greater than median values of the data. This positive skewnes and larger standard deviations may be due to a limited number of the data points in the sampling field. The greater number of samples is likely to result in the lower variance and standard deviation in the data set and the distribution can be much like normal distribution.

Table 2 shows the correlation coefficients and p-values in parentheses for the intervariables. Elevation is always negatively correlated with the variables in the study. This may mean increases in elevation points in the water-well field always result in decreases in the values of random variables. In other words, the highest values of the EC, TDS, pH, and Ks are likely to be found on the foothills and valley bottoms. The elevation and soil EC correlation is significant and may be an indicative of high amount of leaching of soil salts from high elevations to low elevation points by the seasonal precipitation events that may cause accumulation of salts in the foothill slopes of the landscape. Ks negatively correlated with pH and TDS, while soil EC holds a positive correlation with Ks.

Table 2. Correlation matrices of variables (p values in parenthesis).

Variables	TDS	pH	Ks	Elevation
EC	0.471 (0.001)	-0.254 (0.078)	0.133 (0.362)	-0.288 (0.045)
TDS		-0.537 (0.000)	-0.024 (0.872)	-0.145 (0.319)
pH			-0.052 (0.722)	-0.064 (0.661)
Ks				-0.006 (0.969)

Another negative significant relationship exists between pH and soil EC at 10% significance level, whereas TDS and pH are negatively correlated and the relationship is significant at any p-value. The negative pH-EC correlation may be attributed to salt hydrolysis in the soil, result of which doesn't always cause incremental pH in soil. On the other hand, the more salinity doesn't mean the higher pH in soil. Similarly, pH and TDS don't increase and lower as conjugates. The other significant relation occurs between soil EC and TDS ($p < 0.05$) and this relationship is positive. This may be due to the fact that totals dissolved solids contribute in larger part to the soil EC and therefore, very commonly in the soilscape, EC-TDS combination for positive correlation remains valid.

Spatial variability

All the variables were analyzed spatially with kriging, whereas only strongly correlated parameters were analyzed by cokriging on the data set. Generally speaking, all the variables used in kriging tended to be more easily predictable than in cokriging. Cokriging not only calculates the semi-variance of each variable, but also calculates cross-variogram for two or more variables in the cross-autocorrelation process. Cross-variogram model parameters mostly came out of anisotropic spatial distributions. There may be multiple reasons for this. First of all, sampling techniques and sampling times are not known whether to be consistent and locations of the samples are assumed to be the same. Secondly, the variables are not correlated very well with one another and correlation coefficients are generally very low and generally negative. The correlation matrices of the data showed that 2 out of 10 correlations were positive and lower than 50%.

If two random variables are negatively correlated, the rate of increase in cross-variogram is expected to decrease in distance. On the other hand, if cross-vaiogram of two or more variables increases, the random variables are said to be positively correlated. In this data set, anisotropy and trend for all variables prevail. Fortunately, ArcGIS eliminates the trends and computes the spatial semivariance model first. At the end of the model computation, the eliminated trend is added back to the data. This process adds more reliability to ArcGIS geostatistical analyses because in the semivariance model computation process the trend is not involved and model is computed safely.

Kriging models

Figure 2 illustrates spatial distribution of TDS in the study area Total dissolved solids in the water well field are described spacially according to the spherical variogram model. The TDS concentrations reach at the sill value 30 in 1835 m range.

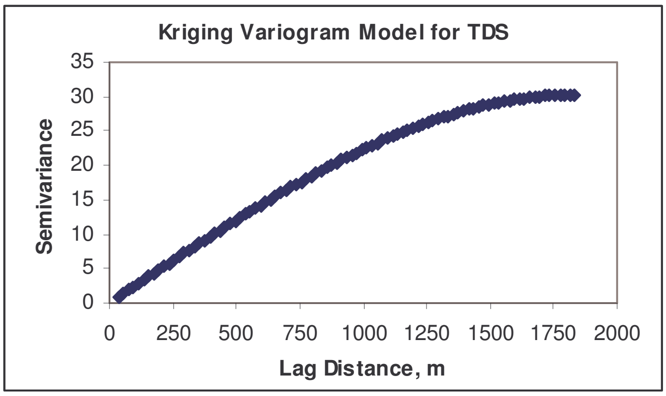

Figure 2. TDS variogram model ($\gamma_{(h)} = 30.3(1.5(h/1835)-0.5(h/1835)^3)$).

Figure 3 illustrates spatial distribution of soil EC in the study area. The soil EC distributes according to spherical variogram model as was the TDS. The range and sill values for the soil EC are 10070 m and 70093 x 10^{-5}. The variability of the soil EC is the highest among the other variables analyzed. The variation coefficient is greater than 40% for soil EC, while this was lower for the soil TDS (not given).

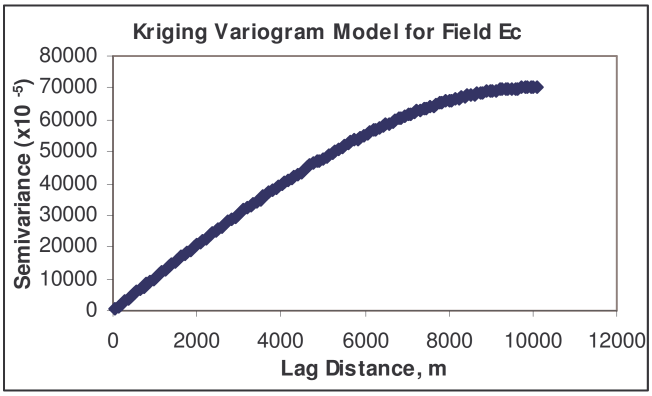

Figure 3. Field variogram model for EC
($\gamma_{(h)} = 70093 \times 10^{-5}(1.5(h/10458)-0.5(h/10458)^3)$).

Like the other variables of the soil, saturated hydraulic conductivity has also distributed according to spherical model with a sill and range value, 0.392 and 10458 m, respectively (Figure 4).

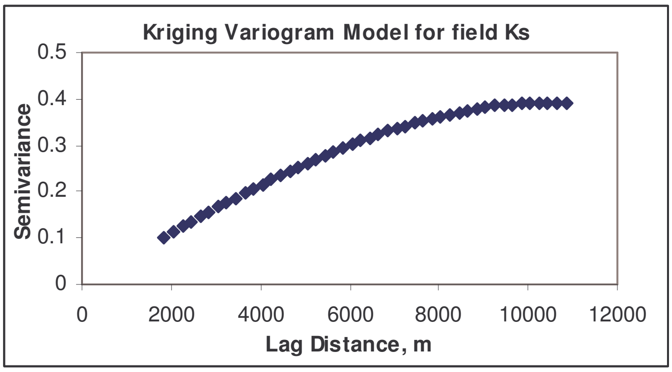

Figure 4. Variogram model for the field saturated hydraulic conductivity ($\gamma_{(h)} = 0.023+0.392(1.5(h/10458)-0.5(h/10458)^3)$.

Comparisons of Kriging Predictions with Cokriging Estimations

The comparisons of cokriging to kriging for some of the significantly correlated parameters of the data set were made. The following method was used to compare results estimated by kriging and cokriging. Relative improvement, or relative reduction of estimation accuracy, is defined by:

$R_E = 100\%(|MES_R|)-(|MSE_E|)/(|MSE|)$ (Pozdnyakova and Zhang, 1999)

where R_E is percentage of improvement or reduction, (positive R_E improvement, negative R_E reduction), MSE_R kriging mean squared error, and MSE_E is cokriging mean squared error. If the R_E is positive, the evaluated method (cokriging) is better than reference method (kriging). On the other hand, negative R_E corresponds to evaluated method that is worse than reference method. The results are given in table 3.

Table 3. Comparison of kriging to cokriging by R_E factor.

Kriging variables	MSEkrig	MSEcokrig	RE %	Cokriging variable
Ks	22.01	19.6	11.04	Ks-Elevation
EC	448505.3	441266	0.02	EC-Elevation
EC	448505.3	38.45	100	EC-TDS
TDS	41.2	38.45	0.067	EC-TDS

Table 3 shows that mean squared errors for the random variables are generally greater for kriging than the ones for cokriging. Depending on the cross-variogram model, the accuracy and improvement of the prediction maps developed in a large range. The improvement of the predictions ranged between 2 and 100 % for the variables that were used in cokriging. For example, if the field EC was predicted by

EC-Elevation cokriging model, the improvement was 2%, while EC –TDS cross-variogram improved field EC prediction as 100%. This shows that cokriging is better to estimate unknown sample locations of EC in the field, rather than kriging.

The cross-variogram is computed as the following;

$\gamma_{12} = 0.5*(\gamma^{+}_{12} - \gamma_{11} - \gamma_{22})$ (Zhang et al., 1995)

where, γ_{12} is cross-variogram of Ks and elevation; γ_{11} is variogram of Ks; γ_{22} is variogram of elevation; γ^{+}_{12} is the variogram of Ks + elevation.

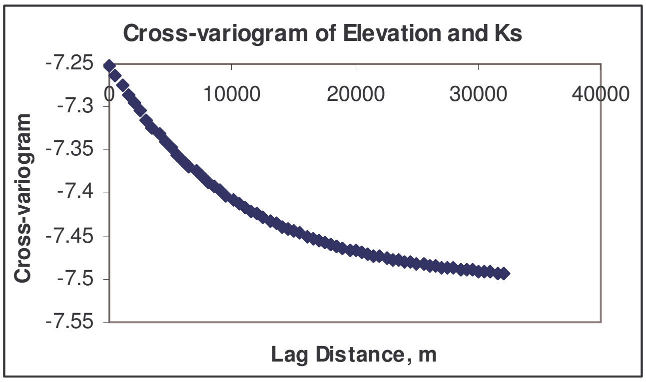

Figure 5. Cross-variogram of elevation and saturated hydrauclic conductivity of the soil ($\gamma_{12(h)}$=-7.25 -0.26 (1-exp(-h/10458)).

Figure 5 shows that cross-variogram decreases with distance for the elevation and Ks variables. The reason for this is because of the fact that both of the variables are negatively correlated (Table 2). Therefore, cross-variogram is not expected to increase. The cross-variograms for the rest of the combination of the variables were not developed for testing the hypothesis that cross-variogram always an increasing function if the random variables are positively correlated. Among the cross-variogram of the variables, the cross-variogram of elevation-Ks was unique to develop because of the fact that Ks and elevation was negatively correlated with the lowest correlation coefficient. Elevation and Ks predict each other via this model given above.

Kriging prediction maps for the variables

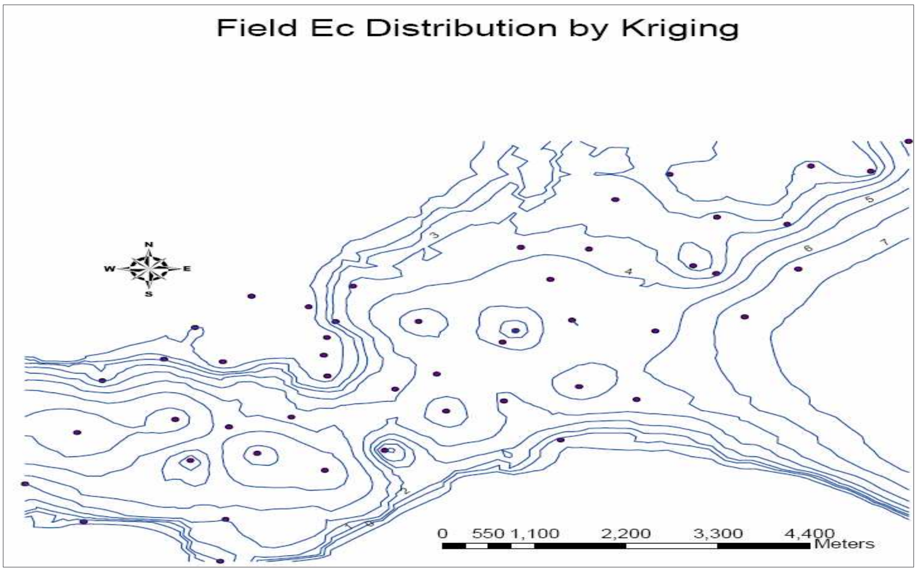

Figure 6. Kriging prediction map of soil EC.

Figure 6 illustrates the kriging distribution of field EC. The EC distribution is very much like homogeneous in the field. The contour lines of EC do not change in their slopes and contour intervals are quite similar with each other. However, level of EC varies for each contour line in the field. According to the contour labels, in the north-east direction, the highest EC values are encountered in the center of the field. This high level of EC decreases when the contour lines come closer on the boundaries of the water well field. This may mean that the factors that influence field EC are spatially different in the areas of center of the field and edges of the field. Therefore, the adverse effects of soil EC can be improved in the center line of the field. Kriging method weighted higher for the pairs of points in the center of the field than the points of samples on the edge of the field. Beside, the north-east border of the central field wasn't given enough weight so that the prediction would be more consistent for allover the field. The lower weighted north-east corner of the field reveals more variability to the kriging method. The reasons for the variability may be various such that the data had a mathematically defined trend and anisotropy was not completely eliminated. In fact, the EC distribution of the field corresponds very well to the field elevation kriging map. Where elevation increases are the places where the soil EC decreases. In the end, it is likely to impact water quality of the well field. For example, withdrawal of water from the basin-fill aquifers via water wells could cause changes in vertical head gradient and that may increase the potential for water quality degradation. Also, the wells themselves, if not properly constructed, could provide pathways for salts, pesticides, and fertilizers to reach the basin-fill aquifer.

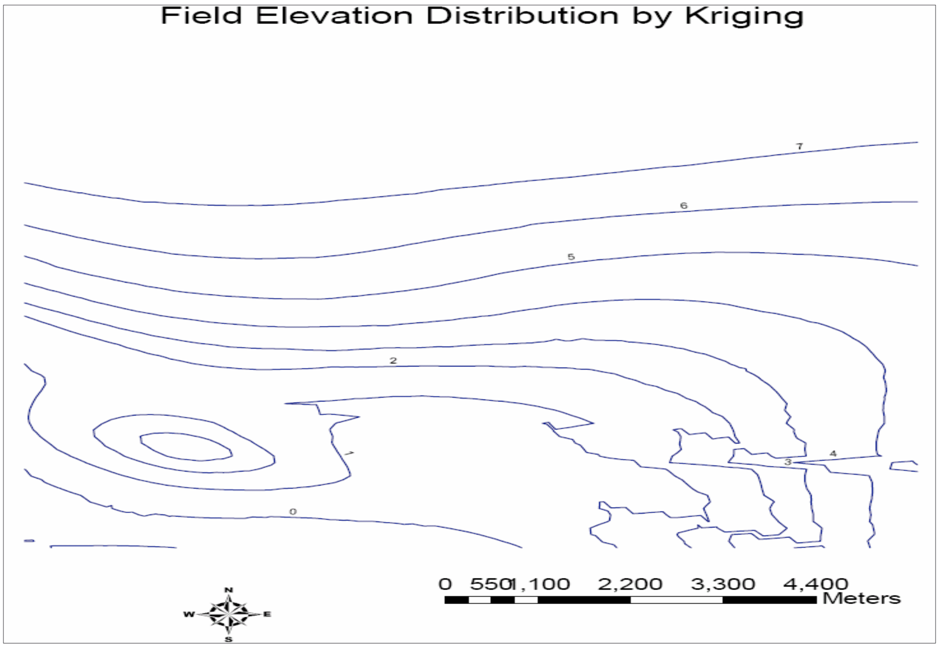

Figure 7. Kriging prediction contour map of sampling point elevations in the field.

Figure 7 shows the elevational changes over the water-well field. In northward increases elevation steadily and a small alluvial channel or valley rift exists on the east direction, while south and southeast corner is gentle slopping. This spatial pattern of the field influences the distribution of the soil and water-well properties. Accordingly, field management options must take the surface topography into consideration for the particular soil unit in the studied area. As a result, any yearly precipitation is highly likely to end up with the accumulation in the lower elevation of the field, which is responsible of the salt content levels of the water-well field. Kriging method predicted anisotropic elevation field. The variogram was not omnidirectional, but changing.

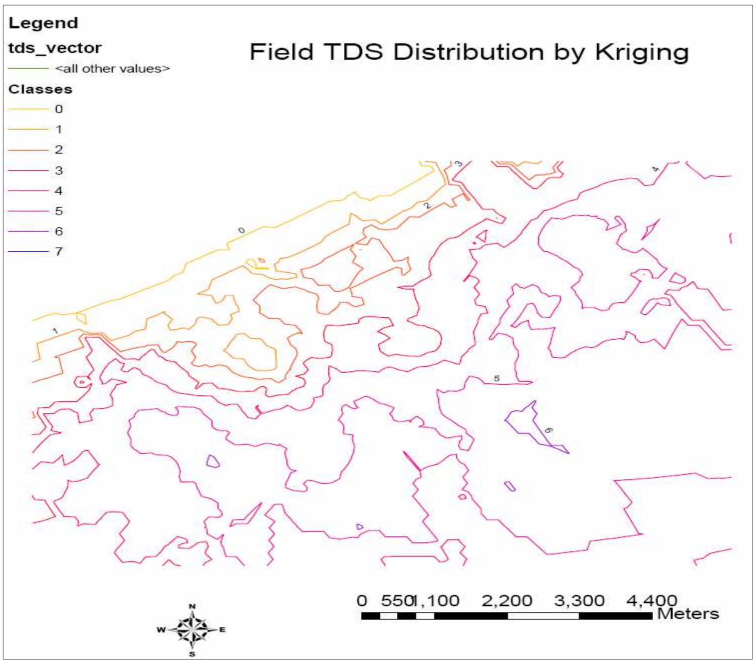

Figure 8. Kriging prediction map of TDS.

Figure 8 depicts TDS distribution contours by kriging method. Although TDS and EC significantly correlate with each other, their distributions prove completely different in the space. The TDS of the well field is not homogeneous as was the case with the field EC. The highest TDS concentrations occur in the center of the field as did field EC, while the TDS concentrations decreases outward of the central field. Similarly, Figure 8 proves that high elevations correspond to low TDS values and low elevations have the highest TDS values, a similar spatial pattern to the field EC. In contrast to soil EC, TDS values did not show strong anisotropy. The search direction had 2.7 degree of tolerance, whereas EC had more than 290 degree of search direction. If the field is a recharge area, return irrigation water may increase TDS in the shallow unconfined aquifers of the basin. High TDS values generally correspond very well with the high soil EC and SAR due to excessive clay dispersion and freed Na+. Therefore, chemical amendment that includes Ca and Mg is always among the reclamation options. Further, they increase aggregation and soil drainage which eventually contributes to favorable crop growth conditions in soil. Various crops can improve soil permeability by removing more Na^+ from soil that would increase aggregate stability and drainage in the soil. According to the data set analyzed, soil pH is fairly high and Na^+ may be problematic issue in the soil. Kriging prediction map of TDS shows that the basin can be improved for TDS and drainage if the hydrologic settings provide excess high quality water that can remove Na^+ and penetrate the soil downward. Furthermore, if Na^+ is replaced with Ca and Mg, the leaching will be facilitated to remove excess Na+ from the soil. As a result, pH will decline to a favorable condition for plant growth and TDS will be lowered. The kriging map provides another option to improve soil management. If the preceding reclamation options do not provide mitigation of the problem, deep tillage may apply to the well field to decline salinity impact to dilute soil salts. The kriging contours of TDS may be the tracking lines to apply point specific land management strategies.

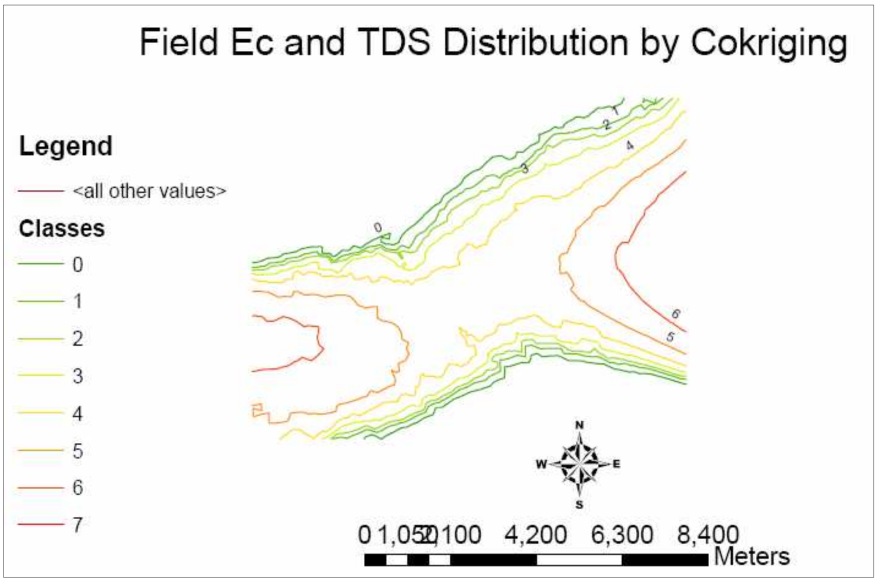

Figure 9. Cokriging prediction map of the EC and TDS.

Figure 9 shows cokriging prediction map of soil EC and TDS. The TDS and EC have predicted each other according to the cross-variogram model that produced the TDS-EC contour map (figure 9). The only obstacles for agriculture are the areas of red contour lined parts, while the rest of the contour lines of concentrations don't pose a stringent threat for the crop species in the basin. The reasons for better prediction of TDS and EC in the basin may be attributed to the closer groundwater to the soil surface, accumulation of the salts and total solids due to storm events and snow melts in the basin, high summer temperature and evaporation and transpiration. In addition, cokriging is an extended kriging that uses more than one variable to predict the other. From the agricultural standpoint, soil quality and land management may be the major goals in the basin. The cokriging map can be utilized to strategize how much and what kind of agrochemicals to be applied when-and- where in the soil. The cokriging map reveals that EC and TDS, collectively and homogeneously, distribute in the field. Therefore, soil may be managed for EC more efficiently if the drainage and irrigation practices suffice.

CONCLUSIONS

The geospatial analyses of the salinity parameters (soil EC, pH, TDS and Ks) used in this study gave detailed prediction maps of the salinity parameters so that they could be used on purpose of land management practices in the study area. The data showed very large trend and anisotropy. However, ArcGIS removed the trend and predicted the maps of random variables by adding the trend to the predictions at the end. This yielded into a better spatial prediction of the variables in the soil. Almost all the variables negatively correlated with each other, except field EC and TDS. The data for the all analyzed variables distributed spherically in the study area. All variables negatively correlated with field elevation. Spatial variability maps showed that the soil spatial variability of all the variables tested was the largest along the central line of the basin. Most of the agricultural constraints occurred in the central area of the basin, also. This was because the basin was an accumulation ditch for the any precipitation event year around and all transportable solids and chemicals accumulated in the basin. The soil EC was the biggest constraint to agriculture in the basin because of its high variability and relatedness to the field TDS. Some of the wells were dry in midsummer in the field. This showed that the basin water pumping rates and evaporation were very high and vertical gradient of the groundwater drops largely in summer. At some points water table was close to soil surface. This increased the vulnerability of the groundwater quality due to salt accumulation, which eventually turned to be a constraint in agricultural use. The results showed that the basin needed improved drainage and irrigation methods. Beyond these practices, chemical amendment of Ca and Mg was required to reduce the adverse effect of soil Na^+ so that soil structural stability and drainage could improve better. For better management purposes, soil water quality and soil properties need dynamic modeling using stochastic approach.

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REFERENCES

Halvarson, A.D. and J.D.Rohades.1976. Field mapping soil conductivity to delineate dryland saline seeps with four-electrode technique. SSSAJ. 40: 571-575.

Istok, J.D. and R. M. Cooper. 1988. Geostatistics applied to groundwater pollution. Global estimates. J. Env. Eng. 144: 915-928.

Journel, A.G., CH.J. Huijbregts. 1981. Mining Geostatistics. Academia Press Inc. (London) Ltd.

Klute, A. and Dirksen, C. 1986. Hydraulic conductivity and diffusivity: laboratory methods. In: Methods of soil analysis. Part I. Physical and mineralogical methods (Ed: A.Klute). 2nd ed. Agronomy No:9, American Society of Agronomy, Madison, WI.pp.687-734.

Mankin, K.R., K.L. Ewing, M.D. Schrock, and G.J. Kluitenberg. 1997. Field measurement and mapping of soil salinity in saline seeps, in: Proceeding for ASAE International meeting . No 90 3145, Minneapolis, MN.

Lesch, S.M., J.D. Rohades, L.J. Lund, and D.L. Corwin. 1992. Mapping soil salinity using calibrated electromagnetic measurements. SSSAJ. 56: 540-548.

Pozdnyakova, L. and R. Zhang. 1999. Geostatistical Analyses of Soil Salinity in a Large Field. Precision Agriculture.1:153-165.

Richards, L.A. 1954. Diagnosis and Imporevements of Saline and Alkali Soils. Agriculture Handbook No.60. US salinity laboratory. Riverside, California.

Szabolcs, I. 1989. Salt-affected soils. CRC Press, Inc, Boca Raton, Florida.

Tabor, J. A. A. W. Warrick, D.A. Pennington, and D.E. Myers.1984. Spatial variability of nitrate in irrigated cotton: I. Petioles. SSSAJ. 48: 602-607.

Tabor, J. A. A. W. Warrick, D.E. Myers, and D.A. Pennington. 1985. Spatial variability of nitrate in irrigated cotton: II. Soil nitrate and correlated variables. SSSAJ. 49: 390-394.

Yates, S.R., R. Zhang, P.J. Shouse, and M.Th. Van Genuchten. 1993. Use of geostatistics in the description of salt-affected soils, In: Water flow and solute transport in soils (Eds.: D. Russo and G. Dogan). Springer-Verlag, New York, 1993, pp. 283-304.

Yates, S.R. and A. W. Warrick. 1987. Estimating soil water content using cokriging. SSSAJ. 51: 23-30.

Zhang, R., S. Rahman, G.F.Vance, and L.C. Munn. 1995. Geostatistical analyses of trace elements in soils and plants. Soil Sci. 159: 383-390.