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MULTIVARIATE GEOSTATISTICAL METHODS FOR MAPPING SOIL SALINITY

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Abstract: Degradation of the lands by salinity under arid climate and poor drainage conditions can be inevitable. In the Harran plain total salt affected areas covers 10 % of total irrigated areas which are mainly located in the low lying parts of the plain where elevation ranges from 350 to 400 m. Soil salinity shows high spatial variability which requires intensive sampling and laboratory analyses. Geostatistical techniques such as simple or ordinary kriging can be used in explaining this spatial variability and estimating soil salinity parameters at unvisited locations. On the other hand, new approaches such as hybrid interpolation methods which incorporate secondary variables into primary variables can help improve the estimation. Estimating soil salinity is a vital issue in soil fertility and management. This study evaluated multivariate geostatistical methods such as regression kriging (RK) and kriging with external drift (KED) and compared them with ordinary kriging (OK) for the estimation of soil salinity parameters. Topographical parameters (i.e elevation, slope and topo wetness index (ln $(A/\tan\alpha)$)) as well as soil EC values at different depths were used as auxiliary variables. Overall results showed that estimation and mapping accuracy may be improved using multivariate geostatistical methods depending upon the power of the relationship between soil salinity parameters and environmental variables used as covariable.
Key Words: Soil salinity, Regression kriging, Kriging with external drift, Topography

1. INTRODUCTION

Soil salinity is a serious environmental problem affecting 20 % of total irrigated lands across the globe. Overall total cultivated areas degraded by salinity and sodicity have been reported to be 1.5 billion ha over 100 countries (Tanji, 2002). Salt affected areas mostly dominate in arid and semi arid regions, some of which are located in the Harran plain. According to recent survey performed, around 10 % of the plain have been degraded by salinity slight to extreme levels (Cullu ve ark. 2002).

In addition to traditional methods based on the measurement of soil salinty parameters from the extractions obtained either from soil saturation paste or different soil and water ratios (Rhoades, 1982), the soil salinity has been monitored using various techniques by earlier researchers. Soil salinity was mapped by taking advantage of spatial interpolation methods (Ardahanlioglu et al. 2000), remote sensing-satelliete imagery- digital image analysis, hyperspectral reflectance spectroscopy and Electromagnetic Induction tools (EM) (Farifteh et al. 2006).

Pozdnyakova and Zhang (1999) estimated soil salinity parameters using both ordinary kriging and co-kriging. In addition to co-kriging, hybrid interpolation methods such as regression kriging (RK) and kriging with external drift (KED) use a secondary variable in order to improve the estimations of target variable. They have been successfully used to improve the estimations of various parameters such as soil horizon thickness, soil heavy metals and yield (Lin, 2002; Kravchenko and Robertson, 2007). These methods combine the information from both primary variables (target) and more densely available and cheap to obtain auxilary variables and they can be used as long as there exist a linear relationship between both variables and also auxilary variable is available at both target's locations and also at locations where the estimations are to be done (Hengl et al. 2004).

In this study, soil salinity parameters were mapped using multivariate geostatistical methods such as RK and KED and the results were compared with traditional OK to see whether the estimation quality of soil salinty at unvisited locations could be improved by the use of secondary variables.

2. MATERIAL AND METHODS

2.1. Study Site

The study area is located in the Harran Plain, Sanliurfa, Turkey, covering a total area of around 1000 ha. The study area is under semi arid climate with a mean annual temperature, precipitation and evaporation of 17 ^oC, 365 mm and 1850 mm, respectively. The soils were mostly formed on calcareous parent material, and are rich in iron. Soils are mostly finely textured, low in organic matter, but high in $CaCO_3$ content on average (Aydemir, 2001).

2.2. Soil Sampling and Laboratory Analysis

A total of 151 locations randomly selected were sampled at two different depths (0 to 15 and 15 to 30 cm). Sampling locations, X and Y coordinates were recorded using a GPS unit. Soil samples were subsequently air dried and sieved (2 mm) to prepare for laboratory analysis. Soil electrical conductivity as an indicator of current soil salinity at both surface and subsurface depths were determined from soil water extracts obtained from saturation pastes prepared using 100 g air dried samples.

2.3. Topographical Indicators

Topographical maps (1:5000 scale) of the study area was digitized to delineate Digital Elevation Map (DEM) (Figure 1). From DEM topographical parameters such as slope (%), flow accumulation and Topo Wetness Index (TPI) were calculated using spatial analysis tools in ArcGIS 9.3 (ESRI Inc.). Digitization was performed using NETCAD (National CAD and GIS Solutions) and DEM creation and analyses of DEM parameters was performed within ArcGIS environment. The information of topographical indicators were extracted by overlapping the sampling locations on the raster maps of each topographical parameters. Calculation of the Topo Wetness Index (TWI) was performed according to the formula below (Sorensen et al. 2005)

$$TWI = \ln\,(a / \tan\beta)$$

where a is the upslope contributing area calculated from flow accumulation and β is percent slope.

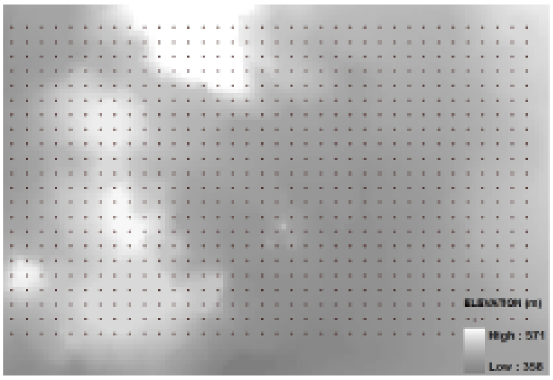


Figure 1. DEM of the study area and 100 m by 100 m grid estimation locations

2.4. Geostatistical Modeling

2.4.1. Ordinary Kriging (OK)

Ordinary kriging estimates the unknown value using a weighted linear combinations of the available samples.

$Z_{OK}(x_0) = \sum_{i=1}^{n} w_i Z(x_i)$, where $Z_{OK}(x_o)$ is the OK 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 i^{th} observation $Z(x_i)$. Weights are determined after computing a semivariogram that models spatial correlation and covariance structure between data points for each variable according to following equation (Wackernagel, 2003):

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

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.

2.4.2. Regression Kriging (RK)

RK as a multivariate geostatistical method is the sum of regression between target (primary) variable and secondary variable(s) and kriging of residuals derived from the regression (Wackernagel, 2003);

$$Z_{RK}(x_0) = \sum_{k=0}^{p} \beta_k . q_k(x_o) + \sum_{i=1}^{n} w_i . e(x_i)$$

where $Z_{RK}(x_o)$ is the RK estimate at unsampled locations (x_o), $ß_k$ and $e(x_i)$ are the regression coefficients and residuals, respectively, obtained from the regression between primary and secondary variables using actual lab observations at calibration locations (x_i), p is the number of predictor (secondary) variables , w_i are kriging weights determined from the variogram of residuals, $q_k(x_o)$ are the values of secondary variables at the target locations, which are topographycal parameters in this case. Regression coefficients and residuals were obtained using Ordinary Least Square (OLS) regression and kriging of residuals was performed with simple kriging. The secondary variables involved in the OLS equation were selected through stepwise regression analysis.

2.4.3. Kriging with External Drift (KED)

KED is another spatial interpolation method that combines primary and secondary variable with the aim of improving the estimations. KED is similar to Universal Kriging where coordinates are used as trend (drift) in the kriging. Whereas in KED, trend is auxilary variable which is correlated with primary variable and exist extensively both in calibration and also validation points. KED is formulized as (Wackernagel, 2003).

$$Z_{KED}(xo) = \sum_{i=1}^{n} w_i . Z(x_i) \;,\; Z(x_i)=m(x)+\varepsilon(x)$$

here wi= weights of KED, m(x) is main trend part where predictor variables are involved and $\varepsilon(x)$ is residuals. Predictor (secondary) variables are available at all points (calibration and validation points).

2.4.4. Validation

All three methods were compared for their quality of the estimation using a seperate validation data set selected randomly from whole data set. Accuracy of predictions were compared using root mean suqare error of prediction (RMSEP) value.

In order to map soil surface and subsurface ECe using geostatistical methods, a 100 by 100 grid was formed and overlapped on raster DEM (Figure 1) belonging to the study area and topographycal values at each node was extracted and used as covariable.

3. RESULTS AND DISCUSSION

3.1. Salinity Parameters

Descriptive statistics related with soil salinity parameters; surface and subsurface ECe and their correlations with each other and topographical indices are shown in Tables 1 and 2, respectively. Soil ECes showed a broad range from 0.5 to 10.2 dS/m for ECe-I and 0.68 to 13.8 for ECe-II. Elevation of the study area ranges 360 m to 370 m.

Soil ECes were highly correlated with each other ($r = 0.77$) and pH ($r = -0.39$ and $r=-0.62$) (Table 2). Other significant correlations ($p< 0.05$) existed between ECe-I and elevation, flow accumulation and topo wetness index (r = - 0.30, 0.23 and 0.20, respectively), between ECe-II and elevation, flow accumulation, flow direction, topo wetness index and soil type (r=-0.33, 0.31, -0.23, 0.23 and 0.21, respectively) while the correlations with slope, curve and aspect were not significant. The areas with high TWI values at low elevations are supposedly become saturated first with capillary movement of groundwater, however either ECe was poorly correlated with TWI.

3.2. Prediction of Soil Salinity using OK, RK and KED

Soil surface and subsurface Ece at unsampled locations (validation points) were estimated and mapped across the study area using traditional OK, and two hybrid interpolation methods; RK and KED and the results were compared for all three. Figure 2 summarizes the estimation procedure of RK that combines the both regression and kriging of residuals from regression equation.

In KED, primary variable of interest was kriged against covariable which was elevation in this case. Figure 4 shows the quality of the estimations by different geostatistical methods. RK or KED using topographycal parameters as covariable improved the estimations of ECe-I and ECe-II slightly as compare to OK (Figure 4a).

Table 1. Descriptive Statistics of soil and environmental parameters

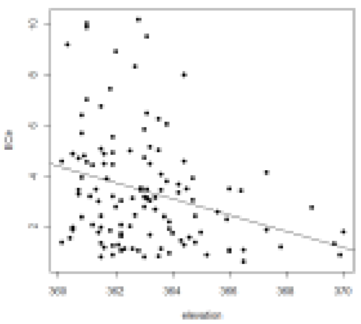
	N	Min	Max	Mean	Stdev
ECe-I	151	0.55	10.2	3.28	221.5
ECe-II	91	0.68	13.8	37.5	278.3
pH-I	68	7	8.7	7.7	0.36
Elv	151	360	370	363	2
TWI	151	6.47	21.9	9.95	2.43

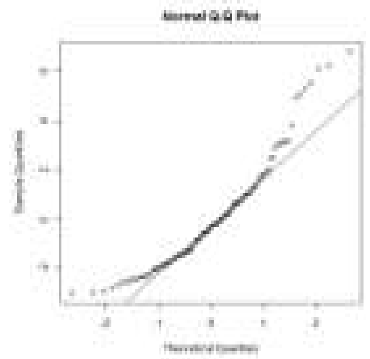
TWI: Topo Wetness Index, Elv: Elevation, pH-I: pH at surface

Table. 2. Correlations among soil ECs and topographycal indices

	ECa-II	pH-I	Stype	Facc.	Slope	Curv	Fd	Asp	Twi	Elv
ECe-I	0.77**	-0.39**	0.13	0.23**	-0.12	-0.19	-0.2	-0.02	0.20*	-0.30**
ECe-II		-0.62**	0.21*	0.31**	-0.13	-0.14	-0.23*	0.06	0.23*	-0.33**

Stype:Soil Type; Facc: Flow Accumulation, Fd: Flow Direction, Asp:Aspect, TWI: TopoWetness Index, Elv:Elevation
**: Correlations significant at p < 0.01 and *: at p < 0.05 levels.


a)



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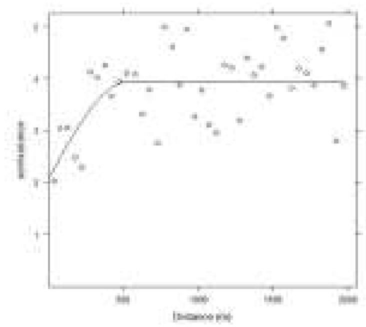
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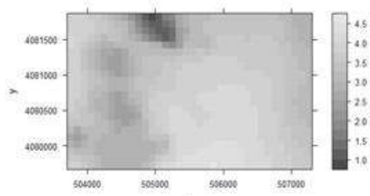
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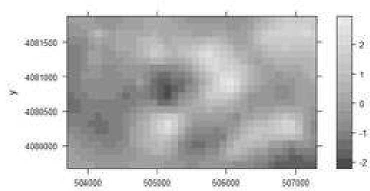
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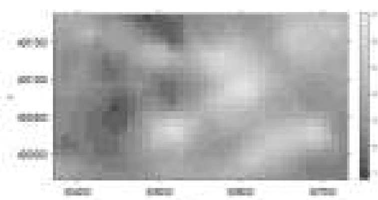
f)

Figure 2. Steps in regression kriging; a) stepwise regression between target and covariable b) residuals from regression c) variogram of residuals d) kriging of residuals across whole study area e) OLS regression across whole study area f) final map (d+ e) as in regression kriging equation

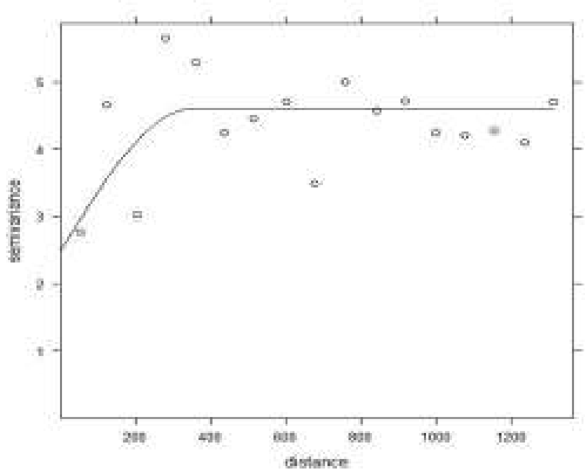

Figure 3. Variogram obtained by soil surface EC and Elevation in KED. (Nugget to sill ratio: 54 %, model: Spherical, range: 349)

This may be attributable to weak correlations obtained between topographycal variables and soil ECe values at surface and subsurface. Rather than topographycal variables, using subsurface soil ECe values as covariable better improved the estimations of soil surface ECe providing lower RMSEP values using either RK or KED than traditional OK (Figure 4 b). But this was not the case for the estimations of subsurface soil ECe which was not improved much using either RK or KED with soil surface ECe as covariable. This is either because of poor correlations between primary and secondary variable or this may be attributable to poor spatial distribution of residuals from regression between two, which would be equal to regression itself (Hengl et al. 2004). The latter can be the reason for this result obtained considering strong correlation available between both (ECe-I and ECe-II).

3.3. Mapping of Soil Salinity

Figure 5 and 6 show the maps of soil salinity at surface and subsurface depths in the study area delineated using different spatial interpolation methods. All three methods had some levels of errors associated with estimations. But in general, maps obtained by OK showed underestimations at some locations (Figure 5 and 6), which can be due to nature of this technique (Wackernagel, 2003). There was a similarity between final maps produced with RK and KED and raster DEM map, which can be clearly seen from the figures. Soil subsurface map had better resolution and accuracy as compare to the surface map. This can be due to the degree of correlation between elevation and soil ECe-I and ECe-II which is relatively higher. Overall, these results confirmed the fact that the accuracy of predictions and mapping of soil variables using multivarite geostatistical methods that combine primary and secondary variables is mostly dependent upon the power of the relationship between two.

4. CONCLUSION

The estimation quality of soil salinity parameters using traditional ordinary kriging was poor due to poor spatial distribution of soil salinity parameters across the study area. The estimations were improved slightly using multivariate geostatistical methods along with topographycal parameters. Better improvements were obtained when using soil ECs at different depth as covariable.

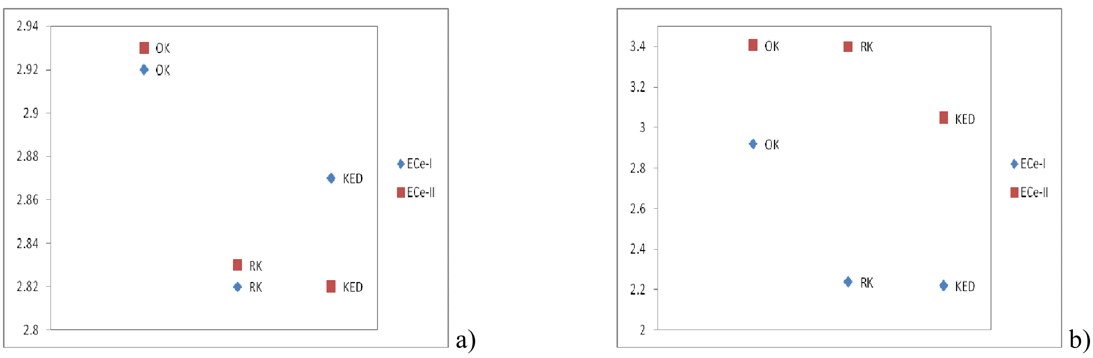

Figure 4. Change in values of Root Mean Square Error of Prediction (RMSEP) among different estimation methods ; OK: Ordinary Kriging, RK: Regression Kriging and KED: Kriging with External Drift for ECa-I and ECa-II. a) Using topographycal parameters and b) Soil ECas as covariable

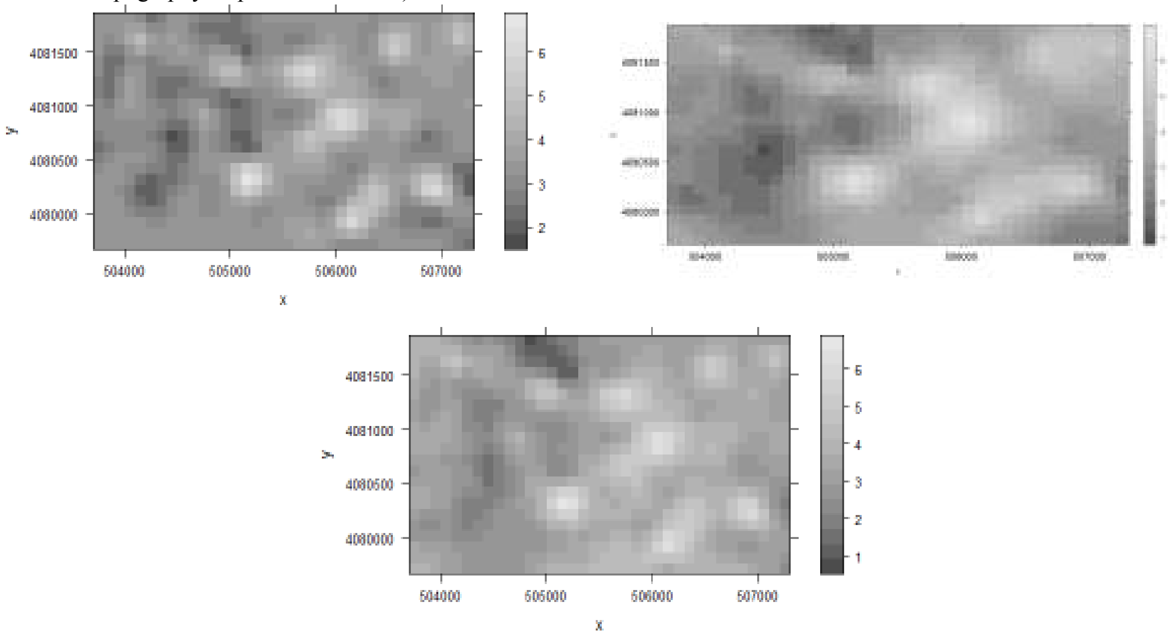

Figure 5. Soil surface salinity (ECe) estimation maps using OK, RK and KED (from top to bottom)

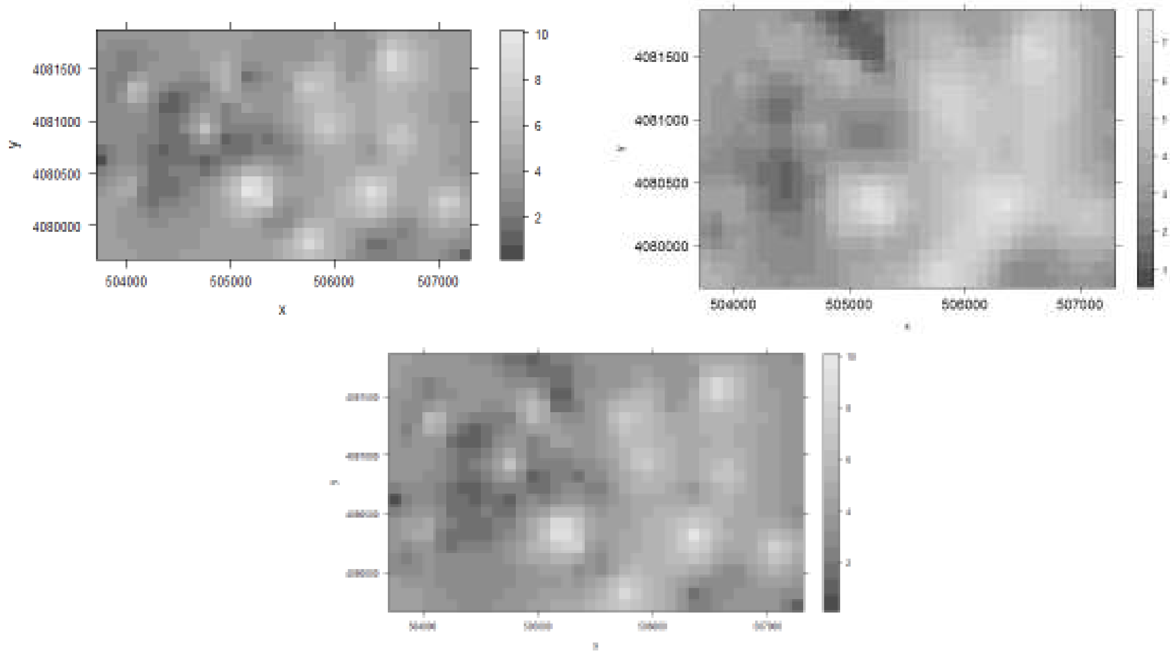

Figure 6. Soil subsurface salinity (ECe) estimation maps using OK, RK and KED (from top to bottom)

5. ACKNOWLEDGMENT

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