Research Contract between Research Institute for Humanity and Nature (RIHN), Harran University, and Adiyaman University

DESIGNING LOCAL FRAMEWORKS FOR

INTEGRATED WATER RESOURCE MANAGEMENT

Harran University & Adiyaman University Research Group

GAP Region Case Site

Activity report FY2012

March 31, 2013
Sanliurfa

ACTIVITY REPORT FOR HARRAN AND ADIYAMAN TEAM

MEETING I

Meeting for training of farmers and WUA

Organizers:DSİ, Harran University

Participants: Governor, general director of DSİ, Rector, other protocol members
Farmers, WUA, Agricultural engineers,

Date: April 4, 2013, DSİ Meeting room, One Day. Sanliurfa,Turkey

Chair. Dr. Mehmet Ali Cullu

One speaker: Dr. Mehmet Ali Cullu

Title of speach: Salinization at the Harran Plain and statues of the GAP Region

At the speach, Some RIHN C09 Project outcomes made in the presentation.

MEETING II

Meeting for Awareness for Drainage and Salinization at the Harran: Agricultural Perspective for 2023

Organizers:Ministry of Food, Agriculture and Livestock, Harran University

Participants: Governor, General Director of Aricultural Reform, Rector, other protocol members, DSİ Members, Members of Food Agriculture and Livestock Directory, Farmers, technical personels, WUA, Agricultural enginers, farmers.

Date: December 28-March 2, 2013, Harran University Agricultural Faculty Meeting room, Sanliurfa,Turkey

Chair. Dr. Mehmet Ali Cullu

Some comments about RIHN C09 Project outcomes made at the meeting and opened to discussion.

MEETING III

Organizers: Adiyaman University. The Sustainable Water Use in GAP Region, TEMA Training Programme for Primary School Teachers. Dr. Erhan Akça made a presentation for the outcomes of RIHN C09 Project

Date: 25 May 2013, Adıyaman University Highschool Conference Hall

Paper accepted:

Erhan Akça, Mehmet Ali Çullu, Takanori Nagano, Tsugihiro Watanabe, Selim Kapur and Suha Berberoglu. International World Irrigation Forum. Sep. 28-5 Oct., 2013 Anatolian Anthroscape: A Model for Natural Resource Management 141. Category: Rainfall Management (Water Harvesting) Track : Workshop 2. Developing Management Strategies for Coping with Drought and Water Scarcity

Published Some Paper related C-09 project

Cullu M. A, A. V. Bilgili, A. Almaca, A.R. Ozturkmen, A. Aydemir, S. Aydemir, M. Aydoğdu, Y. Şahin, S. Karakaş Dikilitaş, A. R. Mermut. 2012. Mapping of Salt Affected Lands Using Combination of Remote Sensing, GIS and Classical Methods: A Case Study in the Harran Plain.8th International soil Science Congress on “Land Dagradation and Challenges in Sustainable Soil Management”. P:140-145. May 15-17. Çeşme İzmir Türkey.

Bilgili, A. V. M. A. Cullu, A. Aydemir, S. Aydemir, A. Almaca.2012. Probability Mapping of Saline and Sodic Soils in The Harran Plain Using a Non Linear Kriging Technique. 8th International soil Science Congress on “Land Dagradation and Challenges in Sustainable Soil Management”. P:128-134. May 15-17. Çeşme İzmir Türkey. Ali V. Bilgili, "Spatial assessment of soil salinity in the Harran Plain using multiple kriging techniques",2013. Environmental Monitoring Asssessment, 185, 777-795 pp., , DOI: 10.1007/s10661-012-2591-3.

Ali Volkan Bilgili, Aydın Aydemir, Osman Sönmez and **Mehmet Ali Çullu**. 2013. "Comparison Of Three Laboratory And Regression Kriging Method For Quantitative And

Qualitative Assessment Of Soil Salinity In The Harran Plain, SE Turkey", Fresinius Environmental Bulletin (ISI) , 22, 1339-1350 pp.,

Ali V. Bilgili, "Spatial assessment of soil salinity in the Harran Plain using multiple kriging techniques",2013. Environmental Monitoring Asssessment, 185, 777-795 pp., , DOI: 10.1007/s10661-012-2591-3.

C09 HARRAN PROJECT ACTIVITIES

1. AREA DESCRIPTION

The Harran is the biggest fertile plain of Southeastern Anatolia Project (GAP) which comprises 161000 ha irrigable land (Figure 1). The plain is under the semiarid climate regime and it is dominated by clay-textured soils. Irrigation started in the plain using water coming from Atatürk Dam since 1995. With irrigation, there is striking change in the crop pattern in the Harran Plain. Before irrigation, wheat, barley and lentil were the main crops. The Harran Plain faces problems of salinity due to excessive and uncontrolled irrigation, an inadequate drainage system and as a consequence of these, an increased groundwater level appears

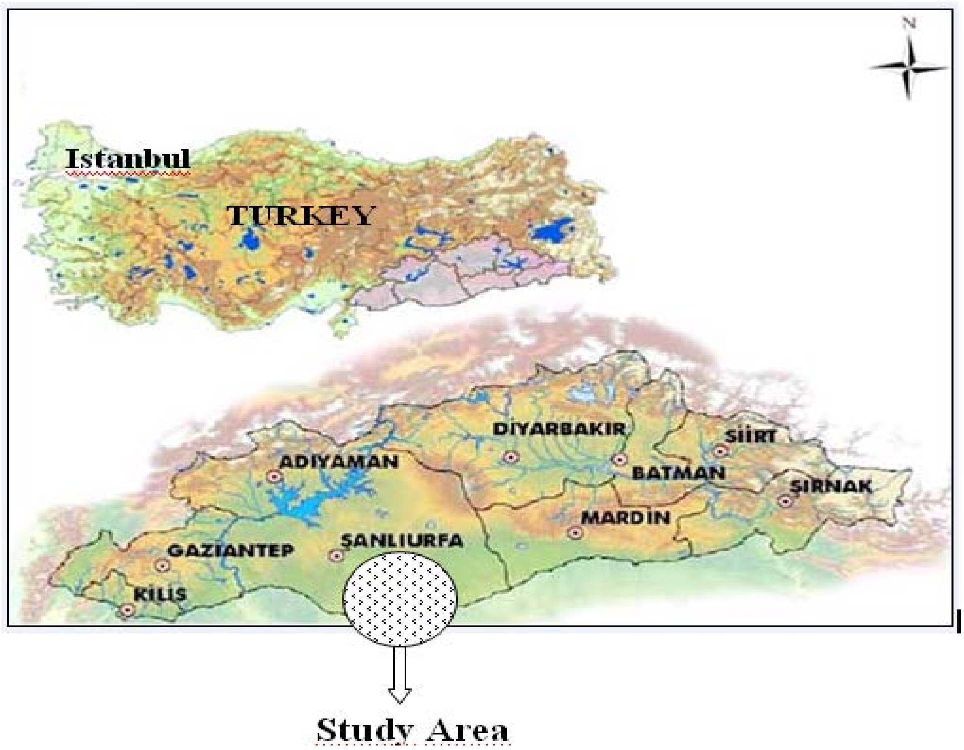


Figure 1. Location of the Study Area

2. FIELD STUDIES, SOIL EC ANALYSES AND SALINITY MAPPING

Approximately 30 % of the plain is affected by the shallow water table and 10 % of the plain isaffected by salinity. In order to determine recent salinity status of the plain, about 100 soil samples were collected from the soil surface (0-30 cm depth) and prepared for analyses. Location of soil samples are shown on the satellite image (Figure 2). Their analayses for salinity mapping were completed and salinity map are being delineated. In order to determine the salinity severity, exchangeable Na, and cation Exchange capacity (CEC) analyses are also being continued.

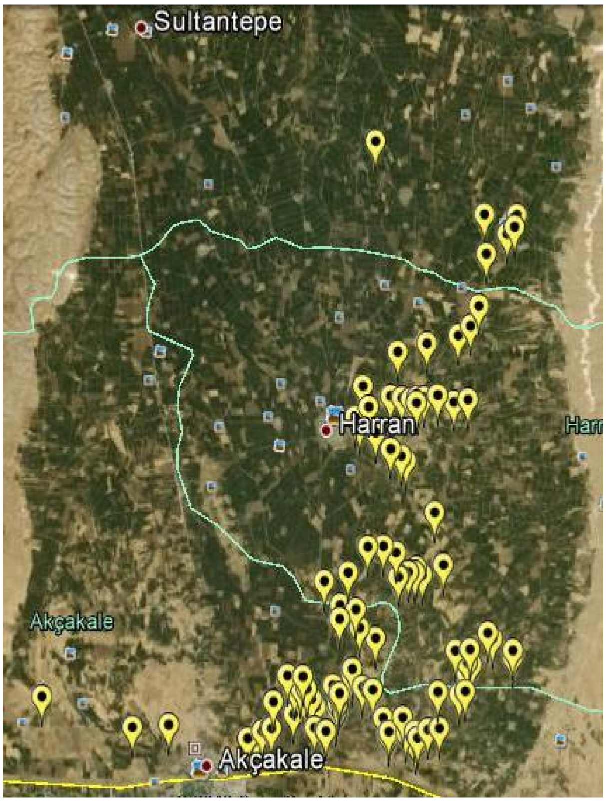


Figure 2. Location of the collected soil samples.

Salt content of all the soil samples were evaluated according to their EC levels. They are shown at the Figure 3. The salinity level of the targeted area were changed between 1 and 52 dS/m. Soil salinity is an increasing threat for yield and also a major factor in reducing plant productivity; therefore, it is necessary to better understand the reasons for its development. Crops have different salt tolerances. All crops have a maximum salt level they can tolerate without a yield loss. Salt levels above a crop's maximum tolerance level sharply reduce yields. The yield loss starts at the EC level of 4 dS/m and yield loss increases with the increase of EC values. Because of the high salt content of the Harran plain, considerable yield losses have been observed. According to soil EC levels and other field studies, salinity map of the targeted areas are being prepared

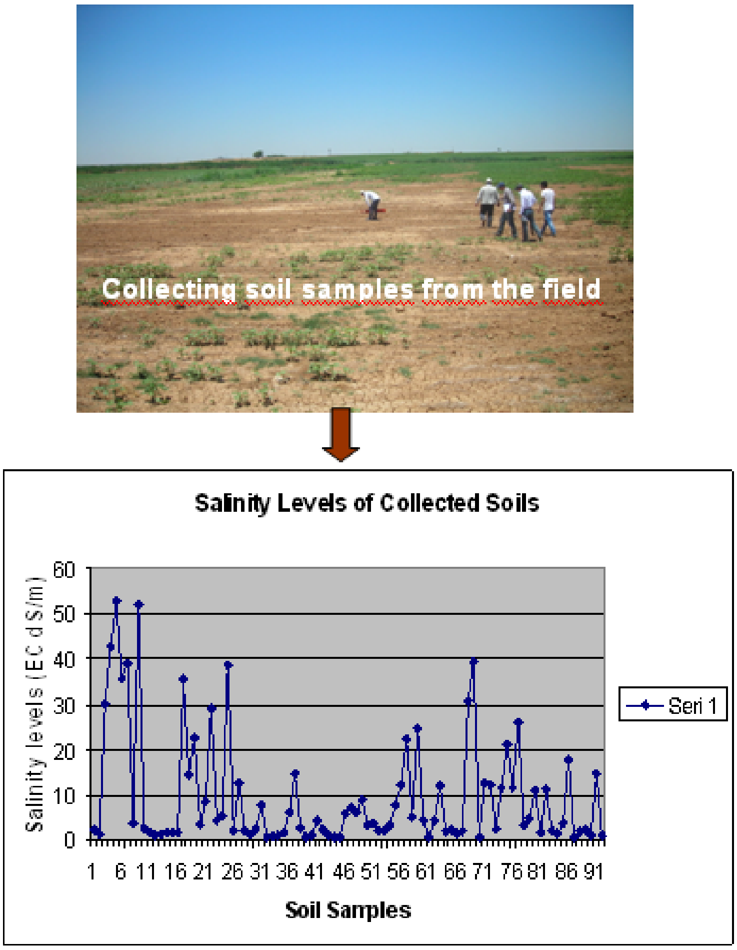


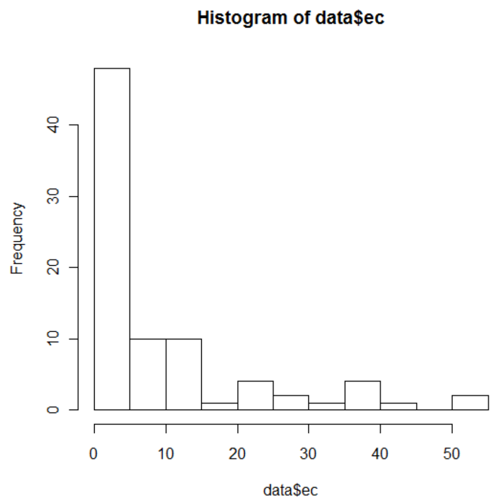
Figure 3. Salinity Levels of the Targeted Lands

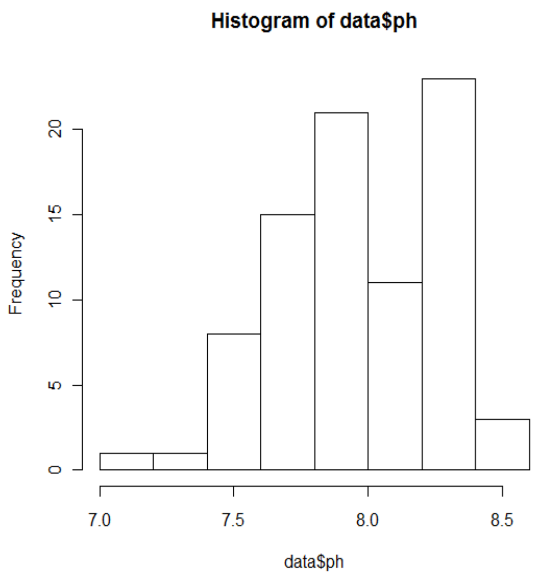
This map will be integrated with landuse type and yield loss will be determined for the year of 2012.

The analyses results of the soil salinity showed that majority of the soil ECs were over the plant tolerance. These findings are valuable data for choosing landuse type and soil to improve processes.

3. DESCRIPTIVE AND GEOSTATISTICAL ANALYSES OF THE SALINITY DATA

At the same time, soil samples were prepared for NIRS analyses to compare with classical analyses results. Soil sampling has been performed in the salt affected areas of the Harran Plain. Figure 4 shows the distribution of soil salinity variables of soil pH and EC and also EM values.Accordingly, soil salinity variables of EC and pH showed a broad range covering different soil salinity groups such as saline, saline-alkaline and alkaline.





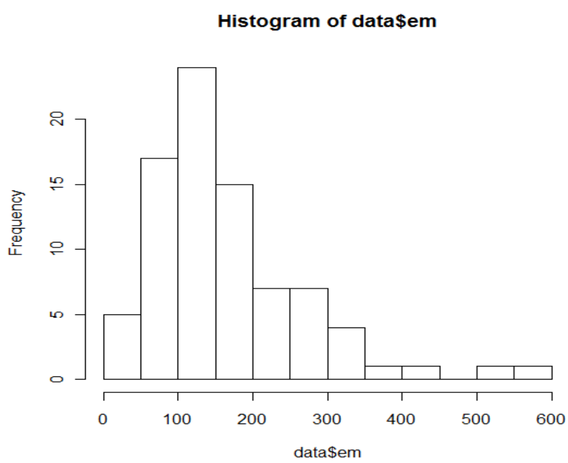
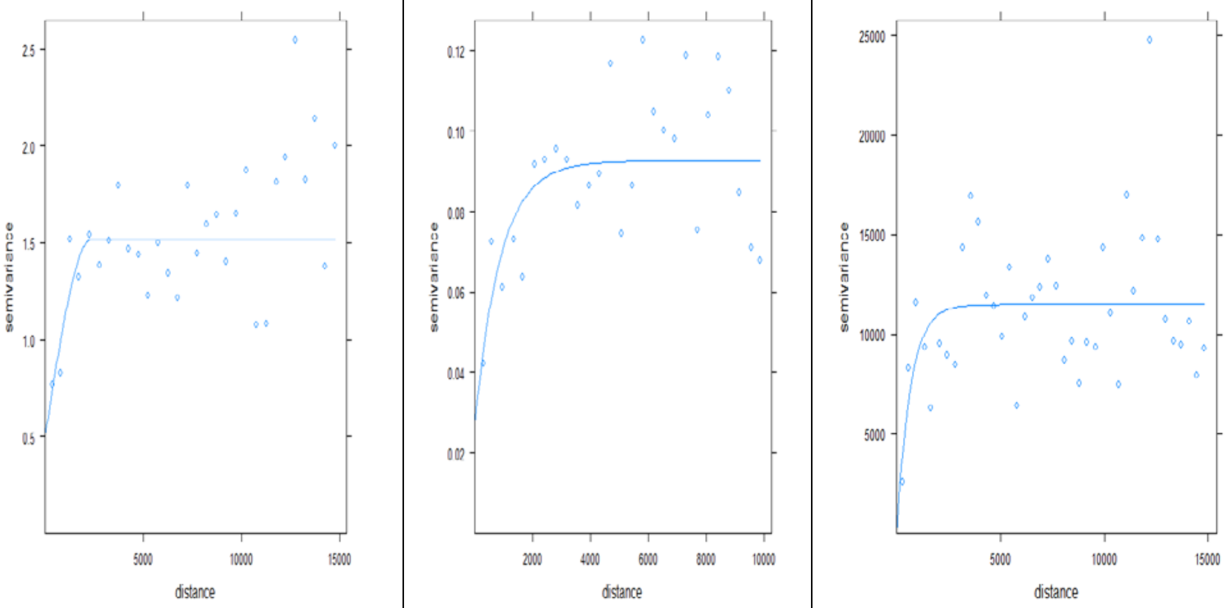


Figure 4. Distributions of soil pH and EC (ds m-1) and EM values (vertical readings)

The obtained values are representing the final status of soils located saline areas of the Harran plain after drainage. pH values ranged from 7.14 to 8.58 and showed a normal distribution, whereas soil EC showed a right skewed distribution ranging from 0.59 to 52.8 ds m-1. EM values showed a distribution as paralel to soil EC values ranging from 30 to 575, which was also broad as soil EC and pH indicating that soils can be in classes of both saline and alkaline.

3.1. Variogram Analyses Of Soil Salinity Parameters And Kriging Mapping

The results of variogram analyses of soil salinity parameters are shown in figure 5.



Variogram of soil EC ds m-1

Variogram of soil pH

Variogram of soil EM values

Figure 5. Experimental variaograms of soil salinity variables and EM values

Table 1. Variogram parameters of available soil salinity variables and EM values

Variables	Model	Range	Nugget	Partial sill	Sill	Nugget/Sill
EC dS m-1[†]	Spherical	2334	0.50	1.01	1.51	0.49
pH	Exponential	883	0.026	0.065	0.091	0.40
EM	Exponetial	650	1005	11498	12503	0.087

† log of soil EC

Variogram parameters of soil salinity variables of pH and EC and EM are shown in table 1. Accordingly, soil EC and pH showed a moderatelly strong spatial distribution while EM showed a strong spatial distribution giving a very low nugget to sill ratio.

Figure 6 shows the maps of soil salinity variables and EM obtained using ordinary kriging methods. The maps of soil EC and EM showed similarity giving areas affected by different levels of salinity. Soil pH map showes affected areas by salinity and also alkalinity.

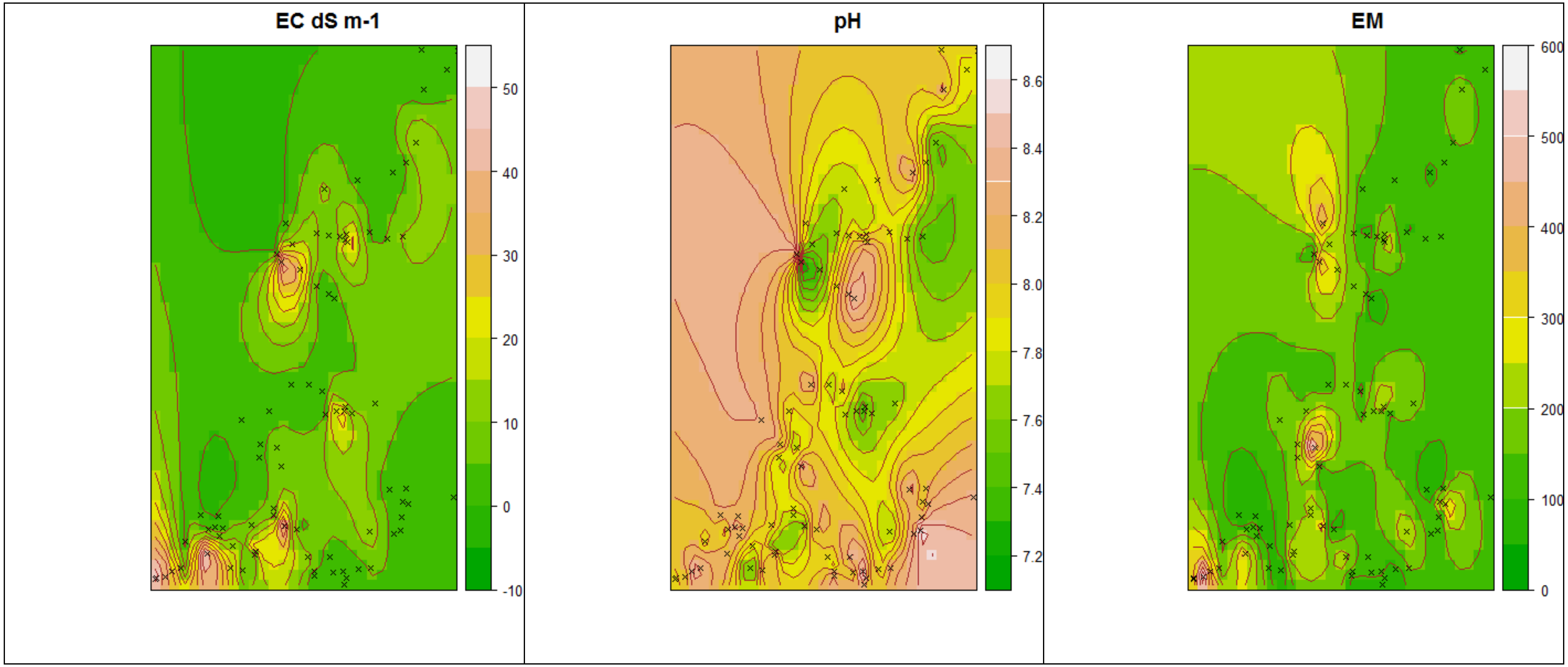
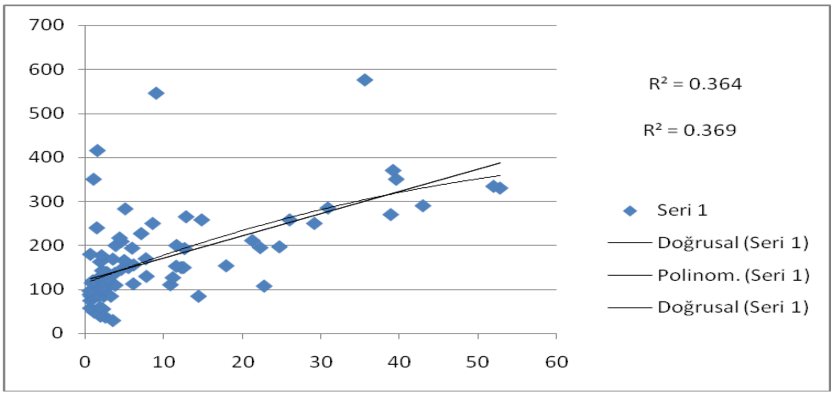


Figure 6. Kriging Maps of Soil salinity Variables and EM Values. Maps With Corresponding Legends hows Salt Affected Locations.

4. CALIBRATION OF EM-38 AND SOIL SALINITY CHARACTERIZATION

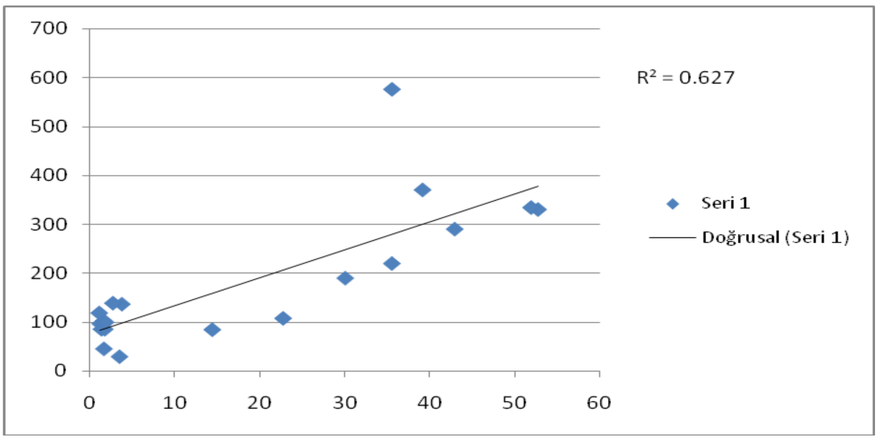
The potential use of EM equipment in the monitoring the soil salinity in the plain were evaluated. The calibration results between laboratory measured soil EC values and EM-38 readings is shown in Figure 7. As seen the figures, EM-38 gave promising results for monitorization of soil salinity. On the other hand, seperating and evaluating the data based on the different sampling days showed that the better results can be obtained only when the calibration could be performed using the same day data and samples taken from similar soil series could be used (Figure 7).

A



Calibration of EM – 38 using whole data

B



Calibration of EM– 38 using only first day sampling data

Figure 7. Relationship Between EM-38 Readings and Soil EC Values

5. IRRIGATION AND DRAINAGE WATER QUALITY

5.1. Irrigation Water Quality

In order to determine the water quality, water samples from irrigation and drainage water were collected and their analyses were completed (Figure 8). Salt content of the irrigation water is a considerable affecting factor on soil salinity increases.

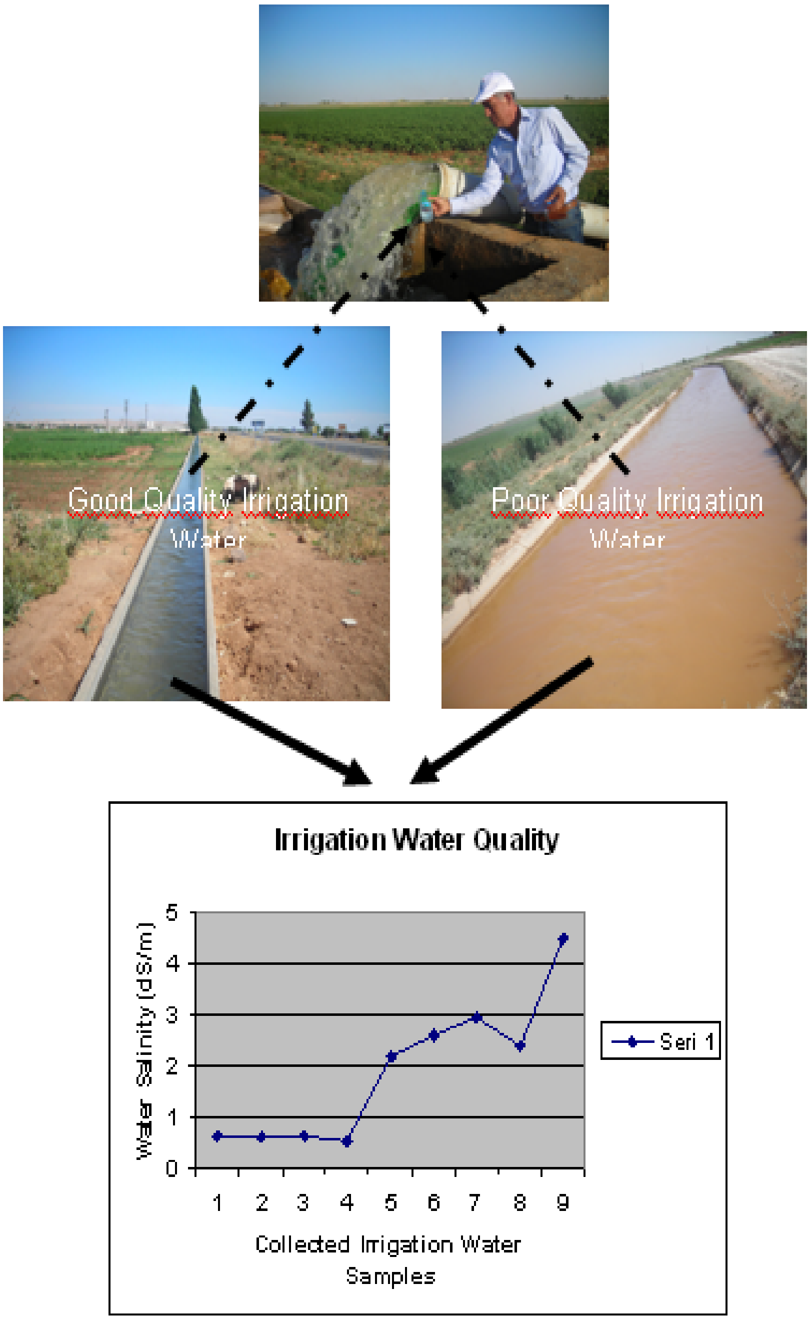


Figure 8. Irrigation Water Quality Analyses

Not only shallow water table effect the soil salinity accumulation at the root depth, also water salt content is another affecting parameter. At the Harran Plain, there were 3 groups of irrigation water:

a) Fresh irrigation water coming from the Atatürk Dam

b) Reused water coming from the main canal

c) Drainage water coming from the drainage canal

According to graph on the Figure 8., analyses results of water quality of both fresh and reused irrigation waters showed that values are over the standart irrigation water quality.

5.2. Drainage Water Quality

After irrigation started in 1995 from Atatürk Dam, cotton (Gossypium hirsutum L.) was chosen as a main crop due to its high income potential. Considering the general perception that the greater the amount of water used for irrigation is, the greater production will be, farmers used excess water with furrow irrigation methods. Irrigation in the area has caused a high water table and caused fluctuations in the groundwater levels and its quality (Figure 9).

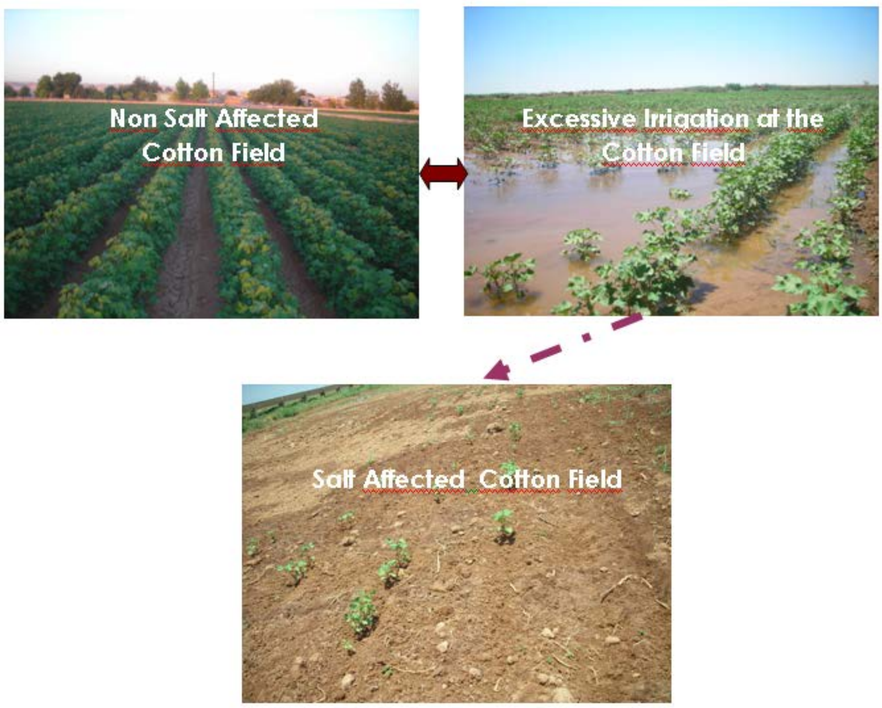


Figure 9. Excessive Irrigation and Yield Losses

At the some part of the plain, drainage water were used for irrigation. Because of the excessive irrigation at the upper places, water can not reach to the areas at lower places of the plain and so farmers used drainage water at some locations. Anaylses results of collected water also showed quite high salt content (Figure 10).

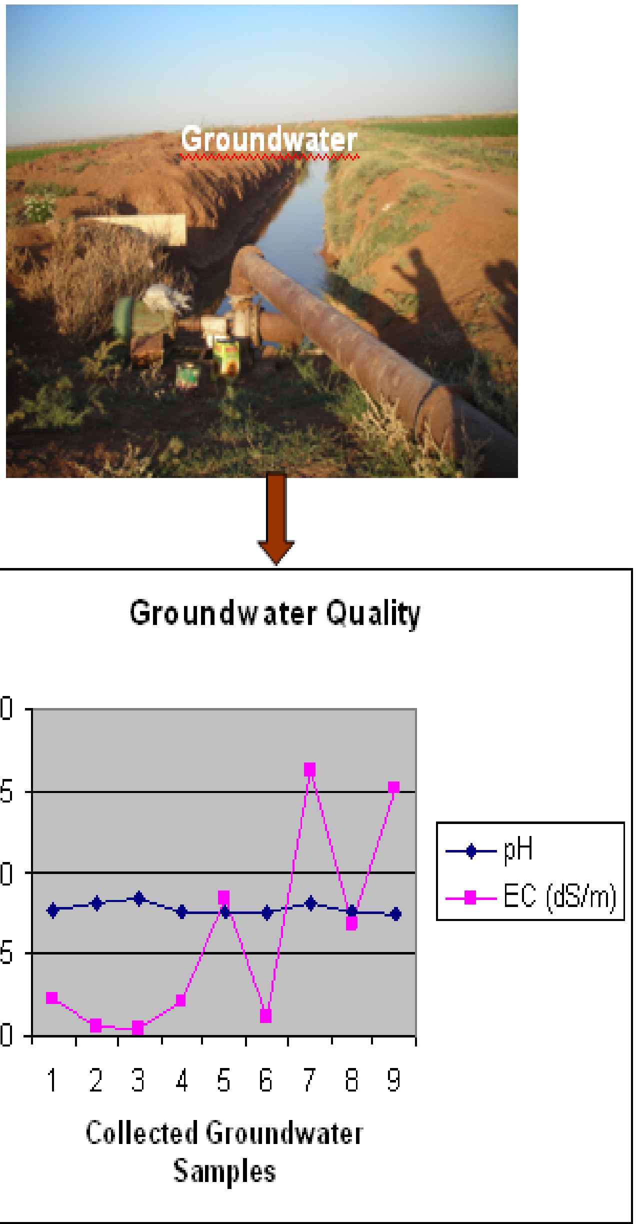


Figure 10. Drainage Water Quality Analyses

6. LANDUSE MAPPING

At the end of 2012, approximately 150000 ha of the Harran Plain will be under irrigation. The value added per capita in the agricultural sector of this area has more than tripled with irrigation. Cotton, maize, wheat and vegetable planted area showed considerable increases. In order to determine landuse map of the plain, 3 temporal SPOT satellite images were obtained. Satellite images were loaded to computer and interpreted for ground control. For each crops planted at the field, ground point data were collected using the enhanced image and GPS data (Figure 11). Landuse map will be created for 2012 using supervised classification technique.

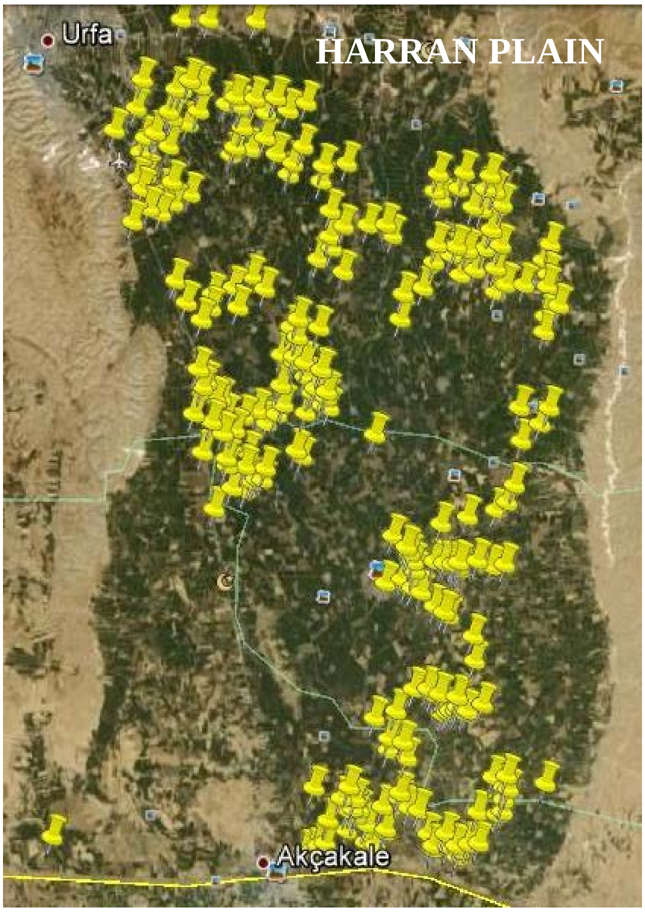


Figure 11. Ground Control Points (GCP) For Landuse Classification

The landuse map will be integreted with salinity map for determination of the yield decreases. These data gives a valuable knowledge for economical losses.

C09 ADIYAMAN PROJECT ACTIVITIES

Adıyaman region represents the upstream of Atatürk Dam (Figure 1) and even within GAP Project irrigation scheme is not sufficient for irrigating majority of arable lands. The economy is dependent on agricultural activities (app. 85%) and rainfed agriculture is the main management in the site (Table 1). The general land use map of the region was prepared (Figure 2)

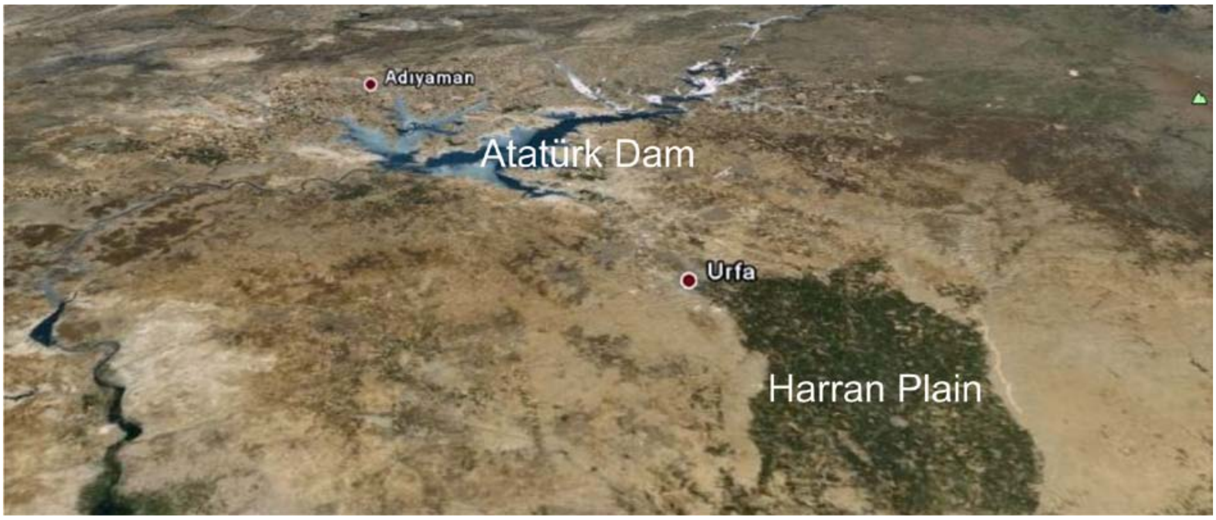


Figure 1. Project Site and location of Atatürk Dam

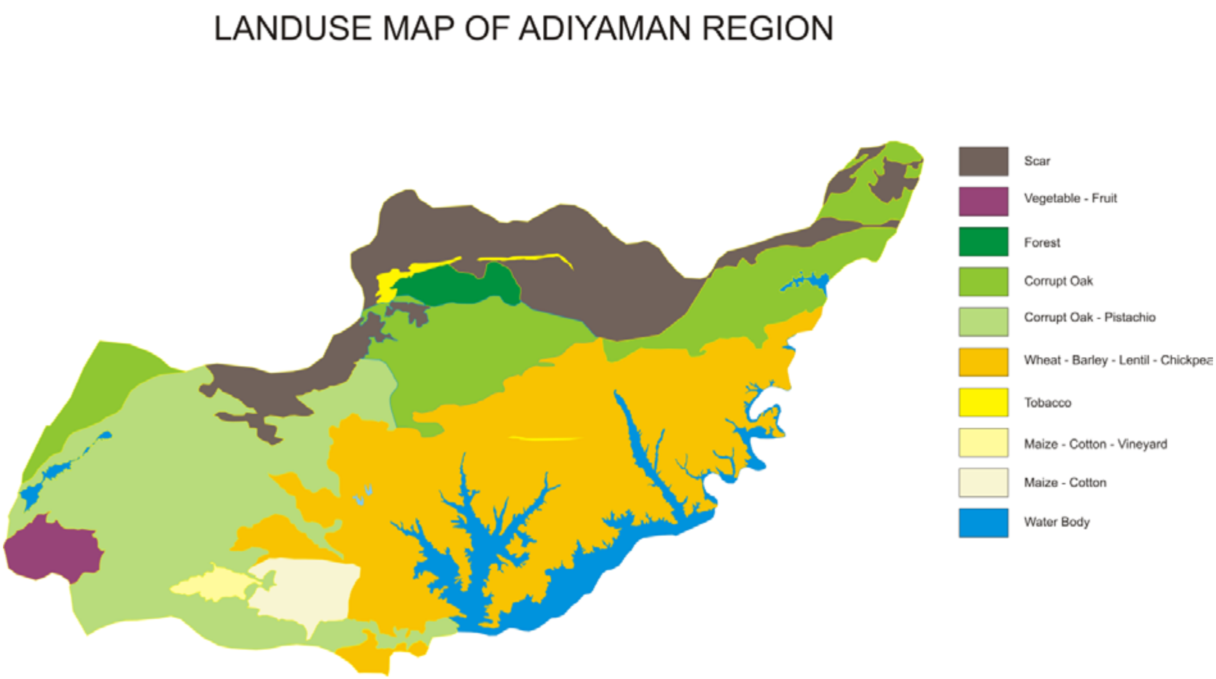


Figure 2. The general land use map of Adıyaman Region

Table 1. Land Use in Adıyaman Region

Land Use	Irrigated ha	%	Rainfed ha	%	Total Cultivated ha	%
Field Crops	42.439	16,83	164.366	65,2	206.806	82,03
Orchards	3.182	1,26	36.118	14,33	39.302	15,59
Vegetables	3.650	1,45	836	0,33	4.488	1,78
Fallow			1.502	0,6	1.502	0,6
Total	**49.271**	19,55	**202.822**	80,45	**252.098**	**100**

However there is a high pressure on politicians, local administrators and institutions (DSI, Regional Agricultural Directorate) for increasing irrigated land since local people believe irrigation is wealth.

Within C09 Project, the Adıyaman University Project members undertake 3 main activities during March – August 2012 which are data collection on soil and waters, determination and comparison of land use and social interviews.

I. SOIL AND WATER

1. SOILS

The region has in general have sloping lands, thus prime soils cover less than 10% of the total arable land. Three major sites were chosen for sampling for determination of land use vs soil quality.

a. Rain fed soils – for centuries
b. Irrigated soils – more than 50 years
c. Recent irrigated soils – irrigated for the last 20 years within GAP or regional projects, or private enterprises.

A. Rain Fed Soils

Main land use in rainfed soils are cereals, vineyard, tobacco, pistachio nut and fig. Rainfed soils are mainly distributed in northern part of Adıyaman town, and Gerger, Sİncik, Besni and Tut ie mountainous towns. 40 soil samples were collected at various land use types. The major soil quality indicator is organic matter. The highest organic matter was determined at fig plantation (Table 2). However the average organic matter contents of soils are below 2%. The major problem in rain fed areas is soil erosion (Figure 3, 4). Other than erosion, shallow depth and organic matter issues no salinity, pH problems were identified at rain fed soils.

Table 2. The average organic matter content of rain fed soils

Land use	Organic matter (%)
Cereal	1.03
Vineyard	1,12
Pistachio nut	1.32
Fig	1.47
Tobacco	1,14
Fallow	1,17

Figure 2. Eroded lands in Kahta

Figure 4. Rain fed agriculture practices in Tut

B. Irrigated Soils

Adıyaman is quite rich for its surface and ground waters due to the topographic properties ie the northern mountainous area stores rain and snow waters and discharges to Adıyaman region. Thus, irrigation has a long history in the area even not spread to large areas. The main crop irrigated is cotton followed by vegetables. Tobacco at terraced soils are also irrigated. The organic matters at irrigated sites particularly vegetable growing sites in Gölbaşı and Adıyaman have the highest value. Cereals are rarely irrigated but at irrigated sites soils' organic matter is higher than rain fed sites (Figure 6). Due to slight sloping and drainage system no salinity was determined at irrigated sites.

Table 3. The average organic matter content of irrigated soils

Land use	Organic matter (%)
Cereal	1.42
Vegetables	2.12
Tobacco	1.47
Cotton	1,55
Corn	1.57
Orchards (Apple, Sharon, Plum, apricot etc)	2,15

Figure 5. Cereal irrigation in Gölbaşı

C. Recently Irrigated Soils

Following GAP Project irrigation to some sites in Adıyaman region were introduced particularly in Çamgazi (W of Adıyaman town), Samsat and Kahta (close to Atatürk Dam) and more groundwater wells are used for irrigation. The irrigation for these sites started app. 20 years ago. The main crop irrigated is cotton, corn and vegetables. There is a slight increase at recently irrigated areas than rain fed areas. The major issue at the recently and longtime irrigated areas are accumulation of phosphorus which sometimes determined as 120kg/ha (Kahta, cotton field) and excess N use. Salinity is still not a problem due to topography of Adıyaman.

Table 3. The average organic matter content of recently irrigated soils

Land use	Organic matter (%)
Cereal	1.35
Corn	1,64
Vegetables	2.04
Tobacco	1.55
Orchards	1.76
Cotton	1,64

2. WATER

For water quality determination water samples were collected from ground, surface (creeks, streams) sources and Ataturk Dam. A total of 42 samples (25 from Atatürk Dam) were collected and analyzed for their pH, EC, heavy metals, nitrate and phosphorous content) (Table 4).

The excess nitrate and phosphorous content was only determined on northern margin of the Ataturk Dam where Adıyaman City sewage water is discharged (Figure 3). However, the pollution effect of discharge zone do not extend more than 2km. The next sampling period will be in December following precipitation to determine dissolution effect of rain.

Ground water quality is quite good and no significant pollution was determined from sampled wells from Adıyaman, Kahta, Besni, Gölbaşı and Tut. But the pressure or opening new wells particularly on mountainous area may increase fertilizer use at these sites which may pollute fresh water sources at relatively low areas.

Table 4. Water properties at selected sites in Adıyaman Region

Sample	pH	EC mmhos/cm	Nitrate ppm	Phosphorous ppm	Cd ppm	Pb ppm	Hg ppm
Ground water – Kahta, 180m	7.76	280	0	0	0	0	0
Göksu Stream	8.12	384	1.12	0	0	0	0
Atatürk Dam – Center part	7.60	330	1,18	0.006	0	0	0
Atatürk Dam – Euphrates entrance	8.10	320	1	0.004	0	0	0
Atatürk Dam – Sewage water discharge zone	7.53	630	5.3	0.12	0	0	0

II. Socio-economic studies

For determination of value of water among three sites in Adıyaman (Rainfed, Irrigated and Recently Irrigated) interviews were initiated. A questionnaire is prepared now it is under evolution of experienced scientist. The interview will be accomplished within the 1st week of December.

C-09-Init GAP Region Activity Report

APPENDIX: JOURNAL PAPER RELATING TO THE PROJECT

Environ Monit Assess (2013) 185:777–795
DOI 10.1007/s10661-012-2591-3

Spatial assessment of soil salinity in the Harran Plain using multiple kriging techniques

Ali V. Bilgili

Received: 6 July 2011 / Accepted: 23 February 2012 / Published online: 15 March 2012

Abstract The Harran Plain is located in the southeastern part of Turkey and has recently been developed for irrigation agriculture. It already faces soil salinity problems causing major yield losses. Management of the problem is hindered by the lack of information on the extent and geography of the salinization problem. A survey was carried out to delineate the spatial distribution of salt-affected areas by randomly selecting 140 locations that were sampled at two depths (0 to 30 and 30 to 60 cm) and analyzed for soil salinity variables: soil electrical conductivity (EC), soluble cations (Ca^{2+}, Mg^{2+}, Na^{+}, and K^{+}), soluble anions (SO_4^{2-}, Cl^{-}), exchangeable Na^{+} (me 100 g^{-1}) and exchangeable sodium percentage. Terrain attributes (slope, topographical wetness index) were extracted from the digital elevation model of the study area. Variogram analyses after log transformation and ordinary kriging (OK) were applied to map spatial patterns of soil salinity variables. Multivariate geostatistical methods—regression kriging (RK) and kriging with external drift (KED)—were used using elevation and soil electrical conductivity data as covariates. Performances of the three estimation methods (OK, RK, and KED) were compared using independent validation samples randomly selected from the main dataset. Soils were categorized into salinity classes using disjunctive kriging (DK) and ArcGIS, and classification accuracy was tested using the kappa statistic. Results showed that soil salinity variables all have skewed distribution and are poorly correlated with terrain indices but have strong correlations among each other. Up to 65 % improvement was obtained in the estimations of soil salinity variables using hybrid methods over OK with the best estimations obtained with RK using EC_{0-30} as covariate. DK–ArcGIS successfully classified soil samples into different salinity groups with overall accuracy of 75 % and kappa of 0.55 ($p<0.001$).

Keywords Harran Plain · Soil salinity · Regression kriging · DEM · Disjunctive kriging · Kriging with external drift

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Introduction

Soil salinity is a concern with irrigated agriculture, and 20 % of total irrigated lands and 10 % of total arable lands covering over 100 countries have been affected by various types and levels of salinity (Ghassemi et al. 1995). This rate increases as more lands are opened to irrigation and cultivation (Tanji 2002). The major concern is with human-induced secondary salinization which is due to inappropriate soil and water management practices. It generally occurs in irrigated arid and semiarid irrigated agricultural areas; one of which is the Harran Plain in southeastern Turkey. Here, some fields have been affected by salinity at various levels since the area was developed for extensive irrigation as a part of the GAP (Southeastern Anotolia Project) development initiative launched by the Turkish government in the early 1990s. Saline soils are located at low lying parts of the plain, primarily due to excessive irrigation and lack of drainage, resulting in shallow groundwater tables (Kendirli et al. 2005). The combination of high evaporation rates and clay soils results in capillary upward movement of shallow ground water and accumulation of salts in the rooting zone.

Soil salinity is an important chemical soil quality indicator (Andrews et al. 2004; Zheng et al. 2009) that also affects soil's physical, chemical, and biological processes (Karlen et al. 2008). Saline soils are generally characterized by an electrical conductivity (EC) >4 dS m^{-1}, a pH <8, and an exchangeable sodium percentage (ESP) of below 15, whereas in alkaline soils, EC is lower than 4 dS m^{-1} and pH and ESP are higher than 8 and 15 %, respectively (USSLS 1969). Soil aggregation, hydraulic conductivity, water infiltration, and soil erosion and fertility are adversely affected by high degrees of soil salinity and alkalinity (Muhammad et al. 2008), and consequent crop growth reductions and yield losses occur (Cullu 2003). Soil alkalinity develops when sodium becomes dominant in soil solution which deteriorates soil structure and causes crust formation and compaction of soil surface resulting in reduced infiltration, water logging, and runoff (Richard 1954).

The best management strategies of saline and alkaline soils require accurate and updated information about the spatial distribution of salinity parameters across the area of interest (Pozdnyakova and Zhang 1999). Careful monitoring is critical in combating salinity and preventing more lands to become saline (Metternicht and Zinck 2008). The lack of knowledge on the true dimensions of the problem hinders abatement efforts, as is the case in the Harran Plain.

Spatial statistical methods can effectively characterize salinity variability and reduce the number of samples to be collected and analyzed. In addition to inverse distance weighting and splines (Voltz and Webster 1990; Phachomphon et al. 2010), kriging methods have been widely used to map the spatial distribution of soil properties, including soil salinity (Pozdnyakova and Zhang 1999; Cetin and Kirda 2003). Kriging methods are based on the theory of regionalized variables which assume that the variance of measured values of properties is a function of the distance between observations (Journel and Huijbregts 1981). This spatial structure can be assessed using variogram analysis. The accuracy of the estimations is affected by the variogram quality (degree of spatial dependence), samples size, sampling density, and the method of estimation (Webster and Oliver 2007). Simple kriging methods may not be sufficient in capturing all variation, and therefore multivariate geostatistical methods can often provide better estimates. Cokriging (COK), regression kriging (RK), and kriging with external drift (KED) use one or more secondary variables that are generally easily obtainable compared to the primary variable. These auxiliary variables can increase precision in estimates or reduce the number of samples to be analyzed (Bourennane et al. 2000). All three methods (COK, RK, and KED) are superior under the existence of spatial correlation between primary and secondary variable(s). COK, in addition, requires the spatial covariance function between primary variable and covariables to be positive definite.

Commonly used auxiliary variables with these methods are satellite imagery, soil type, soil spectral reflectance, terrain indices (elevation, slope, profile curvature, etc.), and hydrological parameters extracted from digital elevation models (DEM; Bourennane et al. 2000; Douaoui et al. 2006; Hengl et al. 2003a, b; Wu et al. 2003; Bilgili et al. 2011). These covariates have been extensively used in the estimation of various soil variables such as soil carbon, soil depth, macro- and micronutrients, heavy metals, and soil emissions. Topographical parameters are most commonly preferred in such estimations (Florinsky et al. 2000; Kravchenko and Robertsen 2007; Takata et al. 2007) because of their importance to soil formation processes, hydrology, and chemical transformations. Development of salinity problems is generally affected by topographical variables as well, with lower areas more likely in developing salinity problems (Jordan et al. 2004). Satellite imagery have also been used with multivariate geostatistical methods in the estimation of salinity (Eldeiry and Garcia 2008), as well as topographical data (Florinsky et al. 2000) and a combination of both (Masoud and Koike 2006). Constraints with imagery data in salinity monitoring are crop interactions, spatial and temporal variation of soil salinity, and spectral confusion with other objects (Metternicht and Zinck 2008).

Another approach is based on estimates of the spatial distribution probability of exceeding thresholds for various variables using nonlinear geostatistical methods such as indicator and disjunctive kriging (DK). The latter is considered more advantageous because no information is lost during transformation. Continuous variables in this case are transformed to binary variables and then kriged to display areas exceeding thresholds (Shi et al. 2007; Dash et al. 2010). Demir et al. (2009) mapped groundwater depth using indicator kriging to show areas under salinization risk.

The objectives of this study were to (1) map soil salinity in the Harran Plain using OK in order to quantify the dimensions and spatial distributions of the problem; (2) evaluate the utility of topographical variables and soil ECs as covariates in RK and KED for the improved spatial estimation of soil salinity; (3) compare OK, RK, and DK using independent validation samples; and (4) classify soils into different salinity classes and test the accuracy of classification using DK.

Materials and methods

Study site

The study area is located in the Harran Plain, Sanliurfa, Southeastern Turkey (37° 9.7′ and 36° 42′ N lat, 38° 49.6′ and 39° 7.9′ E long; Fig. 1), located in upper Mesopotamia between the Euphrates and Tigris Rivers. The plain was developed for irrigated agriculture (152,000 ha) as a part of a multibillion dollar regional development project launched by the Turkish government in the early 1990s. The climate of the study area is semiarid with mean temperature, evaporation, and precipitation of 17.2°C, 365.2 mm, and 1,848 mm, respectively. Most precipitation is

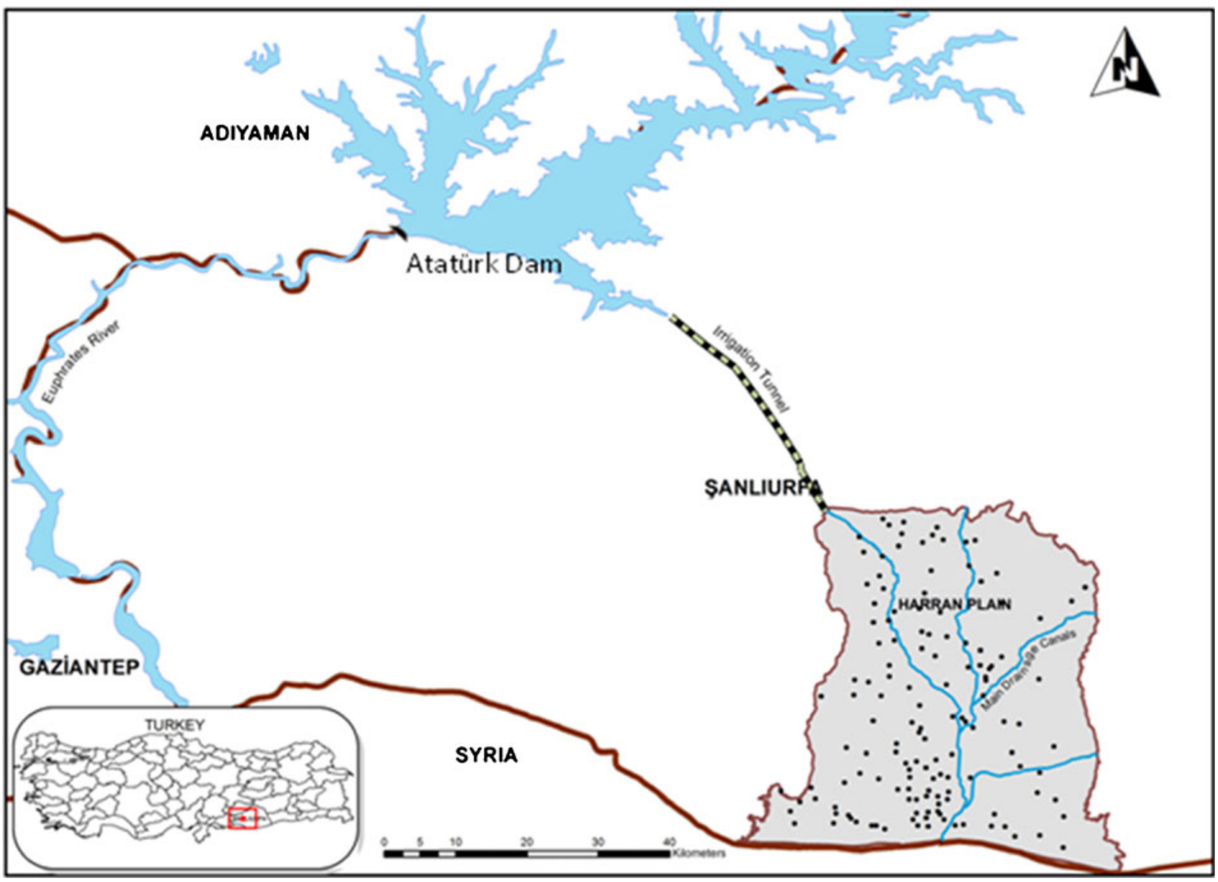


Fig. 1 Study area, the Harran Plain, and sampling locations

received during the fall season. Elevation of the study area ranges from 345 m in the south to 550 m in the north (Fig. 2). The soils have been formed on calcareous materials and are classified as Vertisols, Fluvisols, Calcisols, Cambisols, and Leptosols (FAO/IUSS 1998), and a total of 25 soil series have been described

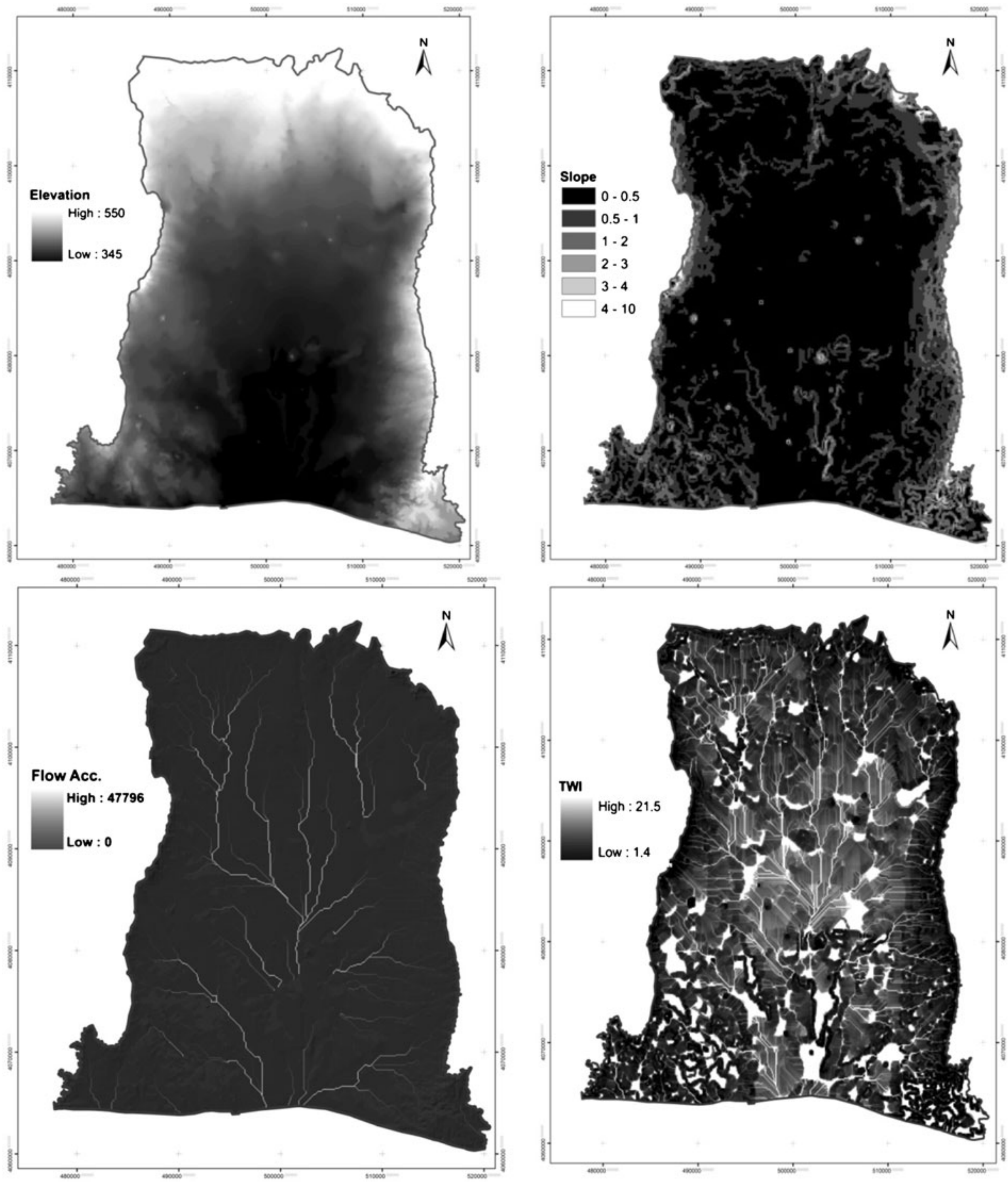


Fig. 2 Topographical derivatives of the Harran Plain: DEM, slope (in percent), flow accumulation (*Flow Acc.*) and Topo Wetness Index (*TWI*)

in the study area (Aydemir 2001). Soils are mostly finely textured (clay loam to clay) and contain very low to low amounts of organic matter (0.5 to 1.5 %) and high amounts of $CaCO_3$ (on average 250 to 350 gkg^{-1}). Dominant clay minerals within salinized area are smectite, polygorskite, chlorite, illite, and kaolonite, in decreasing order of abundance (Seyrek et al. 2005). Cotton, wheat, and corn are the predominant crop types grown in the plain (Cullu 2003). The concavely shaped plain is surrounded by mountains in the north, east, and west directions and groundwater generally moves towards the south, where the more saline soils are located.

Soil sampling

A total of 140 soil samples across the study area were randomly sampled at two different depths (0 to 30 and 30 to 60 cm; Fig. 1) and subsequently air dried and sieved (2 mm) for laboratory analysis. Soil sampling was carried out in October 2009 when the crop season ends, irrigation is terminated, and salt accumulation is generally highest. The geographical locations (UTM coordinates) of the sampling locations were recorded using a GPS unit.

Laboratory analysis

Soil EC and other soil salinity indicators were determined in soil water extractions obtained from saturation pastes that were prepared from 100 g air dried and 2-mm sieved soil. EC (in deciSiemens per meter) and pH were measured using a combination of EC and pH meter (Mettler-Toledo International Inc., Switzerland), and soluble cations—Ca^{2+}, Mg^{2+}, Na^{+}, and K^{+}—were analyzed in the central lab of the Harran University using an ICP-AEAS (Varian-Vista, Palo Alto, CA, USA). Soluble anions—SO_4^{2-}, Cl^{-}—were determined using ion chromatography (Dionex ICS-2000, Dionex Corporation, California, USA). Cation exchange capacity (CEC) and exchangeable sodium (Na_{Exc}; meq 100 g^{-1}) were obtained according to the ammonium acetate method (Hesse 1972). ESP was calculated as follows:

$$\mathrm{ESP} = 100 \times (\mathrm{Na_{Exc}}/\mathrm{CEC}) \tag{1}$$

Terrain attributes

Topographical maps (1:25,000 scale) of the study area were digitized to create a digital elevation map (DEM). From the DEM, topographical parameters such as slope (in percent), flow accumulation, and Topo Wetness Index (TPI) were delineated using spatial analysis tools in ArcGIS 9.3 (ESRI Inc.; Fig. 2). The information of topographical indicators was extracted by overlapping the sampling locations on the raster maps of each topographical parameter. The TWI was calculated as (Sorensen et al. 2005):

$$\mathrm{TWI} = \ln(a/\tan\beta) \tag{2}$$

where a is the upslope contributing area obtained from flow accumulation and β is the slope gradient (in percent).

Geostatistical modeling

Ordinary kriging

Ordinary kriging (OK) is a commonly used linear spatial interpolation method which provides estimates of variables at unsampled locations by using information from neighboring points and assigning weights to these points based on their distance from the point being estimated and the spatial variability structure. The OK method formulized as:

$$Z^*_{\mathrm{OK}}(x_0) = \sum_{i=1}^{n} w_i Z(x_i) \tag{3}$$

where $Z^*_{\mathrm{OK}}(x_o)$ is the OK estimation at an unsampled location (x_o), n is the number of samples in a search neighborhood, and w_i are the weights assigned to the ith observation $Z(x_i)$. Weights are assigned to each sample such that the estimation or kriging variance, $E\left[\{Z^*(x_0) - Z(x_0)\}^2\right]$, is minimized and the estimates are unbiased (Webster and Oliver 2007). Weights are determined after computing a semivariogram that models spatial correlation and covariance structure between datapoints for each variable using Eq. 4 below (Journel and Huijbregts 1981):

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N} [Z(x_i + h) - Z(x_i)]^2 \tag{4}$$

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 observation pairs at the distance h.

Regression kriging

RK is a spatial interpolation method that makes use of secondary variable(s) for the estimation of primary variable at unsampled locations. RK combines regression between primary (target) variable and secondary variable(s) with kriging of residuals derived from a regression analysis (Hengl et al. 2007):

$$Z^{*}{}_{\mathrm{RK}}(x_o) = \sum_{k=0}^{p} \beta_k . q_k(x_o) + \sum_{i=1}^{n} w_i . e(x_i) \qquad (5)$$

where $Z_{RK}(x_o)$ is the RK estimate at unsampled locations (x_o), β_k and $e(x_i)$ are the regression coefficients and residuals, respectively, obtained from the regression between primary and secondary variables using observations at the sampled locations (x_i), 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, soil electrical conductivity in our case, and p is the number of predictor (secondary) variables. Regression coefficients and residuals were obtained using ordinary least square (OLS) regression, and kriging of residuals was performed with simple kriging (Hengl et al. 2007). The secondary variables involved in the OLS equation was soil EC at different depths.

Kriging with external drift

KED is a spatial interpolation method that combines primary and secondary variables with the aim of improving the estimations and is similar to universal kriging where coordinates are used to incorporate trend (drift) in the kriging process. In KED, trend is an auxiliary variable that is correlated with the primary variable and is present both in calibration and validation sampling locations. KED is formulized as in Eq. 6 (Wackernagel 2003):

$$Z_{\mathrm{KED}}(x_o) = \sum_{i=1}^{n} w_i . Z(x_i), \quad Z(x_i) = m(x) + e(x) \qquad (6)$$

where w_i are the weights of KED, $m(x)$ is the main trend part where predictor variables are involved, and $e(x)$ are residuals. Predictor (secondary) variables are available at all points (calibration and validation points). In this study, the primary variables (Z; Z_1) were soil salinity variables. The covariables (Z_2) were the either soil ECs or elevation.

Validation–prediction accuracy

The prediction accuracy of the three kriging methods: OK, RK. and KED was evaluated using separate validation sample subsets. Samples were randomly divided into two subsets containing 70 and 30 % of the total data (n=103 and n=37, respectively). The former one was used to create the kriging models and the latter used to validate the models. Estimation techniques were evaluated using the root mean square error of prediction (RMSEP) between measured and predicted values of samples in the validation dataset as an indicator of estimation error. Lower RMSEPs indicate better methods. RMSEP is formulated as:

$$\mathrm{RMSEP} = \sqrt{\frac{\sum_{i=1}^{n} \left(Z_{\mathrm{predicted}} - Z_{\mathrm{observed}}\right)^2}{n-1}} \qquad (7)$$

where $Z_{\mathrm{predicted}}$ and Z_{observed} are the variables of interested predicted using geostatistical methods and measured in the laboratory, respectively.

The relative performance of the estimation methods was assessed using the Percent Relative Improvement (RI) as adapted by Mueller et al. (2001) and Brouder et al. (2005):

$$\mathrm{RI} = 100\% \times (\mathrm{RMSEP_{OK}}) - (\mathrm{RMSEP_{RK}})/(\mathrm{RMSEP_{OK}}) \qquad (8)$$

where RI is the percentage improvement or reduction in the estimation errors (positive RI improvement, negative RI reduction). Log transformation was applied for soil variables with high skewness and lacking normality (EC, ESP, $Na_{Exc.}$, Ca^{2+}, Mg^{2+}, Na^{+}, and K^{+}) prior to geostatistical analyses. Variables were back transformed before producing the final maps.

Classification

Classification of salt-affected soils was made according to Richard (1954). Soils with EC <4 and ESP <15 were classified as nonsaline–nonalkaline, soils with EC >4 and ESP <15 as saline–nonalkaline, soils with EC >4 and ESP >15 as saline–alkaline, and soils with EC <4 and ESP >15 as nonsaline–alkaline.

DK was performed in order to group soils into different salinity classes. For classification, first disjunctive kriging was separately performed on both soil ECs and ESP, and probability maps were obtained. Probability of 0.5 was accepted as the threshold to reclassify the output into two classes: saline or nonsaline. Similarly, the soil ESP probability map was reclassified into groups: alkaline or non-alkaline, and two maps were then spatially joined in order to obtain the final map.

Disjunctive kriging DK as a nonlinear estimation method is capable of making variable estimations as well as quantifying the probability of exceeding certain threshold cutoff value at unsampled locations. In DK, the original variable, $Z(x)$ is first transformed to a new variable ($Y(x)$), so that the variables have a multivariate normal distribution and are orthogonal to each other. The transformation is achieved using Hermite polynomials:

$$\phi[Y(x)] = Z(x) \tag{9}$$

the transformation function, $\phi[Y(x)]$, consists of an infinite number of Hermite polynomials:

$$\phi(Y(x) = \sum_{k=0}^{k} CkHk(y) \tag{10}$$

where $Hk(y)$ is a Hermite polynomial of order k, and Ck are Hermetian coefficients that are obtained using Hermetian integration (R). Subsequently, these Hermite polynomials are estimated at unsampled locations using simple kriging:

$$H_k^*[Y(xo)] = \sum\nolimits_{k=0}^{k} wik.Hk(Y(x)) \tag{11}$$

and multiplied by coefficients Ck to obtain final DK estimation at unsampled locations:

$$z_{dk(xo)}^* = \sum\nolimits_{i=0}^{n} Ck.H_k^*[Y(xo)] \tag{12}$$

The accuracy of classification was determined using the kappa statistic (κ), which measures the degree of agreement between two methods and tests the hypothesis that the agreement between two methods is only by chance. Kappa statistic analysis was performed in SPSS software (SPSS Inc. 1999). All geostatistical analyses were performed using R programming language software (R Development Core Team 2006) and ArcGIS Geostatistical and Spatial Analyst Extension tools (ESRI 2001).

Results and discussions

Soil salinity parameters

Summary statistics of the soil salinity parameters at two depths are presented in Table 1. These show a broad range of values across the study site, notably

Table 1 Basic statistics for soil salinity parameters at two sampling depths (n=140)

	Depth (cm)	pH	EC (dS m^{-1})	$CaCO_3$	ExcNa (me 100 g^{-1})	CEC (me 100 g^{-1})	ESP (%)	Soluble cations and anions (mg kg^{-1}) Na^+	K^+	Ca^{2+}	Mg^{2+}	SO_4^{2-}	Cl^-
Min	0–30	7.1	0.2	0.0	0.1	9.0	0.3	0.7	0.1	0.4	0.1	0.0	0.0
Max	0–30	8.0	39.7	54.0	13.7	67.8	57.8	173.0	54.5	160.0	44.5	171.2	80.9
Mean	0–30	7.5	3.3	30.0	3.2	3.8	9.0	10.1	1.6	10.1	2.9	9.4	6.3
Std dev	0–30	0.2	6.7	7.2	3.3	11.2	10.9	27.5	6.2	19.7	6.6	18.1	10.5
Skew	0–30	0.2	3.4	0.0	1.4	0.2	2.3	4.3	6.9	4.7	4.5	6.4	3.9
CV	0–30	0.02	2.0	0.2	1.1	2.9	1.2	2.7	4.0	2.0	2.3	1.9	1.7
Min	30–60	7.1	0.2	0.0	0.1	15.3	0.2	0.5	0.0	0.5	0.1	0.0	0.0
Max	30–60	8.1	24.6	49.0	95.3	79.9	261.0	88.0	21.5	226.0	26.6	65.6	41.3
Mean	30–60	7.6	2.0	31.0	3.5	4.0	9.4	5.8	0.5	7.4	1.8	8.7	5.0
Std dev	30–60	0.2	3.5	7.6	8.4	10.8	23.6	12.8	1.9	21.0	3.8	12.1	7.5
Skew	30–60	0.2	3.7	−0.4	9.7	0.5	9.1	4.3	10.2	8.7	4.3	2.9	3.1
CV	30–60	0.03	1.8	0.2	2.4	2.7	2.5	2.2	3.7	2.8	2.2	1.4	1.5

soil EC ,which varied from 0.2 to 39.7 dS m^{-1} and 0.2 to 24.6 dS m^{-1} for surface and subsurface soils, respectively. Soil ESP showed values above 15 % at some locations, indicating the existence of sodic soils (Richards 1954). Soil pH varied from 7.1 to 8.

Surface soils are relatively more saline than subsurface soils at the same location, having higher average values for all salinity parameters. All variables show positively skewed distributions due to some high values within the dataset or outliers. Among measured variables, soluble K^+, showed the highest variation as indicated by higher CV values, followed by CEC at the surface and soluble Ca^{2+} in the subsoil. CV values exceeding 0.35 can be considered highly variable (Wilding 1985), which was the case for all variables except $CaCO_3$ and pH.

Table 2 shows Pearson correlation coefficients among the soil salinity variables. Significant ($p<0.05$) positive and negative correlations were obtained between many of them for both depths. Variables measured for the surface soil were significantly correlated with corresponding ones in the subsoil. Both $EC_{0–30}$ and $EC_{30–60}$ had significant positive correlations ($r>0.16$) with all the variables except exchangeable $Na_{30–60}$ ($r=0.11$). Soil cations were also significantly correlated with each other except K^+. Other significant correlations were generally obtained between ESP and other salinity parameters with a few exceptions.

Table 3 shows correlations between soil salinity and terrain parameters. Only elevation showed significant correlations with soil salinity parameters, although the degree of correlation was relatively low. The correlation of soil salinity variables with other terrain indices were not significant. The areas with high TWI values at low elevations are more likely to become saturated and experience capillary movement of groundwater to the surface, but correlations with EC were nevertheless weak.

Spatial variability of soil salinity variables

All soil salinity variables were skewed and a normal distribution was obtained after log transformation prior to variography. Data were fit using spherical, exponential, and Gaussian models (Table 4; Fig. 3), although exponential models were most common. Fitting semivariograms to the data showed that soil salinity parameters were spatially dependent over distances ranging from 1,140 to 92,040 m (Fig. 4).

The quality of a fitted model to the spatial autocorrelation structure of a dataset affects the quality of variograms and therefore the success and accuracy of the kriging effort (Leenaers et al. 1990). The output of variogram parameters can vary depending on the user's interpretation and the selected lag distance or model. These parameters are selected optimally based on criteria such as mean square error (MSE) obtained from cross validation or R^2 of the model. The models that provided the lowest mean square error were selected as the best fit in this study.

Nugget to Sill ratio (Co/(Co+C) has been used to evaluate the extent of spatial structure of variables (Cambardella et al. 1994). If the ratio is less than <0.25 then the variable is strongly spatially autocorrelated, if between 0.25 and 0.75 it is moderately autocorrelated, and if higher than 0.75, spatial distribution is weak. Accordingly, EC, K^+, and Ca^{2+} showed strong spatial structure within a small range indicated by a low (Co/(Co+C) value, whereas spatial strength of Na_{Exc}, ESP, Na^+, and SO_4^{2-} showed moderate ratios (Table 4). Cl^- in surface soils was characterized by a nugget effect model, which indicates a lack of spatial structure or a random spatial distribution. However, Cl^- in subsurface soils showed strong spatial dependence at short range.

Shi et al. (2007) attributed strong spatial dependence to natural factors such as parent material, topography, or soil type while they considered a poor spatial dependence structure to be more related to anthropogenic effects, e.g., soil management practices such as fertilization. In our case, low spatial autocorrelation can be due to similar factors like irrigation management and drainage patterns. Topography also is a very important factor impacting the spatial distribution of salinity indicators. Soil EC from both soil depths showed very high nugget values and short ranges of influence (a) which is an indicator of short range variability (Table 4; Douaoui et al. 2006).

Spatial estimations

Ordinary kriging

Mapping salinity is a preliminary step towards decision making such as the delineation of contaminated areas and identification of zones that need remediation or adapted management. Soil salinity across the study area was mapped using ordinary kriging. The spatial

Table 2 Pearson correlation coefficients (r) among soil salinity variables at two sampling depths (n=140)

	0–30 cm										30–60 cm									
	pH	EC	ExcNa	ESP	Na^+	K^+	Ca^{2+}	Mg^{2+}	SO_4^{2-}	Cl^-	pH	EC	ExcNa	ESP	Na^+	K^+	Ca^{2+}	Mg^{2+}	SO_4^{2-}	Cl^-
0–30 cm																				
pH	1.00																			
EC	−0.38	1.00																		
ExcNa	−0.11	0.43	1.00																	
ESP	0.08	0.54	0.91	1.00																
Na^+	−0.07	0.64	0.43	0.55	1.00															
K^+	−0.08	0.31	0.18	0.16	0.11	1.00														
Ca^{2+}	−0.12	0.67	0.32	0.40	0.65	0.10	1.00													
Mg^{2+}	−0.06	0.68	0.42	0.57	0.90	0.08	0.82	1.00												
SO_4^{2-}	−0.06	0.49	0.20	0.31	0.78	0.03	0.73	0.77	1.00											
Cl^-	0.05	0.47	0.31	0.36	0.43	0.28	0.17	0.32	0.26	1.00										
30–60 cm																				
pH	0.11	−0.02	0.01	0.06	−0.04	0.04	−0.05	0.03	−0.03	0.03	1.00									
EC	−0.02	0.83	0.38	0.45	0.47	0.20	0.62	0.55	0.30	0.34	0.00	1.00								
Naexc	0.15	0.11	0.23	0.24	0.16	0.01	0.15	0.17	0.12	0.04	0.14	0.09	1.00							
ESP	0.14	0.16	0.23	0.29	0.21	0.03	0.18	0.24	0.18	0.07	0.15	0.11	0.99	1.00						
Na^+	−0.04	0.53	0.33	0.37	0.67	0.04	0.70	0.71	0.52	0.31	−0.05	0.66	0.13	0.13	1.00					
K^+	−0.15	0.50	0.13	0.12	0.06	0.26	0.38	0.12	−0.03	0.07	0.00	0.49	0.00	0.00	0.21	1.00				
Ca^{2+}	−0.19	0.50	0.20	0.20	0.26	0.16	0.67	0.37	0.24	0.03	−0.04	0.52	0.06	0.06	0.48	0.89	1.00			
Mg^{2+}	−0.09	0.62	0.28	0.33	0.58	0.09	0.79	0.68	0.49	0.24	−0.01	0.77	0.12	0.12	0.91	0.47	0.70	1.00		
SO_4^{2-}	0.03	0.37	0.24	0.32	0.59	0.03	0.31	0.44	0.41	0.42	−0.12	0.35	0.04	0.07	0.47	0.03	0.16	0.40	1.00	
Cl^-	0.03	0.27	0.22	0.27	0.27	0.14	0.08	0.17	0.13	0.72	0.03	0.31	0.04	0.06	0.26	0.03	0.02	0.22	0.53	1.00

$|r| \geq 0.16$, significant at 0.05 level; $|r| \geq 0.22$, significant at 0.01 level

Table 3 Correlations of soil salinity variables with terrain parameters

	EC	pH	NaExc.	ESP	Ca^{2+}	Mg^{2+}	K^+	Na^+	SO_4^{2-}	Cl^-
0–30 cm										
Elevation	−0.24*	0.06	0.09	−0.10	−0.17*	−0.25*	0.07	−0.24*	−0.22*	−0.24*
Slope	−0.01	−0.03	0.12	0.06	−0.01	0.07	−0.01	0.07	0.06	−0.02
Flow Acc	−0.03	0.02	−0.07	−0.06	−0.06	−0.05	−0.03	−0.04	−0.05	−0.05
Flow Dir	−0.04	0.09	−0.12	−0.09	−0.03	−0.01	−0.04	−0.02	−0.03	−0.03
TWI	0.10	−0.06	0.15	0.12	0.10	0.13	0.05	0.08	0.12	0.02
30–60 cm										
Elevation	−0.23*	0.07	0.02	−0.03	−0.05	−0.25*	0.01	−0.30*	−0.28*	−0.28*
Slope	−0.09	−0.04	−0.03	−0.04	−0.07	−0.04	−0.07	−0.01	0.01	−0.08
Flow Acc	−0.05	0.02	−0.05	−0.05	−0.03	−0.05	−0.03	−0.05	−0.04	−0.07
Flow Dir	−0.07	0.09	−0.06	−0.05	−0.04	−0.05	−0.05	−0.03	−0.04	0.07
TWI	0.04	−0.05	0.03	0.02	0.03	0.06	0.06	0.08	0.02	0.09

ESP exchangeable sodium percentage, *EC* soil electrical conductivity, *TWI* topo wetness index, *Flow Acc* flow accumulation, *Flow Dir* flow direction

*p=0.05, significant

Table 4 Semivariogram model parameters of soil salinity variables

Variables	Model	Co	Co+C	Lag size (m)	a	R^2	RSS	Co/(Co+C)[b]
0–30 cm								
EC[a]	Exp	0.17	1.41	3,850	3,210	0.40	0.19	0.12
Na_{Exc}[a]	Gaus	0.79	1.91	3,850	7,153	0.85	0.25	0.41
ESP[a]	Gaus	0.85	1.91	3,850	8,054	0.85	0.25	0.45
Na^{+}[a]	Exp	1.00	2.01	3,850	92,040	0.61	0.23	0.50
K^{+}[a]	Exp	0.20	1.30	1,600	3,030	0.19	0.27	0.16
Ca^{2+}[a]	Exp	0.20	1.33	1,250	3,750	0.65	0.09	0.15
Mg^{2+}[a]	Sph	0.87	1.73	3,850	10,160	0.70	0.25	0.50
$SO^{2-}4$	Sph	0.28	0.64	2,100	5,700	0.65	0.04	0.44
Cl^-	Nug	–	–	–	–	–	–	–
30–60 cm								
EC[a]	Exp	0.11	0.99	3,850	1,140	0.10	0.12	0.11
Na_{Exc}[a]	Gaus	0.92	1.87	3,850	8,764	0.85	0.21	0.49
ESP[a]	Sph	0.81	1.76	3,850	12,270	0.85	0.18	0.46
Na^{+}[a]	Exp	0.55	1.25	3,850	32,160	0.84	0.09	0.44
K^{+}[a]	Exp	0.57	1.14	2,050	10,500	0.55	0.11	0.50
Ca^{2+}[a]	Exp	0.20	1.15	2,700	4,470	0.56	0.13	0.17
Mg^{2+}[a]	Exp	0.79	1.58	3,850	21,510	0.84	0.09	0.50
$SO^{2-}4$	Exp	0.64	1.28	2,100	13,620	0.42	0.32	0.50
Cl^-	Exp	0.17	1.27	2,050	2,670	0.40	0.09	0.13

Co nugget effect, *Co+ C* sill, *a* range (meter), *Sph* spherical, *Exp* exponential, *Gaus* Gaussian, *Nug* nugget, *RSS* residual sum of squares

[a] Log transformation was applied; ratio <0.25 (good spatial correlation); 0.25–0.75 (moderate spatial correlation); and >0.75 (poor spatial correlation)

[b] Nugget to Sill ratio

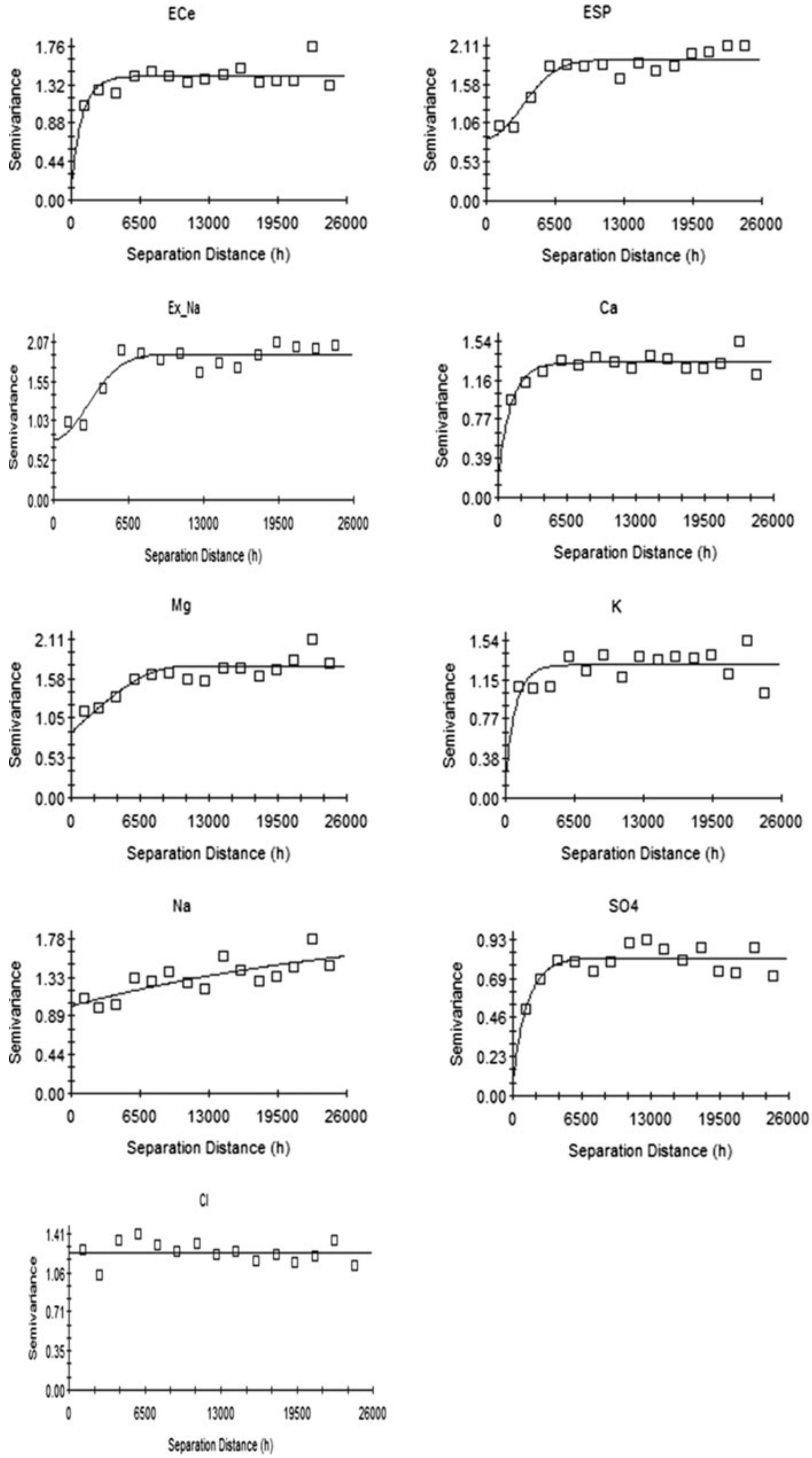


Fig. 3 Theoretical and fitted semivariograms of soil salinity variables at surface depth (0–30 cm)

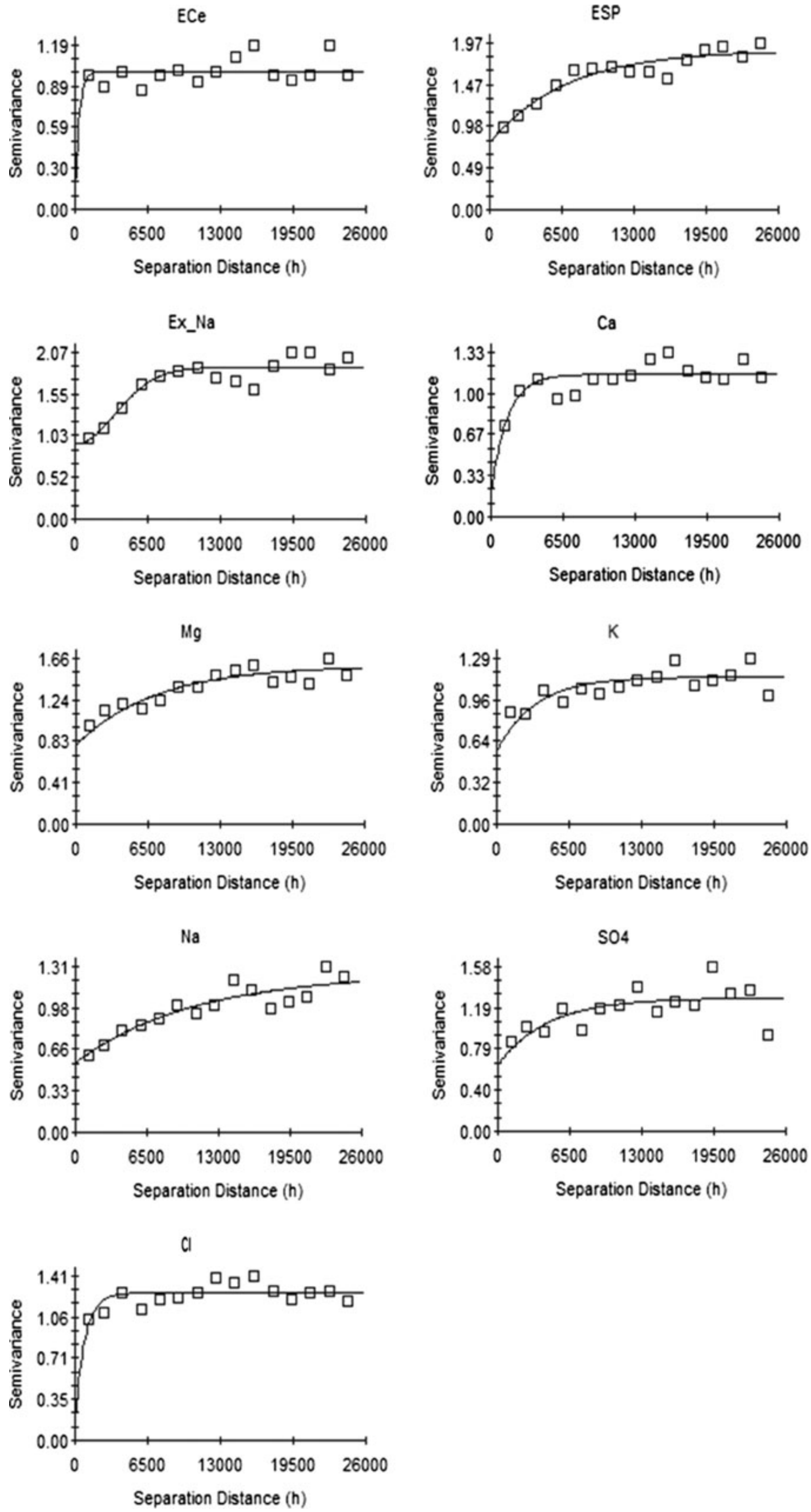
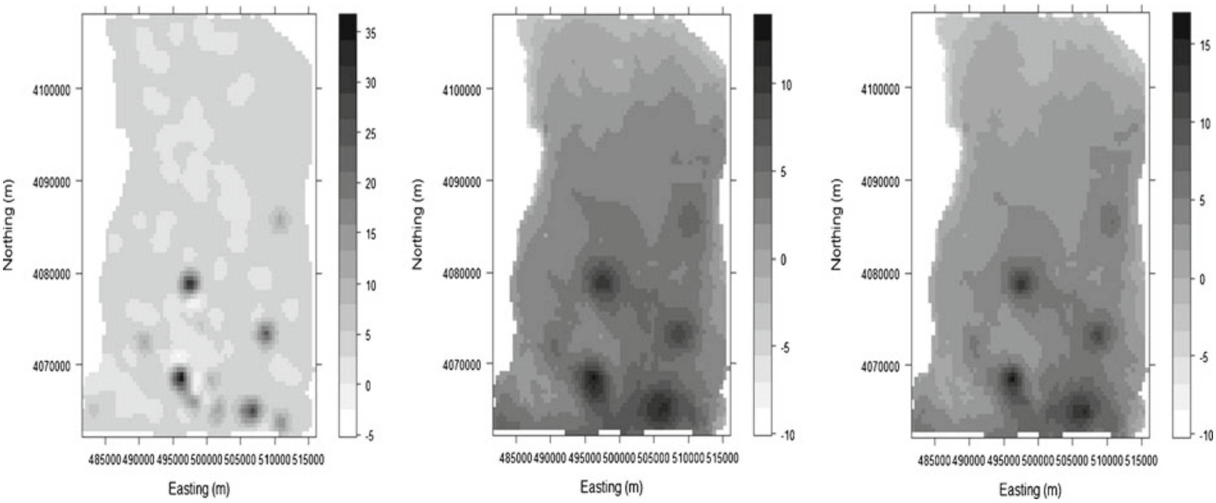


Fig. 4 Theoretical and fitted semivariograms of soil salinity variables at subsurface depth (30–60 cm)

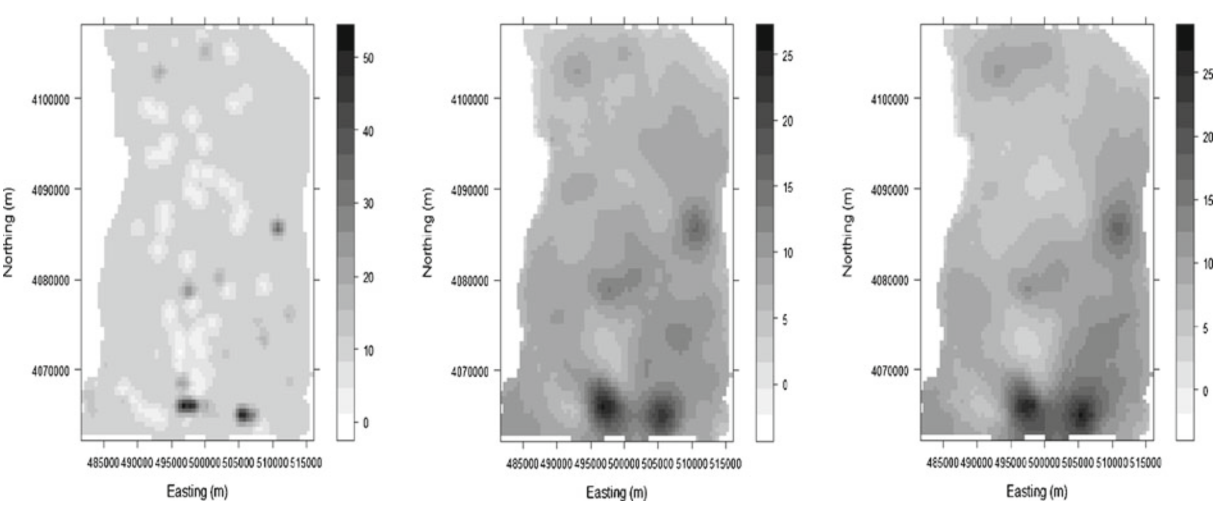


OK map of soil surface EC RK map of surface EC KED map of surface EC

Fig. 5 Mapping soil surface ECe using OK, RK, and KED

distributions of soil ECs and ESP are shown in Figs. 5 and 6, respectively. In general, salinity was higher in southern regions of the study area, similar to the shape of the DEM (Fig. 2). In general, salinity is higher in low lying areas with elevation less than 400 m, than in the north elevation with elevations higher than 450 m. At these areas, excessive irrigation combined with a convex topography and groundwater flow from the mountains cause water depth to approach the land surface. This problem gradually expands towards the north direction according to estimations by Steenhuis et al. (2006). However, northern areas have also been locally affected by salinity. In the study area, the quality of irrigation water is generally high and not considered the primary cause of salinization, but the associated water table rise brings naturally calcareous saline groundwater near the surface.

Soil cations followed a similar pattern to soil EC, although there were variable-dependent differences. ESP as an indicator of alkalinity showed a slightly



OK map of soil surface ESP RK map of surface ESP KED map of surface ESP

Fig. 6 Mapping surface ESP using OK, RK, and KED different distribution from EC, showing some high values at the upper parts of the plain. Apparently, high amounts of gypsum existing in the soil prevented soils from become more alkaline (Aydemir and Sonmez 2008).

Natural factors such as parent material, soil type, geology, climate, and topography, combined with anthropogenic factors such as inappropriate irrigation practices, water logging and land cover, and crop rotations (Bui et al. 1996; Wiebe et al. 2007) are the controlling factors for the distribution of soil salinity within the landscape. In the study area, the formation of saline soils is apparently mostly due to inappropriate irrigation management performed in the smectitic clay soils under high evaporation and topographical factors. Other salinity indicators showed similar patterns to soil EC with high values in the eastern and southern sections and low values in the western and northern parts of the study area.

Multivariate geostatistical methods: RK and KED

Hybrid methods that use covariables that are related to the primary variable can help to improve the accuracy of the estimations. Terrain variables are important factors affecting the distribution of soil salinity as well as many other parameters in the soil. The correlations between terrain and soil salinity variables were nevertheless poor (Table 3). Elevation was the only variable that had statistically significant correlations with other salinity parameters. There were also strong correlations between soil EC and other soil salinity parameters at both surface and subsurface levels. Therefore, both elevation and soil electrical conductivity were used with regression kriging and kriging with external drift methods as covariate in order to improve the estimations of other soil salinity parameters.

The performance of these methods and relative improvements as compared to ordinary kriging were tested using an independent validation sample set containing 30 % of samples. Estimation errors, RMSEP values, and the RI values associated with RK, KED, and OK are shown in Table 5. Overall, both RK and KED methods using elevation and soil ECs ($EC_{0–30}$ and $EC_{30–60}$) at two different depths as covariable improved the estimations of soil salinity variables at surface and subsurface levels as indicated by positive RI values and lower RMSEP values than ones obtained from the OK method. Incorporation of auxiliary variables improved the estimations up to 65 % with the best performance obtained from RK with soil $EC_{0–30}$ as covariate for the estimation of soluble magnesium (Table 5). The improvement was also obtained for other cations at both depths, except for a few subsurface variables, which produced negative RI values (Table 5). For soil EC, improvement was always obtained using either method and covariate. The improvement for Na_{Exc} was minor. The ESP, indicator of soil alkalinity, was able to be improved up to 16 %, but almost no improvement was obtained for ESP at the subsurface depth using either RK or KED.

For anions, the estimation of SO_4^{2-} was improved with auxiliary variables, but no improvement was obtained for Cl^-, i.e., OK provided lower RMSEP values. This was explained by the low correlation between Cl^- and potential covariables (Table 2; Hengl et al. 2007). The estimations of the variables having higher correlations with soil ECs and elevations were improved, especially for the shallow depths (Table 5).

Superiority of hybrid techniques over simple kriging interpolation methods has been previously demonstrated (Zhu and Lin 2010; Hengl et al. 2007). This is mostly due to their ability to include secondary information into the model. On the other hand, some (Kravchenko and Robertsen 2007) reported the opposite outcome and emphasized that simple or ordinary kriging may be sufficient in cases where the correlations between secondary and primary variables are poor. The success of these methods in general depends upon the degree of correlation between primary and secondary variables and secondly on the structure of variogram of residuals (Hengl et al. 2007).

Auxiliary variables

The level of the improvement in the estimations varied depending upon the interpolation method, the covariable, or both ,i.e., KED generally provided more improvement for the estimation of soil salinity parameters at the surface when using $EC_{0–30}$ as covariable, while RK was better in most of the cases with $EC_{30–60}$ as covariable. Using elevation with RK provided better results than using elevation with KED.

Selection among methods used depends on the sampling design of the covariable and the degree of relationship between covariable and primary variable. If the covariable was measured at the same locations as the

Table 5 Estimation performances and comparison of KED and RK with OK with relative improvement values

	OK	Covariable:	RK						KED					
			$EC_{0–30\ cm}$		$EC_{30–60\ cm}$		Elevation		$EC_{0–30\ cm}$		$EC_{30–60\ cm}$		Elevation	
	RMSEP[a]		RMSEP	RI	RMSEP	RI	RMSEP	RI	RMSEP	RI	RMSEP	RI	RMSEP	RI
0–30 cm														
EC	6.86		–	–	2.9	56.6	5.72	16.6	–	–	4.57	33.4	6.7	2.3
ESP	11.0		9.8	10.9	9.2	16.1	11.6	−5.9	9.2	15.9	10.2	6.6	10.2	6.8
$Na_{exc.}$	3.8		3.5	8.9	3.6	6.1	3.3	14.5	3.3	12.9	3.6	6.1	3.7	3.7
Ca^{2+}	23.3		14.2	39.0	13.1	43.7	18.0	22.8	10.4	55.4	11.8	49.4	22.5	3.4
Mg^{2+}	8.4		2.9	64.8	4.6	45.4	3.8	54.6	4.2	49.9	5.4	35.0	8.2	2.0
Na^{+}	36.3		28.3	22.0	24.0	33.9	25.5	29.6	27.0	25.6	32.2	11.1	35.4	2.5
K^{+}	12.6		11.5	8.5	11.7	7.0	12.0	4.9	11.3	10.0	11.9	5.4	12.4	1.6
SO_4^{2-}	17.9		15.0	15.9	14.9	16.8	17.4	2.7	13.4	25.2	15.5	13.3	18.0	−0.6
Cl^{-}	7.0		10.7	−53.1	13.2	−89.1	7.4	−5.4	10.0	−43.1	10.6	−51.4	9.6	−36.9
30–60 cm														
EC	5.7		2.8	50.3	–	–	3.6	36.3	1.9	66.2	–	–	3.5	39.2
ESP	45.7		45.7	0.0	45.6	0.1	45.4	0.6	45.4	0.7	45.4	0.7	45.6	0.2
$Na_{exch.}$	16.6		16.5	0.6	16.6	0.4	16.5	0.9	16.5	1.0	16.5	0.9	16.5	0.8
Ca^{2+}	39.7		36.8	7.3	36.4	8.3	39.9	−0.5	36.7	7.7	36.1	9.2	39.8	-0.1
Mg^{2+}	4.8		3.4	30.6	2.9	39.5	4.5	6.8	3.9	18.8	3.0	38.9	4.5	6.0
Na^{+}	10.9		9.2	15.6	8.5	21.5	11.8	−8.0	10.0	8.2	3.5	68.3	10.6	2.8
K^{+}	3.7		3.5	7.2	3.5	7.2	3.8	−1.3	3.5	7.2	9.4	−151.6	3.8	−0.5
SO_4^{2-}	13.9		14.1	−1.7	14.0	−0.4	13.6	2.4	14.7	−5.8	14.0	−0.5	14.0	−0.8
Cl^{-}	7.9		8.3	−5.7	8.0	−1.5	9.6	−21.4	9.5	−20.3	9.6	−21.3	8.9	−12.7

[a] RMSEP values associated with validation data set containing 30 % of all samples

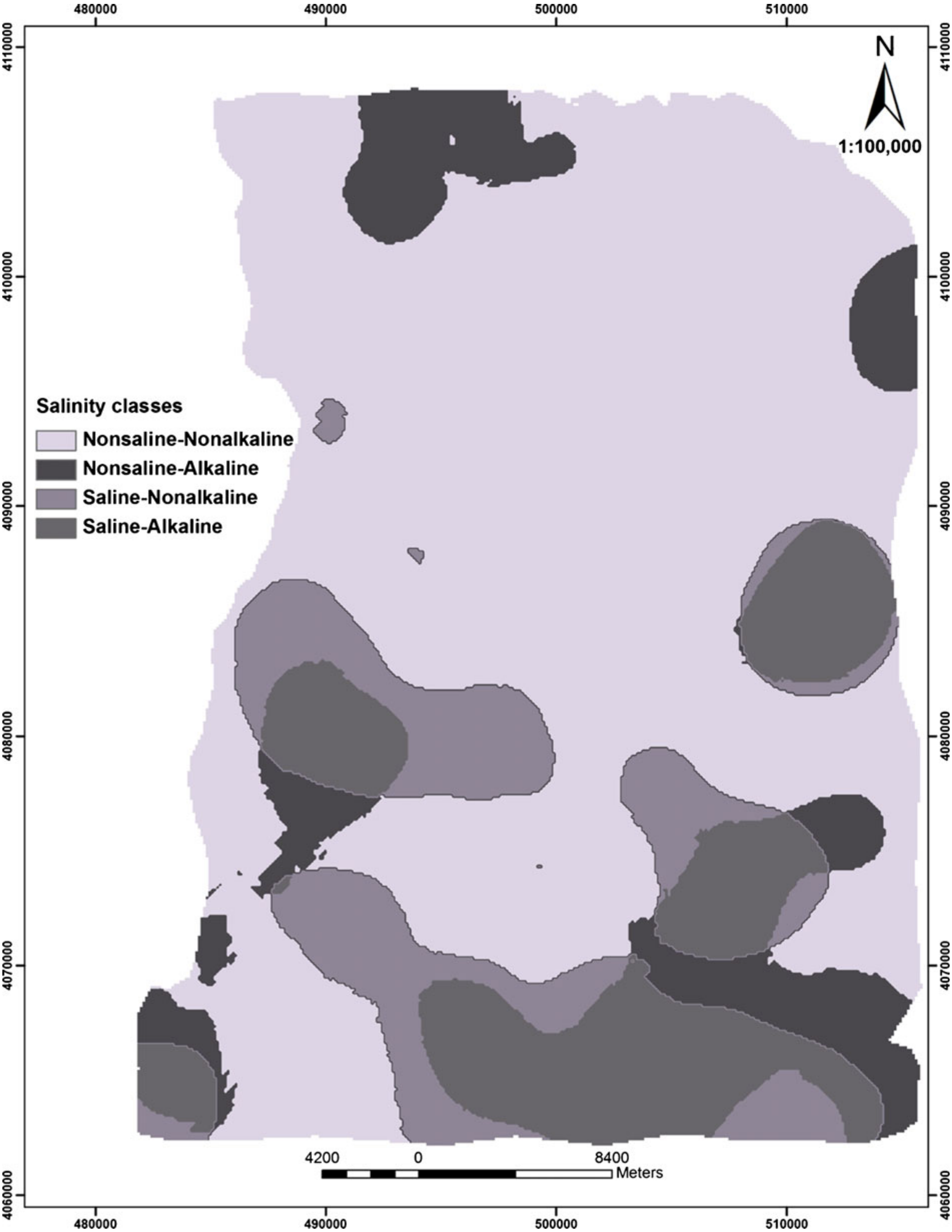


Fig. 7 Soil salinity class map using disjunctive kriging

primary variable and were well correlated to it, then RK and KED are advantageous (Hengl et al. 2003b).

The benefits of covariables alone were not clear, but generally the cases where electrical conductivity was used as a covariate produced more successful estimates. Conversely, elevation had lower correlations than soil ECs, but its use as a covariable provided comparable results with the use of soil ECs as a covariate. Having better correlations with other parameters makes soil electrical conductivity preferable over elevation data, but DEM data are more readily available and could be used for the estimations of various parameters simultaneously. Terrain parameters can therefore provide good auxiliary data if they capture the general trend of the distribution of the variable of interest (McBratney et al. 2003). Zhu and Lin (2010) used indices extracted from DEM and reported that RK can only be preferred over OK if there is strong and statistically significant relationship (R>0.60) between target and secondary variables. Bourennane et al. (2000) used slope gradient extracted from DEM data and improved the estimation of soil thickness by 38 %. Kozar et al. (2002) used slope gradient in COK and successfully improved the estimations of P and K.

Classification

Distinguishing soil samples into different salinity classes was evaluated using GIS-based disjunctive kriging (DK–GIS) (Fig. 7). Wu et al. (2003) stated that comparisons among estimation maps produced by different kriging methods cannot prove which one is the best map. Penizek and Boruvka (2006) used a t test in deciding which maps produced by RK and COK were the best in the estimation of soil depth using actual observation and estimations. In this study, the kappa statistic (κ) was used to evaluate the classification accuracy. κ values equaling to 1 indicate perfect agreement, and if κ is different than 0, the agreement among two methods is more than chance, which is also indicated by significant p values (p<0.001).

Table 6 shows the number of samples that were classified correctly and the percent accuracy. The DK–GIS successfully separated soils as nonsaline–nonalkaline, nonsaline–alkaline, saline–nonalkaline, and saline–alkaline with overall average accuracy of 75 % (κ=0.55, p< 0.001; Table 6). The DK–GIS method, which measures the probability that a variable exceeding a certain threshold, successfully classified soils into different salinity classes. DK has been previously found to be a very useful tool in the assessment of areas under risk of various contaminants such as salinity, NO_3 in groundwater, and heavy metals (Triantafilis et al. 2006; Shi et al. 2007). In general, such variables showed high skewness, and DK was a very useful tool in dealing with non-normal data (Yates and Yates 1988), It has also been found superior to indicator kriging, another nonlinear interpolation method, because it does not lose information when making binary transformations (Lark and Ferguson 2004; Triantafilis et al. 2006). Triantafilis et al. (2006) found that DK provided the lowest misclassification numbers compared to indicator kriging when determining salinity risk areas using low-quality irrigation water.

Conclusions

The spatial distribution of soil salinity and soil salinity variables were assessed using laboratory data with simple OK, hybrid methods like RK and KED, and a

Table 6 Soil salinity classification by two methods (laboratory, DK–GIS) and kappa statistics

Laboratory	DK–GIS				
	Nonsaline–nonalkaline	Nonsaline–alkaline	Saline–nonalkaline	Saline–alkaline	Total
Nonsaline–nonalkaline	74	5	16	4	99
Alkaline–nonsaline	1	10	0	2	13
Saline–nonalkaline	0	1	7	4	12
Saline–alkaline	0	0	1	11	12
Total	75	16	24	21	136
Po (%)					75
Kappa					0.55 (p<0.00)

nonlinear geostatistical method, DK. All soil salinity variables showed skewed distribution with high CV values and were related to DEM-derived topographical variables. Saline areas were mostly located in the southern and eastern parts of the plain, which were generally low-elevation areas. However, topographical variables explained the variation of soil salinity only weakly. This is due mostly to irrigation and drainage practices and patterns.

Soil salinity estimations could be improved by incorporating auxiliary information from either EC measurements or elevation parameters. Up to 65 % of improvement was obtained using RK and KED methods, and gains were higher using EC as covariate than elevation parameters. The classification results showed that DK could classify soils into different salinity groups successfully with 75 % overall accuracy and a kappa statistics of 0.55 (p<0.001). In summary, using geostatistical methods can greatly enhance estimations of soil salinity and alkalinity and assists with abatement and monitoring.

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