Mapping Soil Salinity in El-Tina Plain in Egypt Using Geostatistical Approach

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Abstract

In El-Tina plain soil salinity is the major soil limitation factor for agricultural production. Spatial information on soil salinity is increasingly needed, particularly for better soil management in this area. To explore spatial variability of soil salinity in the study area grid sampling scheme (800 × 800 m) consisting of 96 sample points (81 soil profiles and 15 augers) and 41 observation points was established. Electrical conductivity was determined by laboratory analysis from 1:2.5 soil–water suspensions (EC2.5). Spatial trend and semi-variogram were computed and spatial distribution of field salinity status was further visualized and quantified. Two types of kriging were used: Ordinary Kriging (OK) and Uni-versal Kriging (UK) with three semivariogram models (circular, spherical and ex¬ponential). Mean Prediction Errors (MPE), Mean Standardized Prediction Errors (MSPE) and Root-Mean-Square Standardized Prediction Errors (RMSSPE) were used to evaluate the models. The results suggest that the best model to generate soil salinity map was Ordinary Kriging with spherical semivariogram model (MPE and MSPE close to 0, and RSSPE close to 1). The selected model was used to generate salinity map based on standard soil salinity classification.

1 Introduction

Soil salinity decreases food production in different regions of the world. Soil salinity is divided into two main categories: naturally occurring dryland salinity and human-induced salinity caused by low quality of water. In both cases, the growth of plants and soil organisms are limited leading to low yields (DOUAIK et al. 2005). As the first step for a better management of salt affected soils, soil salinity needs to be monitored and mapped (ZHENG et al. 2009). Currently, research interest is growing in mapping soil electrical conductivity (EC) as a surrogate for either soil salinity (MCCUTCHEON et al. 2006) or other various soil physicochemical properties (RONGJIANG & JINGSONG 2010). For example, DOUAIK et al. (2005) used successfully electrical conductivity determined by laboratory analysis from 1:2.5 soil–water suspensions ($EC_{2.5}$) to map soil salinity.

Digital soil mapping (MCBRATNEY et al. 2003) is generally characterized as a quantitative geostatistical production of soil geoinformation. Geostatistical approaches use sampled and analyzed data to interpolate soil attribute maps (WEBSTER & OLIVER 2007). Geostatistics is frequently used synonymously with kriging, which is the statistical version of spatial interpolation. Ordinary Kriging (OK) is one of the most basic kriging methods (MEUL &

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VAN MEIRVENNE 2003) which plays a major role in efficiently predicting the target soil variable on spatial distribution, interpolation and maps of soil properties (SUMFLETH & DUTTMANN 2008). Therefore a number of researchers have used OK to study soil salinity (TRIANTAFILIS & BUCHANAN 2010 and JUAN et al. 2011). On the other hand, Universal Kriging (UK), a combination of the standard model of multiple-linear regression and OK (Webster 1994) was also used in soil attributes mapping (MEUL & VAN MEIRVENNE 2003).

Soil salinity is the major soil limitation factor for agricultural production in El-Tina plain region, El-Salam canal project, Egypt (NAWAR 2009). Up to now, most soil maps of El-Tina plain were based on traditional soil survey and mapping, as only few studies used pedometric techniques for soil mapping in Egypt (OMRAN 2007). To answer the needs of sustainable agriculture in El-Tina plain region, the main objective of this study was to use geostatistical mapping approach to generate an accurate soil salinity map as a base map for sustainability assessment of the study area.

2 Materials and Methods

2.1 The study area

The study area is located at the northwestern part of Sinai Peninsula, Egypt, between longitudes 32º20'35"and 32º33'10" east and latitudes 30º57'25" and 31º04'28" north, approximately 174 km^2 (Fig. 1). It is located under arid conditions; the annual rainfall ranges from 33.3 mm to 70.2 mm and occurs over a short period (from October to March). Air temperature ranges from 7.6 to 23.4 ˚C and between 16.4 and 35.7 ˚C in winter and summer, respectively. Mean evaporation is high and ranges from 3.7 mm/day to 7.4 mm/day (ALY 2005). El-Tina plain is almost flat and the ground elevation ranges from 0-5 m above sea level (REDA 2000). The soils of El-Tina plain were characterized by shallow to deep soil profile underlain by water table at 50-100 cm. Soil texture varies between sandy loam to clay and soils are extremely saline (REDA 2000). NAWAR (2009) classified the soils of El-Tina plain into two orders, *Entisols* and *Aridisols,* which include eight subgroups: *Typic Aquisalids, Typic Haplosalids, Aquic Torriorthents, Typic Torriorthents, Aquic Torripsamments, Typic Torripsamments, Gypsic Aquisalids* and *Gypsic Haplosalids.*

2.2 Soil sampling and laboratory analysis

Grid sampling scheme, with 800 m × 800 m spacing, was developed to explore spatial variability of the soils in the study area based on previous work (EBRAHEM 2002) and satellite image ETM+ acquired in June 2006. The grid sampling scheme consisted of 96 sample points (81 soil profiles and 15 augers) and 41 observation points (Fig. 1). Sampling points were located in the field with the accuracy of 3m using GPS. Soil profiles were morphologically described according to SOIL SURVEY STAFF (1993) and FAO guidelines for soil description (2006). The collected soil samples were air-dried, crushed and passed throughout a 2 mm sieve. Then, the fine earth (< 2mm) was taken for analysis. Electrical conductivity was determined by laboratory analysis from 1:2.5 soil–water suspensions ($EC_{2.5}$) according to PAGE et al. (1982). $EC_{2.5}$ data were used for geostatistical analysis as weighted average mean of soil salinity values for soil profile layers, in order to represent the soil salinity through the whole soil profile.

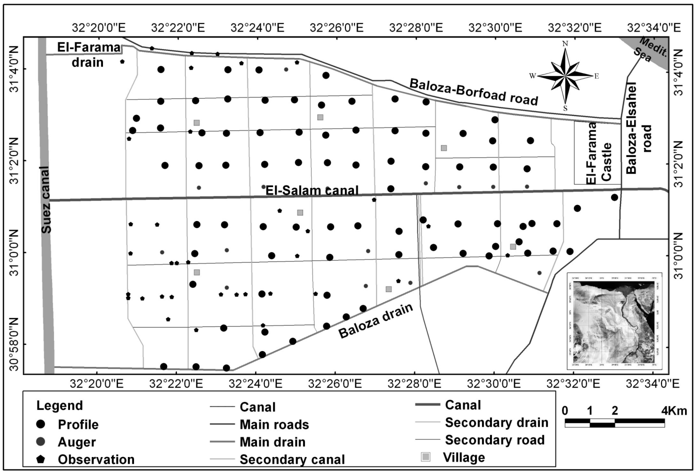

Fig. 1: Study area location and sampling design

2.3 Geostatistical mapping of soil salinity

Geostatistical techniques, including analyses of semivariograms, cross-validation, kriging and mapping of kriged estimates (GOOVAERTS 1997) were used to determine the variance structure of the soil salinity measurements. Geostatistical analysis in the study was performed using the Geostatistical Analyst extension of ArcGIS 9.3 (ESRI 2008).
The semivariogram $\gamma(h)$ is described as follows:

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

where $Z(x_i)$ represents the measured value of the soil property at location x_i, $\gamma(h)$ is the semivariogram for a lag distance h between observations $Z(x_i)$ and $Z(x_i+h)$, and $N(h)$ is the number of data pairs separated by a lag distance equal to h. Three models were fitted to the experimental semivariograms (circular, spherical and exponential; GOOVAERTS 1997). The kriged estimate salinity values were calculated using two types of kriging (OK and UK; GOOVAERTS 1997 and MEUL & VAN MEIRVENNE 2003).

Geostatistical procedures were assessed with cross-validation indicators and additional model parameters (nugget, sill and range) which helped to choose the most appropriate model to predict soil salinity. The calculated statistics served as diagnostics that indicated whether the model was reasonable for soil salinity map production. To evaluate the models, three indices were used (GOOVAERTS 1997): Mean Prediction Errors (MPE), Mean Standardized Prediction Errors (MSPE) and Root-Mean-Square Standardized Prediction Errors (RMSSPE).

Semivariogram $\gamma(h)$ for soil salinity was calculated, and the scatterplot of $\gamma(h)$ versus h was generated. Then, theoretical semivariance models (circular, spherical and exponential) were used to fit the calculated values and the model with the best-fitting value. The smallest nugget values, MPE close to 0, MSPE close to 0, and RMSSPE close to 1.0 were selected. The cross-validation method was then applied to validate the parameters of the model.

Finally, classes of soil salinity were delimited according to a modified Soil Survey Staff classification scheme (1993) with 6 classes: Non saline 0-2, Very slightly saline 2-4, Slightly saline 4-8, Moderately saline 8-16, Strongly saline 16-32 and Very strongly saline >32 dSm^{-1}.

3 Results

3.1 Descriptive data analysis

Exploratory Data Analysis (EDA) of soil properties consisted of the calculation of summary statistics and graphical illustration of data distributions. The frequency distribution of soil salinity is shown as histograms in Fig. (2). The histogram shows a unimodal shape, a small positive skewness (0.1), and kurtosis equal to 2.9. These results indicated that the salinity data has a normal distribution (ISAAKS & SRIVASTAVA 1989).

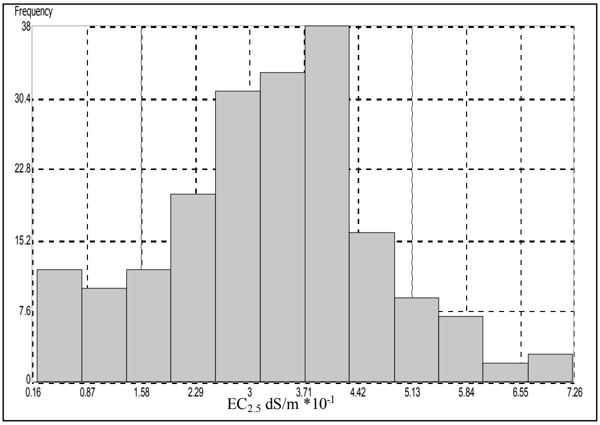

Fig. 2:
The histogram of soil salinity

3.2 Semivariogram analysis

Semivariogram parameters of salinity data and their validation information are summarized in Table (1). These semivariogram parameters include the nugget value C_0, partial sill (C), sill (C_0+C), range value and nugget-sill-ratio ($C_0/(C_0+C)$). Validation information was used to determine the goodness of fit. In this study, positive nuggets of 40 and 98.2 were observed for salinity data (Table 1).

Estimation of semivariances was carried out using a lag size of 800 m. The minor range starts from 700 to 3950m for the raw data and the major range variation is (6740m and 16500m). The range is important both to define the different classes of spatial dependence for soil and to establish the sampling interval (lag size). As a “rule of thumb”, the sampling interval (lag) should be less than half of the range of the raw semivariogram (LOPEZ-GRANADOS et al. 2005).

Table 1: Nugget variance (C_0), partial sill (C), sill (C_0+C) and range (r) of the fitted semivariogram models for (OK) and (UK)

Geostatistical procedures	Model	C_0	C	C_0+ C	r(m)	(C_0/C_0+C)%
OK	Circular	98.25	144.06	242.31	6740.8	0.41
	Spherical	40.00	169.13	209.13	1672.0	0.19
	Exponential	55.00	215.25	270.25	9127.1	0.20
UK	Circular	74.06	188.02	262.08	16500.0	0.28
	Spherical	92.87	177.54	270.41	9127.1	0.34
	Exponential	55.04	215.25	270.29	9127.1	0.20

Partial sill parameters ranged between 144.06 and 215.25, and sill parameter varied from 209.13 to 270.40. The nugget-sill-ratio $C_0/(C_0+C)$ was selected to quantify short-distance autocorrelation (spatial dependency) of regionalized variables (SABY et al, 2006). Low nugget-sill-ratio indicates high spatial autocorrelation or spatial continuity over short distances. CAMBARDELLA et al. (1994) defined nugget-sill-ratio of <25%, 25-75%, and >75% as categories of strong, moderate, and weak spatial dependence, respectively. The nugget-sill ratios ranged from 0.19 in spherical OK to 0.41 in circular OK (Table 1). These results indicate that the spherical model for OK is the best semivariogram model to show the strong spatial dependency for soil salinity variable (Fig. 3b).

3.3 Spatial distribution of soil salinity

Kriging methods were applied to estimate the value of salinity data at unsampled locations using parameters of semivariogram models (Table 1). The salinity data presented normal distribution, and did not require any transformation before generating the spatial distribution maps. Raster maps (30 m × 30 m) of salinity were computed for the study area (Fig. 4).

The maps prove that the spatial distribution of soil salinity is impacted by many factors such as micro-topography, differences in land use patterns and local agricultural activities (intensive farming) in the study area. It was also apparent that the northern region of the study area was the most salinized one compared to other regions.

3.4 Error assessment and cross-validation results

OK and UK results were validated by qualitative assessment, error assessment and cross-validation procedures using MPE, MSPE, RMSSPE indices (Table 2). MPE ranged from 0.000002 to -0.06878, indicating that OK with spherical semivariogram provided an unbiased prediction procedure, because of low MPE value and lack of systematic error (DIODATO & CECCARELLI 2004). The superior prediction accuracy of OK with spherical semivariogram procedure is evident also by a lower MSPE (0.00045) in comparison to values received for other models. RMSSPE values for OK with spherical semivariogram were close to 1.0 and indicated that its prediction accuracies were comparable to other models (GOOVAERTS 1997). It might be concluded that the best model for salinity prediction and mapping is OK with spherical semivariogram model (Fig. 4b).

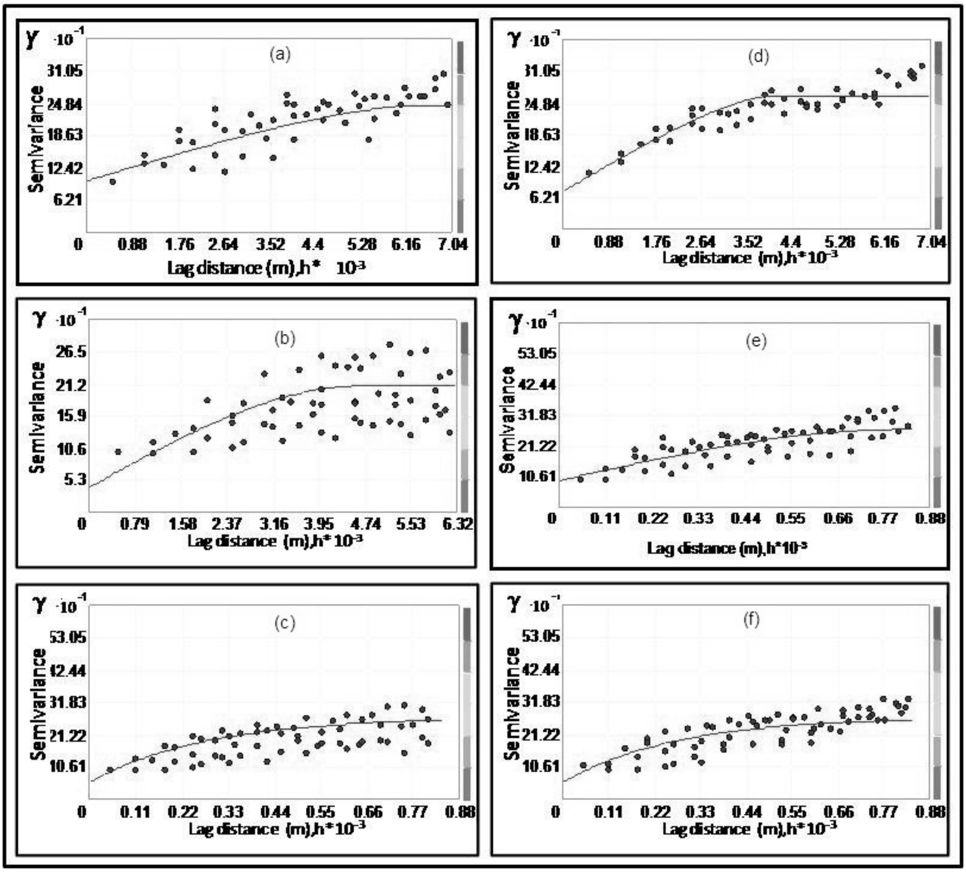

Fig. 3: Experimental semivariogram (dots) and the fitted mathematical model (line): (a) circular, (b) spherical, (c) exponential models (OK); (d) circular, (e) spherical and (f) exponential models (UK)

Tab. 2: Validation indices of ordinary and universal kriging.

Geostatistical procedures	Semivariogram Model	MPE	MSPE	RMSSPE
OK	Circular	-0.026710	-0.00049	0.96
	Spherical	0.000002	0.00045	1.06
	Exponential	-0.067800	-0.00207	1.01
UK	Circular	-0.068780	-0.00111	1.03
	Spherical	-0.038400	-0.00141	0.97
	Exponential	-0.060900	-0.00140	1.01

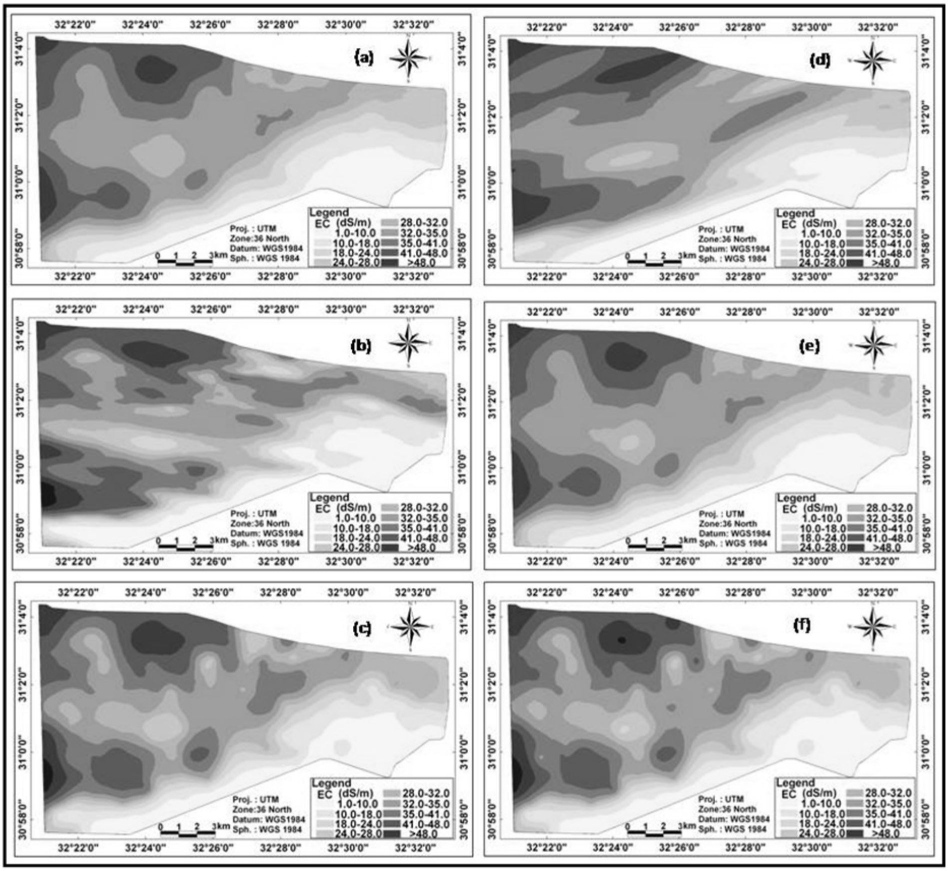

Fig. 4: Soil salinity distribution maps: (a) circular, (b) spherical, (c) exponential models (OK); (d) circular (e) spherical (f) exponential models (UK)

3.5 Classification of soil salinization

Classification of soil salinity does not only provide quantitative evaluation of salinized soil resources, but also may serve as a scientific reference to the management and high-efficiency utilization of salinized soil. Spatial distribution of 6 delimited soil categories varies (Fig. 5). Very strongly salinized and Strongly saline soils were the predominant soil types, accounting for 53.1% and 27.5% of total survey area, respectively. The area of Moderately and Slightly salinized soils was comparatively small and covered 10.2% and 4.7% of the study area, respectively. Based on the area surveyed, the area with salinity in the range of 2-4 dSm^{-1} (Very slightly saline) was 7.8 km^2, accounting for 4.5% of the total study area. Salinity map can provide a helpful reference for crop allocation to reduce yield loss due to salinity.

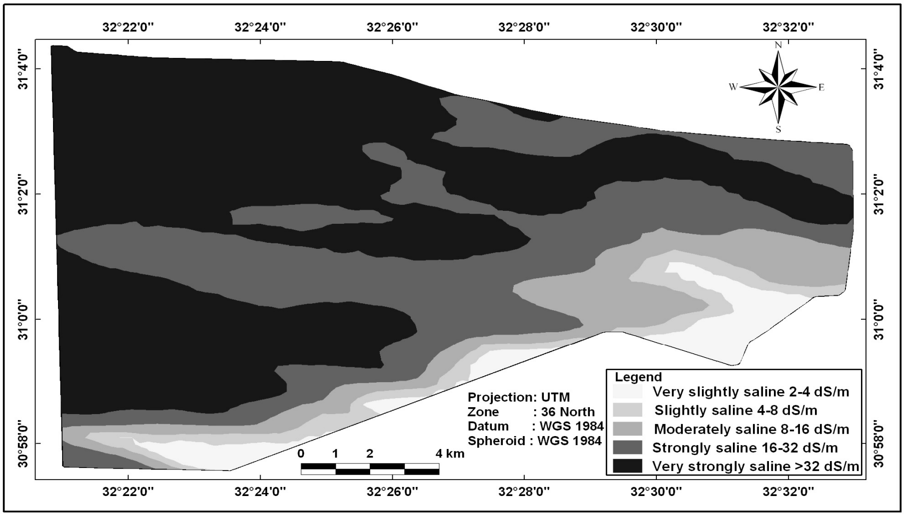

Fig. 5: Salinity map of El-Tina plain

4 Conclusion and Outlook

With the application of GIS and geostatistical mapping, spatial distribution of soil salinity at the study area was mapped and quantitatively evaluated based on the grid sampling and laboratory measurements. The results of validation suggest that the best model for generating soil salinity map was ordinary kriging with spherical semivariogram model. Quantitative evaluation showed that the mean soil salinity was high across the study area, generally pertaining to heavy salinized soil types.

To increase the accuracy of soil salinity prediction the authors suggest to improve the sampling scheme and use ancillary information, e.g., satellite imagery and Digital Elevation Models (DEMs). Multi-spectral satellite images with spatial resolutions in the range of 10-100 m (e.g., Landsat ETM+) are usually cheap or free and readily available for the whole study area. The spectral information can be used in an efficient way to complement the scarcity of direct measurements of soil salinity, with less bias and more accuracy, adding several opportunities to traditional soil surveys, e.g.:

- determination of spectral responses (average ground radiance measurements recorded in various spectral bands) of vegetation and bare soil colors at sampling sites,
- calculation of the normalized difference vegetation index (NDVI) for all samples,
- calculation of the Combined Spectral Response Index (COSRI) for bare soils and vegetation by adjusting NDVI (FERNÁNDEZ BUCES et al. 2006),
- analysis of regression between EC of soils and spectral responses of bare soil and vegetation (COSRI) allowing to predict EC (FERNÁNDEZ BUCES et al. 2009).

In combination with the traditional surveys, remote sensing should allow to detect, with reasonable accuracy, the presence of salt in the surface layer of the topsoil. In addition, changes in salinity can be easily monitored in time using subsequent satellite images of the studied area. Integration of remote sensing with traditional soil surveys and modern soil spatial analysis leads us in this way towards a more accurate approach of the digital soil mapping (LAGACHERIE 2008).

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