ASSESSMENT OF SPATIAL VARIABILITY OF SOME SOIL PROPERTIES IN SALT AND SODIC AFFECTED SOILS IN ARSANJAN PLAIN, FARS PROVINCE, SOUTHERN IRAN

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ABSTRACT

Spatial patterns for several soil parameters (soil texture, exchangeable sodium percentage (ESP), electrical conductivity (ECe), soil pH, cation exchange capacity (CEC)) were examined in salt and sodic affected soils in Arsanjan plain, southern Iran, in order to identify their spatial distribution for implementation of a site-specific management. Soil samples were collected from 0-30, 30-60 and 60-90 cm soil depths at sampling sites. Data were analyzed both statistically and geostatistically on the basis of the semivariogram. The spatial distribution model and spatial dependence level varied in Arsanjan plain. Soil pH had the minimum and ESP had the maximum variability at all depths. Soil properties indicated moderate to strong spatial dependence. ECe was moderately spatially dependent at three depths; pH and ESP were moderately spatially dependent at 0-30 cm and strongly spatially dependent at 30-60 and 60-90 cm depths. Clay and CEC exhibited strong spatial dependence for first layer and weak spatial dependence at 30-60 and 60-90 cm depths. Sand and silt had a weak spatial dependency at 30-60 and 60-90 cm depths. The spatial variability in small distances of ECe, CEC, pH and ESP generally increased with depth. All geostatistical range values were greater than 1168 m. It was inferred that the strong

spatial dependency of soil properties would lead to the extrinsic factors such as ground water level and drainage.

1. INTRODUCTION

Precision agriculture applies principles of farming according to the field variability, which creates new requirements for estimating and mapping spatial variability of soil properties. In the last decades, important contributions has been made by geostatistics for understanding of soil distribution patterns within the landscape, which is required for effective land management. Soil variability occurs because of effect and interaction of various processes in soil profile (Parkin, 1993). Webster (1985) stated that soil characteristics generally show spatial dependence. Samples close to each other have similar properties than those far from each other. However, the classical statistic, assuming the measured dada independent, is not capable to analyze the spatial dependency of the variable (Vieria et al., 1983). Currently, there is a global need for tools to evaluate the ramification of soil resource management upon special temporal changes in soil quality to ascertain sustainability of farm management practices (Corwin and Lesch, 2005). The interpolation techniques commonly used in agriculture include inverse distance weighting (IDW) and kriging (Franzen and Peck, 1995; Weisz et al., 1995; Ardahanlioglu et al., 2003). Both methods estimate values at unsampled location based on the measurements from the surrounding locations with certain weights assigned to each of the measurement. IDW is easier to implement, while kriging is more time-consuming and cumbersome; however, kriging provides a more accurate description of the data spatial structure, and produces valuable information about estimation error distribution (Kravchenko and Bullock, 1999). There have been many conflicting reports concerning the use of basic statistics to predetermine both interpolation methods and their parameters (Dalthrop et al., 1999; Hoseini et al., 1994; Weisz et al., 1995; Nalder and Wein, 1998). In a simulation study by kravchenko (2003) IDW was compared with kriging in which spatial structure was known (i.e., semivariogram models were determined from an exhaustive dataset). As might be expected, the performance of kriging improved relative to IDW when spatial structure was known. Given the importance of spatial structure, it may be possible to use geostatistical indices to predict the relative performance of ordinary kriging and IDW. Generally, kriging techniques are currently being used to estimate soil properties, such as electrical conductivity, pH, nutrient or contaminant concentrations based on limited set of samples for which these properties have been monitored. Surface soil properties (Brejda et al., 2000), nutrient content of soils (Newman et al., 1997), soil chemical conditions and properties (Lee et al., 2001; Yost et al., 1982; Ardahanlioglu et al., 2003), nitrate leaching (Ersahin, 2001), pesticide distribution in soils (Rao and Wagenet, 1985) and ecological parameters (Rossi et al., 1992) could be analyzed with geostatistical methods to predict spatial variation in soil properties.

Although these works provided very precise information for site-specific recommendations, similar information from soils under semiarid Arsanjan plain conditions was lacking and needed to be assessed. More precisely, it is necessary to consider the fact that spatial variability of soils depends on the specific soil studied. The Arsanjan plain is one of the most important agricultural production areas of Fars province (southern Iran). Crop productivity is threatened in this region due to the lack of outlet for drainage water, high ground water level and low water quality used for irrigation water. Therefore, the assessment of salinity, sodicity and other important soil properties in Arsanjan plain is needed to establish data of salt and sodic affected soils and to evaluate spatial variability for site-specific management. The aims of this study were (1) to examine spatial variability in exchangeable sodium percentage (ESP), electrical conductivity (ECe), soil pH, particle size distribution, cation exchange capacity (CEC) and (2) to assess spatial distribution patterns of salt and sodic affected soils in Arsanjan plain, southern Iran. This would enable the identification of areas where remediation is needed to improve crop growth.

2. MATERIALS AND METHODS

2.1. DESCRIPTION OF THE STUDY AREA

The study area (within Arsanjan plain) is located in Fras province, southern Iran (29˚ 43′ to 29˚ 47′ N latitude and 53˚ 09′ to 53˚ 16′ E longitude). The mean annual precipitation, evaporation and temperature are 323.8 mm, 989.1 mm and 18.2 ºC, respectively. Soil moisture and temperature regime are xeric and thermic, respectively. The prominent soils of Arsanjan plain suffer from some degree of salinity and/or sodicity because of high evaporation. The soils of the study area formed from highly calcareous parent material and according to the USDA-NRCS Soil Taxonomy (1998), the soils were classified as Fine, mixed (calcareous), superactive, Typic Calcixerepts. The study area has been under conventional tillage system and under production of maize, tomato, wheat and sugar been. Salinization due to the high groundwater level and use of its low quality water for irrigation together with inappropriate irrigation methods is most limiting factor to agricultural production in Arsanjan plain. As a result, sustainable use of such fertile soils was threaten and has declined significantly the soils fertility in the last decade.

2.2. SOIL SAMPLING AND LABORATORY ANALYSIS

Soil samples in the 85 sampling site were collected from 0-30, 30-60 and 60-90 cm depths of soil profiles in a representative of 10187 ha, georefrenced using GPS receiver (accuracy of ± 5 m), and analyzed for ESP, ECe, pH, CEC and particle size distribution. ESP was determined using the ammonium acetate (NH_4OAc) method (Thomas, 1982), soil pH was determined using a glass electrode pH meter (Mc Lean, 1982). Soluble salts were calculated from the measurement of ECe in the soil extraction by the use of a conductivity meter device (Rhoades, 1982) and CEC was determined using the sodium saturation method (Rhoades, 1986). Particle size distribution was determined using disturbed soil samples sieved through a 2 mm sieve by the hydrometer method (Gee and Bauder, 1989).

2.3. STATISTICAL ANALYSIS AND INTERPOLATION

The data analyses were conducted in three stages: (a) normality tests were applied (Kolmogrov-Smirnov); (b) distribution was analyzed by classical statistics (mean, maximum, minimum, standard deviation, skewness and coefficient of variation); (c) geostatistical parameters were calculated for each variable as a result of corresponding semivariogram analysis. Skewness is the most common form of departure from normality. If a variable has positive skewness, the confidence limits on the variogram are wider than they would otherwise be and as a result, the variances are less reliable. A logarithmic transformation is considered where the coefficient of skewness is greater than 1 and a square-root transformation applied if it is between 0.5 and 1 (Webster and Oliver, 2001). Exploratory statistical analyses were performed by SPSS (2000) software.

A semivariogram was calculated for each soil property as follows (Isaaks and Srivastava, 1989; Journel and Huijbregts, 1978):

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

where $\gamma(h)$ is the experimental semivariogram value at distance interval h; *N(h)* is number of sample value pairs within the distance interval h; $z(x_i)$, $z(x_i + h)$ is sample values at two points separated by the distance interval *h*. All pairs of points separated by distance *h* (lag *h*) were used to calculate the experimental semivariogram. Semivariograms were calculated both isotropically and anisotropically. The anisotropic calculations were performed in four directions (0˚, 45˚, 90˚ and 135˚) with a tolerance of 22.5˚ to determine whether semivariogram functions depended on sampling orientation and direction (i.e., they were anisotropic) or not (i.e., they were isotropic). Spherical, exponential or pure nugget models were fitted to the empirical semivariograms. The parameters of the model: nugget semivariance, range and sill or total semivariance were determined. Model selection for semivariograms was done on the basis of regression (r^2), visual fitting and residual sum of squares (RSS).

Nugget semivariance is the variance at zero distance; sill is the lag distance between measurements at which one value for a variable does not influence neighboring values; and range is the distance at which values of one variable become spatially independent from others. Nugget variance that was expressed as the percentege of total semivariance was used to define for spatial dependency of soil variables. To define different classes of spatial dependence for the soil variables, the ratio between the nugget semivariance and the total semivariance or sill was used (Cambardella et al., 1994). If the ratio was ≤25%, the variable was considered to be strongly spatially dependent, or strongly distributed; if the ratio was between 26 and 75%, the soil variable was considered to be moderately spatially dependent; if the ratio was greater than 75%, the soil variable was considered weakly spatially dependent; if the ratio was 100%, or the slope of the semivariogram was close to zero, the soil variable was considered non-spatially correlated (pure nugget or no spatial dependency). Geostatistical software (GS+5.1, 2001; Gamma Design Software) was used to conduct semivariogram and special structure analysis for variables.

3. RESULTS AND DISCUSSION

A statistical summary of the studied soil parameters is presented in Table 1. A histogram, box plot and normal plot were constructed for all soil properties, revealing three and two outliers for pH at 0-30 cm and 60-90 cm depths, respectively. Their removal significantly reduced the coefficient of skewness (CV) (lower than 0.4) avoiding the need for data transformation. Two (21.2, 19.2) and one (0.2) potential outliers with ECe at depth of 0-30 and 30-60 cm, respectively, found from exploratory analysis for electrical conductivity. The bulk of the data has an ECe of approximately 5 dS m^{-1}, which dramatically affects the normality of the distribution. However, these oullier data are of most interest to the analysis of salinity and hence, they are kept in the dataset. Furthermore, since the coefficients of skewness in some soil properties (ECe and ESP at three depths and sand at 0-30 cm) are greater than 1, the natural logarithm is applied for a kriging analysis to stabilize the variance (Goovaerts, 1997). Appling ordinary kriging to logarithmic transformed data is the essence of lognormal kriging. Explanatory analysis for CEC revealed two potential outliers (34.6 and 31.2), however, visualization showed that this value is located on the periphery of the study area and therefore it will not be included in many lags. It also has relatively large values contiguous to it. Consequently, the decision was to include the data in the analysis. Although the coefficient of skewness for CEC at 0-30 cm is located in the range where a square-root transformation is appropriate, it is that outlying value on the periphery that is skewing the data, so the data were left in its original form. The exploratory analysis and descriptive statistics of the other soil parameters at each depth suggested that they were all normally distributed and therefore no transformation was used for geostatistical analysis (Table 1).

Table 1
Descriptive statistics for studied soil properties

Parameters	**Depths (cm)**	**Mean**	**S.D[a]**	**C.V[b]**	**Min**	**Max**	**Skewness**
pH	0-30	7.83	0.27	3.4	7.5	8.4	1.46
	30-60	8.27	0.31	3.8	7.83	9.3	0.44
	60-90	8.4	0.34	4.1	7.61	9.4	1.75
ECe	0-30	6.52	4.25	65.2	2.8	21.2	2.11
	30-60	6.73	3.41	50.7	0.2	12.5	1.25
	60-90	8.4	5.17	61.5	2.2	13.2	1.84
ESP	0-30	10.8	11.19	103.6	3.21	70.17	3.81
	30-60	14.13	12.46	88.2	3.27	55.2	2.86
	60-90	16.7	14.21	85.1	2.53	52.6	1.68
Clay	0-30	44.61	23.73	53.2	17.8	73.2	-0.17
	30-60	40.56	26.69	65.8	19.4	65.2	0.45
	60-90	32.82	24.68	75.2	18.4	71.8	0.35
Silt	0-30	38.89	19.48	50.1	20.4	60.2	0.13
	30-60	38.1	20.27	53.2	14.2	62.1	-0.06
	60-90	37.36	19.46	52.1	16.8	58.9	-0.72
Sand	0-30	16.47	2.44	14.8	7.1	55.1	2.02

	30-60	20.16	3.35	17.6	6.8	43.3	0.74
	60-90	22.54	4.54	20.3	6.1	51.7	0.95
CEC	0-30	26.27	11.87	45.2	17.3	34.6	0.81
	30-60	23.12	7.51	32.5	15.2	30.5	0.34
	60-90	17.91	5.23	30.2	10.7	34.5	0.44

[a]Standard deviation; [b]Coefficient of variation

Table 2

Semivariogram models and models parameters for studied soil properties

Parameters	**Depths (cm)**	**(+)Spatial distribution and model**	**Nugget (C_0)**	**Sill (C_0+C)**	**Range (m)**	**Nugget /Sill (%)**	**r^2**	**RSS***
pH	0-30	S. Spheroid	0.11	1.2148	1811	9	0.81	0.00021
	30-60	S. Exponential	0.22	1.4865	2081	14.8	0.72	0.00084
	60-90	S. Exponential	0.76	4.1989	7342	18.1	0.77	0.00032
ECe	0-30	M. Spherical	0.51	1.1806	2121	43.2	0.81	0.00024
	30-60	M. Spherical	0.73	2.2813	2321	32	0.72	0.0001
	60-90	M. Spherical	1.30	4.3046	1680	30.2	0.74	0.00054
ESP	0-30	M. Spherical	7.80	12.704	3642	61.4	0.61	0.0008
	30-60	S. Exponential	5.40	26.601	6368	20.3	0.84	0.0021
	60-90	S. Exponential	14.80	77.487	11631	19.1	0.73	0.00014
Clay	0-30	S. Spherical	7.20	36	1611	20	0.69	0.00015
	30-60	W. Spherical	49.30	63.449	17191	77.7	0.78	0.0044
	60-90	W. Spherical	55.30	68.953	10352	80.2	0.7	0.00022
Silt	0-30	Pure nugget	73.30	73.3	-	100	0.31	0.025
	30-60	W. Exponential	60.35	62.8	-	96.1	0.35	0.0054
	60-90	W. Exponential	53.18	54.6	-	97.4	0.44	0.0021
Sand	0-30	Pure nugget	58.10	58.1	-	100	0.55	0.0054
	30-60	W. Spherical	65.43	70.2	-	93.2	0.47	0.0074
	60-90	W. Spherical	61.02	63.5	-	96.1	0.35	0.00031
CEC	0-30	S. Exponential	21.40	89.167	11031	24	0.62	0.00091
	30-60	W. Exponential	58.10	76.337	9012	76.11	0.77	0.00021
	60-90	W. Exponential	66.40	83.417	6377	79.6	0.71	0.00124

(+) Spatial distribution (S-strong spatial dependence; M-Moderate spatial dependence; W-weak spatial dependence; Pure Nugget- no spatial correlation) and spatial distribution model.

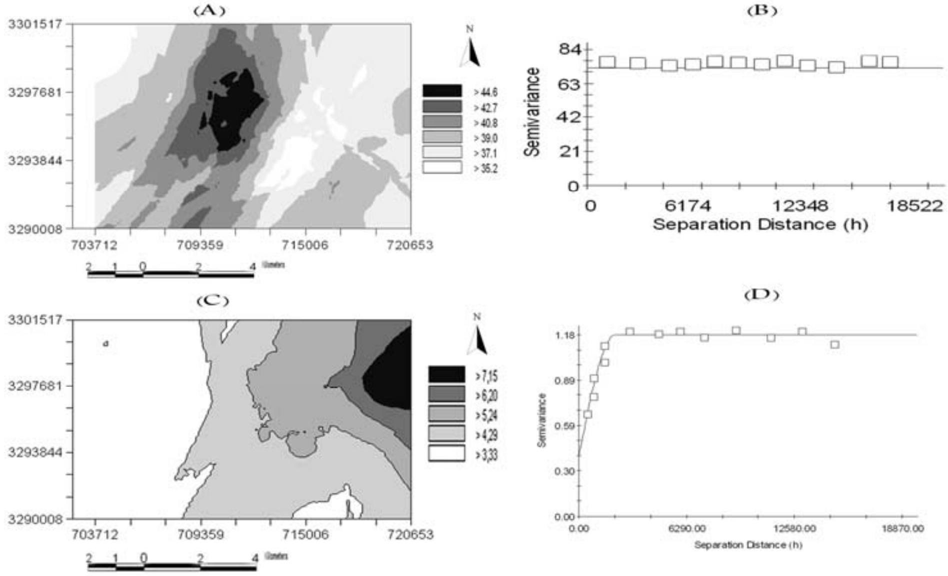
*Residual sum of squares (often the model with the lowest RSS chooses as optimal).

Among the soil properties, low CV (between 1 and 8 %) for pH, medium CV (16 to 55%) for silt and sand, and high CV (>55%) for ECe, ESP, clay and CEC, were found in study area (Table 1). The CV of soil properties except pH was fairly high, indicating that soil properties were generally heterogeneous. The CV value for ESP was the greatest, while that for pH was the lowest in all the three depths. In general, the CV obtained for the other soil characteristics, except for ECe, decreased with soil depth. However, the mean values of pH, ECe and ESP increased whereas the mean values of CEC decreased with soil depth due to the fact that, clay content decreased with soil depth. Application of poor quality water would result in an increase in pH, ECe and ESP at Arsanjan plain.

A highly significant positive correlation between soil salinity and water content was found in a field with Entisols, with high clay content, having low infiltration capacity (Miyamoto and Chacon, 2005). Another reason for high values of these soil properties in the lower layers was that the clay content decreased with soil depth (Table 1). Kachanoski et al. (1988) found that ECe was affected by volumetric water content and increased with increasing water content when clay content was low.

The geostatistical analysis indicated different spatial distribution models and spatial dependence levels for the soil properties. Anisotropic semivariograms did not show any differences in spatial dependence based on direction, for which reason isotropic semivariograms were chosen .the geostatistical analysis indicated different spatial distribution models and spatial dependence levels for the soil parameters. Exponential, spherical and pure nugget models were used to define soil properties (Table 2). Nugget effect was higher for CEC, clay, silt, sand and ESP compared to pH and ECe. This indicated that ECe, CEC, clay, silt, sand and ESP had spatial variability in small distances. The nugget effect of ECe, pH, clay and ESP were generally increased with depth.

The large nugget semivariance and the non-spatial dependence for some soil variables, e.g., silt, sand suggest that the lag *h* apparently did not characterize the spatial variation and that an additional sampling of these variables at smaller lag distances and in larger numbers is needed to detect spatial dependence. However, under no research circumstances (which means in a commercial context) a larger sampling density usually is not feasible. The recent research showed that using geostatistical and remote sensing approaches for mapping soil surface characteristics such as sand and silt in this study could improve the prediction quality (Lopez-Granados et al., 2005). Lopez-Granados et al. (2005) showed that the best prediction method for mapping organic matter, pH and potassium was kriging with varying local means in combination with the spectral data from the blue waveband with the smallest



mean square error indicating the highest precision.

Figure 1. (A, C) maps of estimated silt (%) and ECe (dS m^{-1}) in 0-30 cm depth, respectively; (B, D) Experimental and modeled semivariograms for silt (%) and ECe (dS m^{-1}) in 0-30 cm depth, respectively

When the distribution of soil properties is strongly or moderately spatially correlated, the mean extent of these distributions is given by the geostatistical range of the semivariogram. A larger range indicates that observed values of the soil variable are influenced by other values of this variable over greater distances than soil variables which have smaller ranges (Samper-Calvete and Carrera-Ramírez, 1996). Range value varied from 1168 m (ECe in the 30-60cm depth) to 17191 m (clay at 60-90 cm depth). Thus, clay had a range of more than 17000 m at 30-60 cm depth at study area. This indicates that clay contents influenced the neighboring values of clay over greater distances than other soil variable, e.g., ECe, which had a range of less than 1200 m at 0-30cm depth. Generally, range values of ECe and pH were smaller than that of the other soil properties. Soil properties exhibited both a consistent and non-consistent spatial pattern regarding the sampling depth at three locations.

There were soil properties, e.g., ESP, clay and CEC following a different spatial distribution at each depth that showed moderate spatial dependence in 0-30 cm depth, and a strong spatial dependence in 30-60 and 60-90 cm depths (Table 2). Similarity, ECe and pH showed a similar trend at three sampling depths in Arsanjan plain and followed the same spatial pattern. Cambardella and Karlen (1999) reported a similar consistent and non-consistent spatial distribution according to the sampling depths, e.g., NH_4-N showed three spatial patterns: moderate spatial dependence at 0-10 cm depth, no spatial dependence at 10-20 cm depth and strong spatial dependence 20-30 cm depth, while pH exhibited a strong spatial dependence at all depths. ECe was moderately spatially dependent for three depths.

The low nugget variance/total variance ratio and small range values for some soil properties exhibited patchy distribution pattern. The patchy distribution can be related to the groundwater level and topography. This study emphasizes that even though the previous agricultural management was similar, the spatial distribution and spatial dependence level of soil properties can be different. These results support the importance of collecting information in every agricultural region to know how a site specific system should be undertaken. Long-term field management histories should be known, because even the same farming practices clearly effectively affect both spatial distribution and the level of spatial dependence. Strong spatial dependency of soil variables may be controlled by intrinsic variations in soil characteristics (Cambardella et al., 1994). The results presented here suggested that extrinsic factors such as ground water level, drainage and irrigation systems would be important factors affecting in strong spatial dependency of soil properties studied. Soil salinity (EC) and sodicity (ESP) had generally high values in the northeast side of the study area. Values for ESP and ECe ranged between high and very high in the northeast side, suggesting that proper soil management, and drainage techniques should be applied to decrease soil salinity and sodicity in these regions. Jackknifing analysis was used to test if the chosen semivariogram models accurately predicted soil properties at unsampled locations. The results indicated that the mean reduced error was near zero and the squared differences between the jackknifed and the original values, the variance of the reduced error, was lowest for the fitted models. This means that the kriging estimates are accurate, and the spatial relationships derived from the studied part of the research site may be applicable to other areas with similar characteristics in the Arsanjan plain.

4. CONCLUSIONS

In general, most of the studied soil properties indicated strong spatial dependency in 0-30 cm depth, while they exhibited moderate spatial dependency in the 30-60 and 60-90cm depths. Geostatistical range values for most studied soil properties, were greater than 1200 m, indicating that soil-sampling distance for further sampling designs should be taken as 1200 m. The nugget effect of ECe, CEC, pH, clay and ESP were generally higher in 0-30 cm depth than in 30-60 and 60-90 cm depths. The majority of soil properties showed a strong spatial dependency at small distances could be attributed to different in the fluctuation and drainage of the groundwater in the Arsanjan plain and other places in arid and semiarid areas that have similar conditions. The results emphasized that irrigation deteriorated the salinity and sodicity in the study area and the most important reason of this problems were due to the low quality of irrigation water, extreme water use and insufficient drainage. Besides, this study suggested that distribution maps of these soil properties may be used confidently to develop indicator maps, which can separate areas within the Arsanjan plain, according to their management and reclamation requirements. Recently, the amount of irrigation water was decreased in order to lower the adverse effects of irrigation water on soils. In the study area, furrow irrigation is in progress. Sprinkle or subsurface irrigation methods should be preferred over furrow irrigation to decrease the amount of irrigation water used. Also, local areas with high salinity and sodicity or having salinity and sodicity risk should be continuously monitored for depth of ground water table and groundwater salinity to avoid upward transportion of soluble salts during irrigation season.

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Figure caption:

Figure 1. (A, C) maps of estimated silt (%) and ECe (dS m-1) in 0-30 cm depth, respectively; (B, D); Experimental and modeled semivariograms for silt (%) and ECe (dS m-1) in 0-30 cm depth, respectively