A NEW APPROACH FOR QUANTITATIVE LAND SUITABILITY EVALUATION USING GEOSTATISTICS, REMOTE SENSING (RS) AND GEOGRAPHIC INFORMATION SYSTEM (GIS)

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ABSTRACT

The objective of this study was to incorporate geostatistics, remote sensing and geographic information system methods due to improving the quantitative land suitability assessment in Arsanjan plain, southern Iran. The primary data was collected from 85 soil samples from tree depths (0-30, 30-60 and 60-90 cm) and the secondary information from remotely sensed data "LISS-III receiver from IRS-P6 satellite". In order to identify the spatial dependence of soil important parameters, we used ordinary kriging and simple kriging with varying local means (SKVLM) methods. The results indicated that best method with the lowest mean square error for mapping pH and electrical conductivity (EC_e) (0-30 cm) obtained from SKVLM method that spectral values of band 1 of LISS-III receiver was used as secondary variable. While, other soil properties indicated moderate to strong spatial dependence in the study area and interpolated in unstamped point by ordinary kriging method with the reliable accuracy. The land suitability evaluation method (parametric) has applied on the density points (150×150 m^2) that obtained by kriging or SKVLM methods, instead of applying on the limited representative profiles conventionally. Overlaying the information layers of dada was used by GIS for preparing the final land suitability evaluation. Therefore, changes in land characteristics as locally could be identified even in the same soil units. In addition, it is recognized that many of the land characteristics vary over a short distance within soil uniform mapping units. In general, this new method can easily present the squares and limitation factors of different land suitability classes with considerable accuracy in arbitrary land indices.

Keywords: Quantitative land suitability, Geostatistics, GIS, RS

INTRODUCTION

Land suitability analysis is a prerequisite for sustainable agricultural production. It involves evaluation of the criteria ranging from soil, terrain to socio-economic, market and infrastructure. In fact, land suitability evaluation is an examination process of the degree of land suitability for a specific utilization type (Sys, et al., 1991) and/or description method or estimation of potential land productivity (Rossiter, 1996). Soil maps are the traditional source of information for land suitability analysis (Daigle et al., 2005), but there are a number of difficulties encountered. The coverage of soil maps, especially those with enough details, is usually limited and the cost of extending this coverage is high (McKenzie et al., 2000). A study by Drohan et al. (2003) indicated that the purity of mapping units is less than 50%, which may lead to erroneous conclusions when these maps are used to derive suitability maps (Riezebos, 1989; Ziadat et al., 2003). Ziadat (2000) indicated that the accuracy of site-specific suitability using a high detail soil map (1:10,000) was only 60–70%, which is questionable in terms of providing reliable information for land use planning. Soil variability has implications when soil survey data are used for land evaluation purposes. Soil mapping unit acts as a basic subdivision of land, the suitability being assigned to the unit by calculating the average and/or modal values of the soil parameters at each of several observation points (Khalil et al., 1995).

The rational is that the mapping units encompass homogenous soils. However, it is recognized that many of the land characteristics vary over a short distance within any mapping unit (Zhou et al., 1991). The simplification of this variability into one representative value for the mapping unit may reduce the accuracy of the suitability map and raise questions about the reliability of such maps. It is therefore unlikely that the land units distinguished in the traditional mapping procedure for land evaluation are homogeneous. Nevertheless, the variability does not necessarily lead to inaccurate suitability maps. Much of the effect of a large variance may be subdued by the width of the suitability classes. However, when suitability classes are narrowly defined and spatial variation is large, the site suitability cannot be unambiguously determined (Riezebos, 1989). A common concept in soil survey is the association of different taxonomic units within one mapping unit.

Recent development in utilizing soil data requires more details about the spatial distribution of soil properties, which calls for an alternative approach to support the land use planning process (McKenzie et al., 2000; Coughlan and McKenzie, 2002; Drohan et al., 2003). Developments in new technologies such as geostatistics, Geographic Information Systems (GIS) and Remote Sensing (RS) provide new approaches to meet the demand of resource-related modeling (Mermut and Eswaran, 2001; Salehi et al., 2003). Satellite remote sensing data are useful for updating an existing map or generating new thematic maps. During observations many earth features of interest have already been identified, mapped, and studied on the basis of their spectral characteristics (Lopez-Granados et al., 2005). Prediction methods that incorporate secondary information available on a large scale, such as remote sensing data have been also developed to reduce sparse and expensive soil measurements, e.g. simple linear regression, regression trees, and geostatistical methods such as co-kriging or kriging with varying local means (Moore et al., 1993; McKenzie and Ryan, 1997; Odeh et al., 1995; Goovaerts, 1997; Bishop and McBratney, 2001; Lopez-Granadus et al., 2005).

GIS and remote sensing are essential tools for planning of aquaculture development (Burrough 1998). GIS also serve as analytical and predicting tools for aquaculture development and to test the consequence of various development decisions before their use in the landscape (Aguilar-Manjarrez and Ross 1995).

Other uses of GIS include efficient storage, management, and analysis of spatial and non-spatial data (Kapetsky et al. 1987; Rajitha et al., 2007; Giap et al., 2005). However, so far these new technologies were not used together for land suitability evaluation. The objective of this study was to develop a new quantitative land suitability method using geostatistics, RS and GIS in Arsanjan plain, Fars province, southern Iran.

MATERIALS AND METHODS

DESCRIPTION OF THE STUDY AREA

The study area (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 are somewhat affected with salinity and/or sodicity because of high evaporation. Dominant soils in the study area are Calcic Haploxeralfs and Typic Calcixerepts (Soil survey staff, 1999). Extensive areas of the Arsanjan plain have become and continue to be degraded by salinization due to the use of low-quality irrigation water with inappropriate irrigation methods. The most important climate characteristics necessary for suitability determination (temperature, rainfall, relative humidity, etc.) were collected for 20 years. As a result, agricultural production of the Arsanjan plain has declined significantly in the last two decades.

SOIL SAMPLING, STATISTICAL ANALYSIS AND INTERPOLATION

Soil samples in the 85 sampling site (10187 ha) were collected from 0-30, 30-60 and 60-90 cm depths, georefrenced using GPS receiver (accuracy of ± 5 m), analyzed for ESP, ECe, pH, CEC, slope, volume percentage of coarse fragment, $CaCO_3$, $CaSO_4.2H_2O$ and particle size distribution according to the Sparks et al., 1996. The data analyses were conducted in three stages for interpolation: (a) normality tests were applied (Kolmogrov-Smirnov); (b) distribution was analyzed by classical statistics (mean, maximum, minimum, standard deviation, skewness and coefficient of variations); (c) geostatistical parameters were calculated for each variable as a result of corresponding semivariogram analysis. 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. Spherical, exponential or pure nugget models were fitted to the empirical semivariograms. Model selection for semivariograms was done on the basis of regression (r^2), visual fitting and residual sum of squares (RSS). 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). Geostatistical software (GS^+5.1, 2001; Gamma Design Software) was used to conduct semivariogram and special structure analysis for soil variables. Several comparison indices can be used as a measurement of the prediction quality, the most common of which is the mean square error (MSE) which measures the average square difference between the actual soil variable *Z(xi)* and its estimate *Z*(xi)*:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left[Z(xi) - Z^{*}(xi)\right]$$

where n = soil variable data set (Goovaerts, 2000).

Geostatistical software (GS^+5.1, 2001; Gamma Design Software) was used to conduct semivariogram and special structure analysis for soil variables.

METHODOLOGY OF NEW APPROACH OF QUANTITATIVE LAND SUITABILITY EVALUATION

To obtain reliable semivariograms, which is the main tool of geostatistics and maps of soil properties initially requires about 100 sampling points, which is costly (Kerry and Oliver, 2003) in developing countries. However, to solve these budget limitations some authors have reported accurate prediction maps from sparsely sampled observations of a primary attribute, for example rainfall erosivity (Goovaerts, 1999), rainfall distribution (Goovaerts, 2000) and evapotranspiration maps (Vanderlinden, 2001), complemented by digital elevation models as exhaustive secondary attributes that are more densely sampled and using different interpolation techniques. In this research we used the remote sensing data of LISS-III receiver from IRS-P6 satellite that is now considered as an appropriate tool for deriving information in spatial and temporal domains by providing multi-spectral reflectance data at regular intervals in a synoptic mode. The satellite data used in this research is IRS-P6 scene, dated 08 September 2006. Both geometric the correction and conversion of original digital number measures to the surface reflectance values was carried out in conjunction with the atmospheric correction. The imaging sensors on IRS-P6 that was used is a multispectral Linear Imaging Self-Scanner (LISS-III) in visible (0.52-0.59 µm, **band 1**; 0.62-0.68 µm, **band 2**), near-IR spectral bands (0.77-0.86 µm, **band 3**) with spatial resolution of around 23 meters and a Short Wave IR (SWIR) band (1.55-1.75 µm, **band 4**) with a resolution of around 70 meters. Every sampled soil point was located in the satellite image and its corresponding digital value in four bands (band 1, 2, 3 and 4) was extracted. It was verified that all variables (i.e., soil properties and spectral values in visual range) were normally distributed. Pearson linear correlations were determined between soil variables and spectral values in four bands, accepting a confidence level of 95%. Significant correlation was obtained only between pH and EC (-0.61, $p< 0.01$ and 0.57 $p<0.01$, respectively) with band 1. It should be imply that band combinations and principal component analysis obtained from four bands had not any more accuracy than these four main bands.

Simple kriging (SK) is the most basic form of kriging. With SK, the mean is assumed to be constant and known. If we can estimate the mean at locations in the domain of interest then this locally varying mean can be used to inform prediction. SKLVM prediction is defined as:

$$\hat{z}\, SKLVM\ (\mathbf{u}_0) - \hat{m}_{SK}(\mathbf{u}_0) = \sum_{\alpha=1}^{n} \lambda_{\alpha}^{SK}(u0)\left[z(\mathbf{u}_{\alpha}) - \hat{m}_{SK}(\mathbf{u}_{\alpha})\right],$$

where $\hat{m}$ simple kriging is a known locally varying mean. The locally varying mean can be estimated in various different ways. One approach is to use regression (obtained in simple linear regression) to predict at all observation locations and all locations where SKLVM predictions will be made. Then, the semivariogram of the residuals was computed, modelled, cross-validated and simple kriging on the residuals was carried out. The final estimate of every soil property was obtained by adding the trend estimate to the simple kriged estimate of the residuals (Goovaerts, 1997; Vanderlinden, 2001). This method was applied to the soil variables showing significant correlations with digital values in four bands at $P \leq 0.01$, i.e., pH and ECe with band 1.

Using ordinary kriging and SKVLM methods that described above we can interpolate 4235 point ($150 \times 150\ m^2$) with reliable accuracy that could be beneficially used for applying the quantitative land suitability assessment methods. Performance of different methods of land suitability evaluating conventionally carried out on limited representative profiles that with this new approach we can determine changes of soil properties in each soil mapping unit by sufficient data of these new technologies. In this study we used square root method that recognized is better than other commonly method in this regions (Jafarzadeh and Abbasi, 2006).

RESULTS AND DISCUSSION

STATISTICAL DESCRIPTION OF SOIL PROPERTIES

A statistical summary of the studied soil parameters is presented in Table 1. It should be noted that parameters such as drainage, flooding and slopes in the study area have no limitations, so in the square root method we consider these parameters with 1 coefficient. 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 consequently, 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 (1997) software.

Among the soil properties analyzed, the coefficient of variation (CV) for ECe and ESP was greatest, while that for pH was lowest in all the tree layers studied

(Table 1). Generally, the CV of the other soil properties except pH was fairly high, indicating that soil properties were generally heterogeneous. In general, the CV obtained for the other soil properties, except gypsum and ESP, decreased with soil depth. However, the mean values of pH, sand, CCE, gypsum and clay increased with soil depth while silt, ESP and ECe decreased. Extensive removal of groundwater in this regions due to lack of good water quality caused ECe and ESP increased in soil surface compared with subsoils.

A highly significant positive correlation between soil salinity and water content was found in a field with Entisols having low infiltration capacity (Miyamoto and Chacon, 2005). Kachanoski et al. (1988) found that EC was affected by volumetric water content, increasing with increasing water content when clay content was low.

GEOSTATISTICAL ANALYSIS

Anisotropic semivariograms did not show any differences in spatial dependence based on direction and therefore isotropic semivariograms were chosen. The geostatistical analysis indicated different spatial distribution models and spatial dependence levels for the soil parameters.

Table 1. Statistical characteristics of some soil properties

	Depth	CV	Max	Min	Mean	Unit	Skewness
pH	0-30	4.53	8.4	7.58	7.91	-log(H+)	0.48
	30-60	3.57	9.2	7.61	8.11	-log(H+)	1.79
	60-90	3.8	9.3	7.8	8.44	-log(H+)	1.77
ECe	0-30	60.5	21.2	2.8	6.27	dSm-1	2.17
	30-60	40.3	12.5	2.2	5.34	dSm-1	1.36
	60-90	35.5	13.3	2.1	5.19	dSm-1	0.88
ESP	0-30	55.4	50.55	1.4	14.85	%	2.38
	30-60	63.6	44.1	3.44	13.6	%	1.79
	60-90	60.6	43.3	2.4	10.8	%	0.96
Sand	0-30	51.3	55	1	16.48	%	1.63
	30-60	48.4	53	7	20.87	%	0.97
	60-90	45.5	51	4	21.4	%	1.04
Clay	0-30	29.6	73	17	38.5	%	-0.06
	30-60	26.2	65	19	40.76	%	0.49
	60-90	21.2	71	19	44.7	%	-0.06
Silt	0-30	23.4	72	20	41.01	%	0.5
	30-60	20.2	62	14	38.35	%	-0.09
	60-90	20.2	85	16	38.8	%	1.37
CCE	0-30	18.3	80	37.5	53.6	%	0.45
	30-60	17.5	88	38.75	56.79	%	0.42
	60-90	16.5	87	40	60.45	%	0.29
Gypsum	0-30	45.2	3.87	0.37	1.85	%	0.27
	30-60	63.2	5.16	0.18	1.55	%	0.58
	60-90	25.2	5.6	0.43	2.2	%	0.51

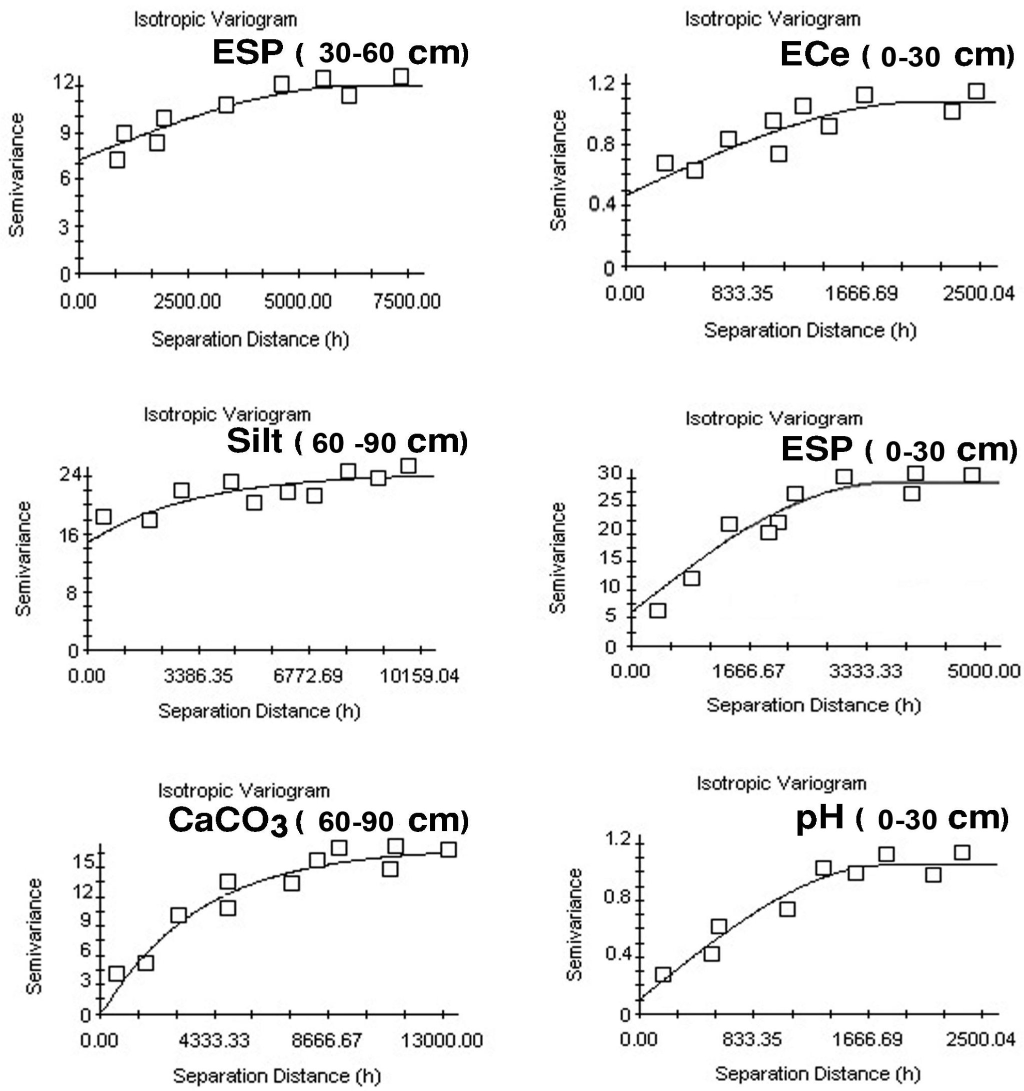

Figure 1. Semivariograms of some soil properties in the study area

Some of semivarograms of important soil properties of soil illustrated in figure 1. Exponential and spherical models were used to define soil properties (Table 2). 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 soil properties, were greater than 1200 m, indicating that soil-sampling distance for further sampling designs should be taken as 1200 m.

When the distribution of soil properties is strongly or moderately spatially correlated (for example for pH at 0-30 cm depth), the mean extent of these patches is given by the 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 1161 m (pH in the 0-30cm 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. This indicates that clay contents influenced the neighboring values of clay over greater distances than other soil variable, e.g., pH, 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. Some soil properties such as ESP, clay and CEC following a different spatial distribution at each depth, showed a moderate spatial dependence in 0-30 cm depth, and a strong spatial dependence in other two depths (Table2). Similarity, ECe and pH showed a similar trend at three sampling depths 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.

Table 2. Semivarograms parameters and MSE of some selected soils properties

	Depth	Model	Classes1	Range	Sill	Nugget	MSEa	MSEb
pH	0-30	Exp	*)S(9	1161	1.2148	0.11	1.813	0.62
	30-60	Exp	)S(14.8	2081	1.4865	0.22	1.14	-
	60-90	Sph	)S(18.1	2342	4.1986	0.76	0.39	-
ECe	0-30	Spher	*)M(43.2	1121	1.18	0.51	3.234	0.87
	30-60	Exp	)M(32	1821	2.281	0.73	1.2	-
	60-90	Exp	)M(30.2	2280	4.304	1.3	1.12	-
ESP	0-30	Sph	)S(20.3	3642	26.60	5.4	0.55	-
	30-60	Sph	)M(61.4	6368	12.70	7.8	1.17	-
	60-90	Sph	)S(19.1	4613	77.48	14.8	0.31	-
Sand	0-30	Sph	)M(29.3	3310	8.53	2.5	1.38	-
	30-60	Sph	)M(35.7	3500	15.68	5.6	0.24	-
	60-90	Expl	)M(45.4	2881	21.14	9.6	2.1	-
Clay	0-30	Sph	)S(20	3611	36	7.2	3.02	-
	30-60	Sph	)S(14.7	12352	63.45	9.3	0.41	-
	60-90	Exp	)M(30.9	17191	55.95	17.3	2.01	-
Silt	0-30	Sph	)M(47.4	3210	2.32	1.1	0.55	-
	30-60	Sph	)M(30.2	3117	4.63	1.4	1.31	-
	60-90	Exp	)M(62.2	9882	23.31	14.5	0.47	-
CCE	0-30	Sph	)M(41.3	3254	12.59	5.2	0.14	-
	30-60	Exp	)M(30.2	3415	7.28	2.2	0.14	-
	60-90	Exp	)S(6.6	11240	14.39	0.95	3.24	-
Gypsum	0-30	Exp	)M(45.5	3285	20	9.1	2.57	-
	30-60	Exp	)M(62.5	2345	7.2	4.5	1.12	-
	60-90	Exp	)M(55.9	2995	7.33	4.1	0.47	-

* S indicates strongly, and M indicates moderately spatial (Cambardella et al., 1994) dependence

[1] (Nugget/Sill)*100; MSEa: MSE for ordinary kriging method; MSEb: MSE for SKVLM

method

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 confirm the importance of collecting information in every agricultural region to select the proper a site specific system. Long-term field management histories should be known, since even the same farming practices, clearly effectively affects 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. Soil salinity (ECe) 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 are needed to decrease soil salinity and sodicity in these regions. Interpolated data in ordinary kriging methods from GS^+ software was extracted and prepared for applying the square root method for quantitative land suitability evaluation. SKVLM method was used for increasing the accuracy of surface soil properties maps. This method was applied to the soil variables showing significant correlations with digital values in four main bands at $P \leq 0.01$, i.e., pH and ECe with band 1. This kriging method is an interpolation that incorporates secondary information into the kriging system. It uses the ancillary (or secondary) information to characterize the spatial trend of the primary (target) variable and performs simple kriging on the residuals (Goovaerts, 1997). The Nugget effect, sill, semivariogram model and range of the residuals semivariograms for pH and ECe were approximately similar of raw semivariograms indicating the lag distance between measurements at which one value for a variable does not influence neighboring values. Goovaerts (1999) found a similar trend when he incorporated a digital elevation model into the mapping of annual erosivity values using the same kind of kriging.

There was some similarity in the map pattern of pH and ECe as produced by ordinary kriging and SKLVM methods. However, ordinary kriging over-smoothed the spatial variability of pH and ECe. MSE was better for SKVLM than ordinary kriging in both properties. Comparatively, it seems that SKLVM reflects local variation more than ordinary kriging. After interpolating the effective soil properties intensively for quantitative land suitability evaluation using ordinary kriging (for most properties) and SKVLM (only for ECe and pH) FAO framework, root square method, used for finding the final land suitably classes. The FAO framework for land evaluation states that land use requirements should be match with land resources important for the land use (FAO, 1976). Land suitability criteria for field crops and range crops were determined for four suitability classes; highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and not suitable (NS), using the FAO procedure (FAO, 1976). Overlaying the information layers of dada was used by GIS (Arc View 3.2) for preparing the final land suitability evaluation.

Based on obtained information about topography, soil, climate, and suitability evaluation methods (Sys et al., 1991) parametric method (square root methods) was selected and the land suitability class for crops was determined. Suitability is largely a matter of producing yield with relatively low inputs (Vink, 1960) and there are two stages in finding land that is suited to a specific crop. Firstly, the requirements for the crop need to be known, or alternatively which soil and site attributes adversely influence the crop. The second stage is to identify and to delineate land with the desirable attributes but without the undesirable ones. In the present study reported specified requirements for tomato, potato, maize and wheat by Sys et al. (1991) were used.

There is an optimal climatic condition for these six irrigated crops which makes that the region received a high suitable class (S1) for these crops. Therefore, the most important limiting factors in the area studied are ECe, ESP, pH, texture and structure, gravel and lime. Their effects can appear alone or in combinations. Soil attributes data such as ECe, pH, lime, and texture & structure had influence on the land suitability for potatoes and resulted: The accuracy of obtained results by the

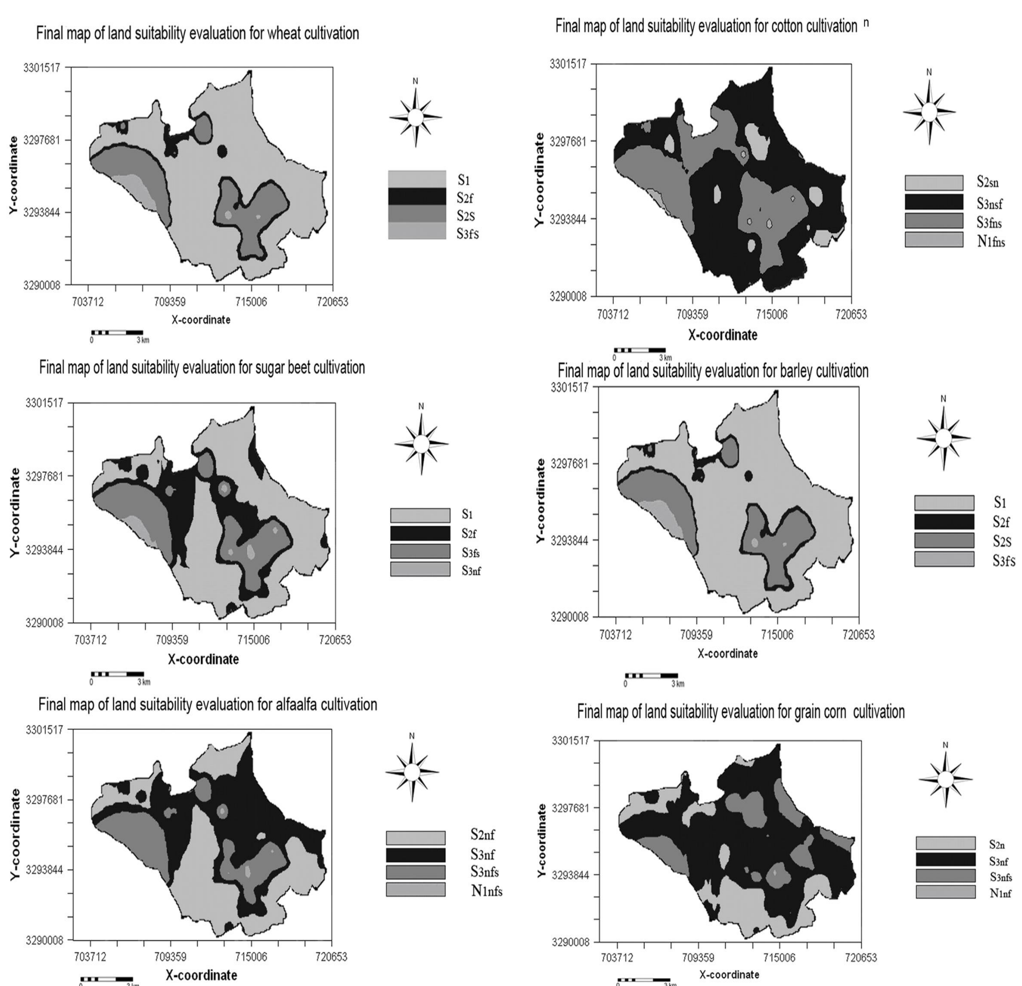

Figure 2. Final land suitability maps of irrigated crops in Arsanjan plain

square root method is high and more realistic when compared with previous land suitability evaluation maps that all indicated same suitability class. Briefly in figure 2 final maps of land suitability evaluation prepared for wheat, cotton, grain corn, alfalfa, sugar beet and barley.

CONCLUSION

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 soil properties, were greater than 1200 m, indicating that soil-sampling distance for further sampling designs should be taken as 1200 m. The results indicated that best method with the lowest mean square error for mapping pH and electrical conductivity (EC_e) (0-30 cm) obtained from SKVLM method in which spectral values of band 1 of LISS-III receiver was used as secondary variable. While, other soil properties indicated moderate to strong spatial dependence in the study area and estimated in unstamped point by ordinary kriging method with the reliable accuracy. The new proposed method that is used in this study, has applied the land suitability evaluation method (parametric) on the density points ($150 \times 150\ m^2$) that obtained by kriging or SKVLM method, instead of applying on the limited representative profiles conventionally. Overlaying the information layers of dada was used by GIS for preparing the final land suitability evaluation. This approach is recommended in future studies when suitability classifications from different sources are compared. Because most of our decisions about the land use and management are based on the validity and accuracy of land suitability classifications.

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