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Spatially-based model of land suitability analysis using Block Kriging

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Abstract

In recent years, methods of fuzzy reasoning have been successfully developed for land evaluation. The accuracy of such land evaluation depends on the quality of weighing land characteristics with respect to their effects on crop production. This paper presents a spatially-based model of land suitability analysis. The main purposes were to (1) establish land suitability indices for irrigated wheat yield and (2) use of geostatistics technique for mapping of fuzzy land suitability index using kriging method. The fuzzy set methodology was employed in the modeling procedure, and block kriging method was used to spatial interpolation approach. The study area was divided into 14 land units and 9 land characteristics considered to be relevant to irrigated wheat. Due to higher weight, gravel volume percentile in the soil was the most significant characteristic (criteria) and the soil depth was the least significant criteria among all effective criteria in irrigated wheat yield. The correlation coefficient between land index and observed yield in the study area was 0.77 (r = 0.77) for the fuzzy method. The best model for fitting on experimental variogram was selected based on less RSS values and the gaussian model was selected for estimation of fuzzy land indices. Use of the kriging technique that exploits spatial variability of data is useful in producing continuous land suitability maps and in estimating uncertainties associated with predicted land suitability indices.

Keywords: Characteristic matrix; Land suitability index; Membership functions; Spatial interpolation

Abbreviations: AHP (Analytical hierarchy process); Bd (Bulk density); $CaCO_3$ (Calcium Carbonate); CEC (Cation Exchange Capacity); CV (Coefficient of Variation); E (Final matrix of land suitability); EC (Electrical Conductivity)
FK (Farmers' Knowledge); GIS (Geographical Information System); OC (Organic Carbon); R (Characteristic matrix)
RSS (Residual Sum of Square); SP (Saturation Percentage); W (Weight matrix)

Introduction

Appropriate land use decisions are vital to achieve optimum productivity of the land and to ensure environmental sustainability. This requires an effective management of land information on which such decisions should be based. Land suitability evaluation is one of the effective tools for such purposes. There are two general kinds of land suitability evaluation approaches: qualitative and quantitative. A qualitative approach is used to assess land potential at a broad scale, or employed as a preliminary to more detailed investigations (Baja et al., 2002). The results of classification are generally given in qualitative terms only, such as highly suitable, moderately suitable, and not suitable. The second approach is that using parametric techniques involving more detailed land attributes which allow various statistical analyses to be performed. Land evaluation is a tool to predict land performance, both in terms of the expected benefits from and constraints to productive land use, as well as the expected environmental degradation due to these uses (Rossiter, 1996). Therefore, for land to be suitable (for a given purpose) and for the use to be sustainable, it must address the values that are related to both aspects: degree of suitability, and potential degradation (from long-term perspective) resulting from land management practices. Although the need to make value judgment in land evaluation is inevitable, it is important to utilize information/knowledge engineering techniques that minimize human bias to improve the pragmatic value of land evaluation results (De la Rosa et al., 2004). The first application of fuzzy sets and logic to environmental sciences was in land evaluation. Subsequently, the approach has been extended to many other applications. For example, at the Lacombe Experimental Farm in Alberta, fuzzy and boolean sets were combined to generate maps of clay content in C horizon of the soil, interpolated by ordinary kriging. Both approaches were used to estimate soil pollution. In drainage net studies, a fuzzy approach was used as an alternative procedure for classifying abrupt transition data such as single pollution spots (Burrough et al., 1992). Another reported application is the acquiring and representing of knowledge on soil–landscape relationships and applying that knowledge to digital soil mapping (Feng et al., 2006; Amini et al., 2005). Prediction mappings of samples are often based on geostatistical methods, which calculate unbiased estimates at unsampled locations. This approach is increasingly used to characterize spatial variability of soil properties (Romic and Romic, 2003; McGraph et al., 2004). Since soil properties present a continuum in their spatial variations, it is difficult to categorize soil samples without introducing errors or over-simplifications. Therefore, class boundaries are usually chosen arbitrarily by imposing (1) an uncertainty about the accuracy of the critical threshold or range used to specify membership in a certain class and (2) an uncertainty about the quality of the input maps. Nevertheless, with crisp classifications, values close to class boundaries can fall into different classes, even though their uncertainties are the same within the range of the standard measurement or interpolation error; consequently, the resulting classifications can be erroneous. As an alternative, fuzzy logic methods can be used to estimate the degree of membership in each class, thereby treating transition areas more realistically and eliminating imprecise and subjective concepts that are present in variables of the physical environment (Feng et al., 2006).

Geostatistical methods were developing to create mathematical models of spatial correlation structures with a variogram as the quantitative measure of spatial correlation. Wagner Lourenco et al. (2010) studied the concentrations of heavy metals using geostatistical techniques and fuzzy classification in southern coastal region of the State of Sao Paulo, Brazil. The maps showed that areas of high pollution of Ni and Cu are located at the northeast, where there is a predominance of industrial and agricultural activities. The results also indicated that combining geostatistics with fuzzy theory can provide results that offer insight into risk assessment for environmental pollution. Emadi et al. (2010) incorporated geostatistics, remote sensing, and geographic information system (GIS) technologies to improve the qualitative land suitability assessment in arid and semi-arid ecosystems of Arsanjan plain, southern Iran. The primary data obtained from 85 soil samples collected from tree depths (0-30, 30-60, and 60-90 cm); the secondary information acquired from the remotely sensed data from the linear imaging self-scanner (LISS-III) receiver of the IRS-P6 satellite. Ordinary kriging and simple kriging with varying local means (SKVLM) methods used to identify the spatial dependency of soil important parameters. Braimoh and Stein (2004) used block kriging method for estimation of fuzzy land index in the study as the title of “Land Evaluation for Maize Based on Fuzzy Set and Interpolation” in Ghana. Six soil variables influencing maize yield were selected for each data point based on the opinion of experts at the Savannah Agricultural Research Institute (SARI), Tamale in Northern Ghana, and a preliminary study on land-use/land-cover change (Braimoh and Vlek, 2004).Their results showed that interpolated land suitability shows a high correlation (R^2 = 0.87) with observed maize yield. This indicates that land suitability is closely related to maize yield in the study area. This paper presents a spatially-based model of land suitability analysis. The main purposes were to (1) establish land suitability indices for irrigated wheat yield and (2) use of geostatistics technique for mapping of fuzzy land suitability index using kriging method. The fuzzy set methodology was employed in the modeling procedure, and block kriging method was used to spatial interpolation approach.

Results

Land suitability analysis

Soils classification in the study area based on soil taxonomy (USDA, 2010) are presented in Table 1. The suitability of a crop is related to the type of soil. 19.98 and 80.02 % of soils belong to Entisols and Aridisols orders, respectively. The studied area was divided into 14 land units and 9 land characteristics considered to be relevant to irrigated wheat (Table 2). In land unit 9, gypsum content is equal to 9.37 %. In other land units, gypsum content is equal to zero. Climate index is equal to 92.3 for all land units in the study area. The land suitability evaluation for irrigated wheat yield on 14 land units is performed according to the fuzzy set method.

In order to generate weighting factors, pair-wise comparison matrix and normalized pair-wise comparison matrix are developed (Tables 3 and 4). It was supposed that comparison matrix was reverse and reciprocal that means if a criterion A in comparison with criteria B has a double priority, it could be inferred that criteria B has a priority half of criteria A. The criteria priorities are defined according to expert’s judgments. After generation of pair-wise comparison matrix, the criteria weights are calculated that includes sum of each column of pair-wise comparison matrix and division of each component by the result of each relevant column sum. The resulted matrix is knows as normalized pair-wise comparison matrix. The average of each row of the pair-wise comparison matrix is calculated and these average values indicate relative weights of compared criteria.

Due to larger weight, gravel volume percentile in soil was the most significant characteristic (criteria). The soil depth was the least significant criteria among all effective criteria in irrigated wheat yield. After development of weight matrix (W), this matrix multiplied by characteristic matrix (R) for each land unit based on fuzzy operator (combination) and resulted in the final matrix of land suitability (E). Then, land indices were calculated based on final E matrix in each land units. In order to judge the efficiency of the fuzzy set method in land suitability evaluation, the results are compared with the observed irrigated wheat yield. The calculated linear regression between land index and observed irrigated wheat yield (Fig. 3) was 0.77 for fuzzy method. Major limitations to wheat production are gravel and organic carbon. Emphasis should be placed on soil management techniques that conserve organic matter and enhance nutrient and soil water-holding capacity.

Geostatistical analysis

Before performing geostatistical analysis, the normality was

Table 1. Classification of soils in the study area based on soil taxonomy (USDA, 2010)

Soil mapping unit	Soil classification
1	Fine-loamy, mixed, superactive, thermic, Xeric Haplocambids
2	Coarse-loamy over fragmental, mixed, superactive, calcareous,shallow, thermic, Xeric Torrifluvents
3	Coarse-loamy, mixed, superactive, thermic, Xeric Torrifluvents
4	Coarse-loamy, mixed, superactive, thermic, Xerofluventic Haplocambids
5	Sandy-skeletal over coarse loamy,mixed, superactive, calcareous, thermic, Xeric Torrifluvents
6	Fine, mixed, semi active, thermic, Xeric Haplocalcids
7	Fine-loamy, mixed, active, thermic, Xeric Haplocalcids
8	Fine-loamy over clayey, mixed, active, thermic, Sodic xeric Haplocambids
9	Fine-loamy, mixed, superactive, thermic, Typic Haplogypsids
10	Fine, mixed, active, thermic, Xeric Haplocalcids
11	Fine-loamy, mixed, superactive, thermic, Xeric Haplocalcids
12	Fine, mixed, active,thermic, Xeric Haplocalcids
13	Fine-loamy, mixed, superactive, thermic, Xeric Haplocalcids
14	Coarse- loamy over fragmental, mixed, superactive, calcareous, shallow, thermic, Xeric Torriorthents

tested by SPSS 15 software and Kolmogrov-Smirnov method. According to levels of skewness and kurtosis, raw data set was not transformed. Anisotropic variogram did not show any difference in spatial dependence based on direction, and therefore, isotropic variogram was chosen. The coefficient of variation (CV) for fuzzy land index was 6.99 %. Statistical summary of the fuzzy land indices is presented in Table 5. The first step in using of kriging method is to investigation of the presence of spatial structure among the data by variogram analysis. Omni-directional variogram related to kriging method is presented in Fig. 4. Land suitability indices were predicted for block sizes of 2 km×2 km being the maximum distance between two profiles in two neighbor land units in study area. The best model for fitting on experimental variogram was selected based on less RSS values (Table 6). Therefore, the gaussian model is selected for estimation of fuzzy land indices.

Table 6 illustrates the parameters of the variogram. The ratio of nugget variance to sill expressed in percentages (C_0/C+C_0) can be regarded as a criterion for classifying the spatial dependence of fuzzy land index parameters. If this ratio is less than 25%, then the variable has strong spatial dependence (Shi et al., 2005). As shown in Table 6, fuzzy land index has strong spatial structure. The range effect for fuzzy land index is approximately 20.71 km. After variogram modeling, block kriging method was used for prediction of spatial distribution of fuzzy land index in study area. Finally, Land suitability index map was prepared in SURFER 7.0 environment (Fig. 5). The spatial pattern of fuzzy land index (Fig. 5) shows that land suitability for wheat increases from the north and the south to the center of the landscape. This map may be used to identify the proportion of land area below or above a given land index. The map could also be used to plan land improvement and fertilizer input distribution. Finally, the map could be further combined with other information to develop an environmental sensitivity index for environmental management.

Discussion

The structure of the land suitability evaluation in the FAO framework makes the assessment rigorous. Only one low parameter is enough to reduce the suitability from high to moderately suitable or not suitable, even if the relevance of this parameter is lower compared to the others. The selection of land characteristics and their limits are a sensitive issue when performing the evaluation. In this research, we selected 9 land characteristics. Both previously established requirement tables (Sys and Debaveye, 1991) and conditions proper to studied area were considered. The crop requirements in terms of land characteristics are presented in Table 2. Similarly, Van Ranst et al. (1996) and Sanchez (2007) used 7 and 8 land characteristics, respectively. Our results showed that sigmoid and Kandel membership functions are suitable for computation of membership values and were also in agreement with the findings of Torbert et al. (2008) and Keshavarzi et al. (2010).

Sicat et al. (2005) used fuzzy modeling incorporating the farmers' knowledge (FK) to assign the weights of the membership functions. The final objective was to produce land suitability maps for agriculture in Nizamabad district of Andhra Pradesh State in India. In this study, through interviews, local perception of cropping season, soil color, soil texture, soil depth and slope were obtained to generate multi-class fuzzy sets using the S-membership functions. Because the FK is binary for color and crop season, binary fuzzy factors maps were generated. For these binary maps, fuzzy memberships between 0.05 and 0.95 were assigned instead of 0 and 1 because farmers are not absolutely certain about suitability or non suitability. The factor weights were obtained assigning grades to the ranks of suitability for each factor. The use of different membership functions will introduce slightly variations to the final results. A more important role in the final suitability is caused by the weights given to the parameters. Analytic Hierarchy Process (AHP) was employed to obtain the different weights for the fuzzy calculation. AHP relies on pair-wise comparisons between different parameters to assign importance levels. This process may be subjective and requires expertise knowledge and common sense. For this reason different land evaluators may assign different importance and different weights, which may result in different suitability maps. Our results showed that use of AHP method can regard all of land characteristics and more efficiency for explanation of different criteria in land suitability. Prakash (2003) also reported that fuzzy AHP hybrid approach has superior to AHP method in multi-criteria evaluation for land suitability. For comparing of our findings with observed yield we investigated the correlation coefficient between land index and observed yield in the study area. The results showed that the correlation coefficient was equal to 0.77 ($r = 0.77$). Similarly, Tang et al. (1992) reported the high correlation coefficient ($r = 0.96$) for fuzzy method. Spatial variability can be theoretically estimated by the ratio Nugget /Sill in geostatistical studies, and the result may be used as a criterion for measuring the spatial dependence of regional variables. The results in Table 6 showed strong spatial structure. In this study, the best model for fitting on experimental variogram was selected based on less RSS values and the gaussian model was selected for estimation of fuzzy land indices. Wagner Lourenco et al. (2010) also used fuzzy

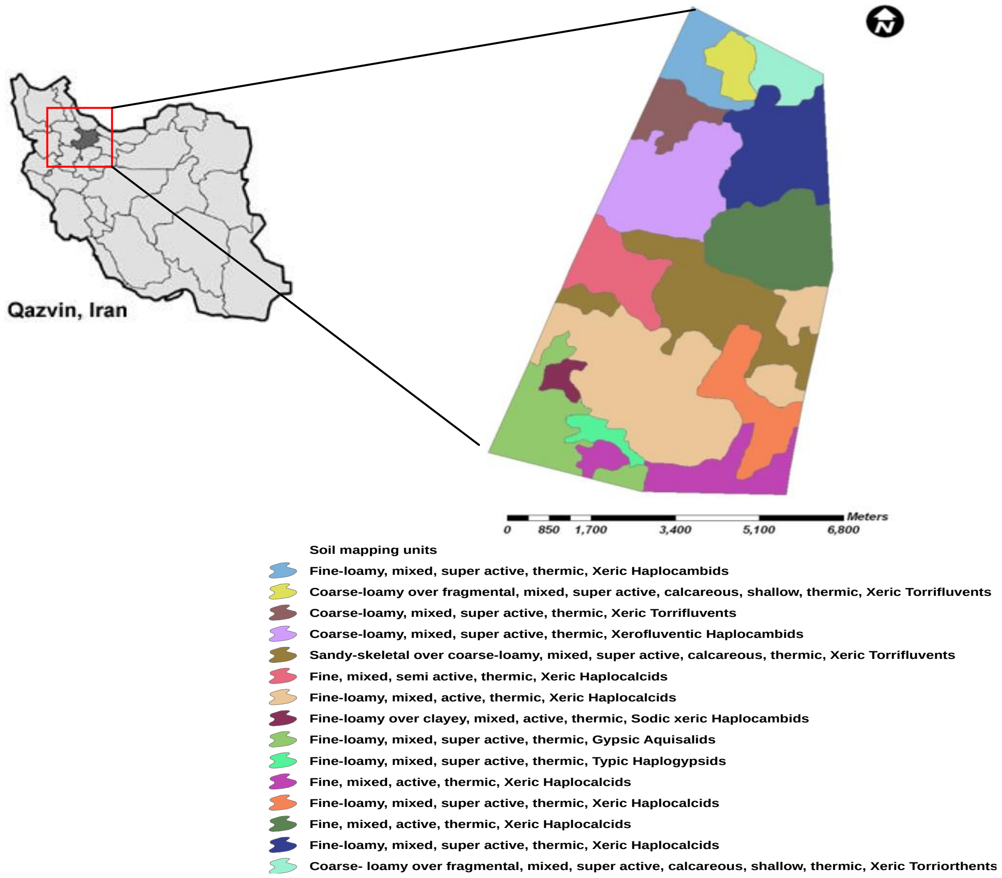

Fig 1. Location and soil mapping units of the study area

classification and ordinary kriging method for mapping of spatial distribution of heavy metals in southern coastal region of the State of Sao Paulo, Brazil. The results showed that soil containing Ni, Zn, Pb, and Cu were best fit with the exponential model. According to findings of Emadi et al. (2010), in order to improve the qualitative land suitability assessment in arid and semi-arid ecosystems of Arsanjan plain, exponential and spherical models were selected and final land suitability maps were developed. Braimoh and Stein (2004) by block kriging determined land suitability index map for maize in Ghana and reported that there was a high correlation (R^2 = 0.87) with observed maize yield and fuzzy land indices. From the perspective of fuzzy set methodology, the strength of our spatially-based model of land suitability analysis comparing with similar researches (Sicat et al., 2005; Sanchez, 2007; Joss et al., 2008) is that can be supervised and implemented on the basis of the expert knowledge using different weighting factors according to expert judgments and it's possible to deal with a great level of detail about the most important parameters that affect the final matrix of land suitability like shape of membership functions, cross-over points and weight values for different land characteristics.

Materials and methods

Site description

This study is focused on Ziaran area, located in Qazvin province in Iran, which covers approximately 5121 hectares; between latitudes of 35° 58´ and 36° 4´ N and between longitudes of 50° 24´ and 50° 27´ E. The average, minimum and maximum elevation of Ziaran area are 1204, 1139 and 1269 meters above the sea level, respectively. Figure 1 shows the study area in Iran. The soil moisture and temperature regimes of the region by means of Newhall software are Weak Aridic and Thermic, respectively. The soils were classified according to USDA classification system (Soil Survey Staff, 2010) as belonging to the Entisols and Aridisols orders (USDA, 2010) (Table 1). Irrigated wheat is one of the most important food crops in Ziaran area. Yield information is considered of interest to land users (interviews with farmers) and policy makers (government officials) who are responsible for rural development.

Soil sampling and data analysis

To generate prediction mapping of fuzzy land suitability index and obtain reliable soil data, the available soil survey reports were inspected and, based on this, 14 soil profiles were chosen for a more detailed investigation within different land units. Soil profile descriptions, samplings and analyses were made using standard terminology and procedures (Soil Survey Staff, 1993). 65 soil samples were collected from different horizons of 14 soil profiles located in Ziaran area in Qazvin Province. Measured soil parameters included texture (determined using Bouyoucos hydrometer method), Organic carbon (OC) was determined using Walkley-Black method (Nelson and Sommers, 1982). The clod method (Blake and Hartge, 1986) was used to determine bulk density (Bd). The moisture contents at field capacity and wilting point were determined with a

Table 2. Selected land characteristics in Ziaran area

Land unit No.	Land characteristics						
	Slope (%)	ESP	OC (%)	EC (dSm^{-1})	Soil texture (class)*	Gravel (%)	Soil depth (cm)
1	1.50	1.53	0.37	1.18	C.L	5.88	170
2	2.50	1.42	0.61	1.16	S.L	25.63	50
3	1.50	1.19	0.61	0.94	L	0.00	200
4	1.50	9.18	0.76	1.40	L	1.88	175
5	1.50	2.34	1.04	1.20	S.L	23.38	170
6	0.75	7.49	0.75	2.35	C	0.00	170
7	0.75	9.10	0.94	3.47	L	0.10	180
8	1.50	23.5	0.75	6.03	C.L	0.00	180
9	4.00	1.95	0.67	2.00	S.C.L	0.00	170
10	1.50	9.09	0.47	2.34	C	0.00	190
11	0.75	7.05	0.56	1.67	S.C.L	0.70	170
12	1.50	1.83	0.38	1.06	C.L	1.39	160
13	1.50	8.98	0.57	1.92	S.L	1.04	180
14	2.50	1.14	0.76	0.96	L	14.05	40

*C=Clay, L= Loam, C.L= Clay Loam, S.L= Sandy Loam, S.C.L= Sandy Clay Loam

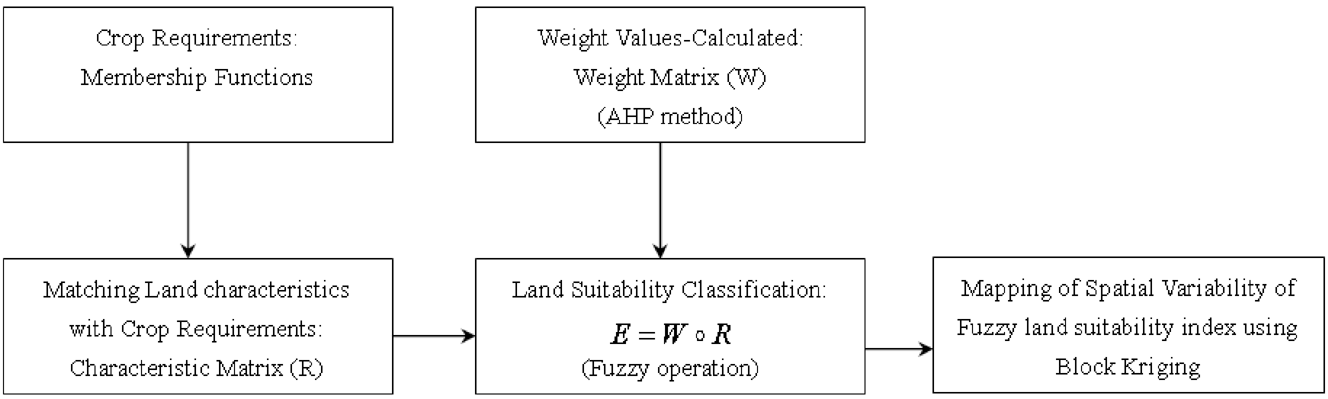

Fig 2. Graphical representation of the application procedure

pressure plate apparatus (Cassel and Nielsen, 1986) at -33 and -1500 kPa, respectively. Water saturation percentage (SP) was determined using gravimetery method, $CaCO_3$ content was determined using Calcimetry method, gypsum content was determined using Acetone method and CEC (Cation Exchange Capacity in cmolc kg^{-1} soil) determined by the method of Bower (Sparks et al., 1996). pH, electrical conductivity (EC), dissolved Ca^{2+} ,Mg^{2+}, Na^{+} and K^{+} were determined using standard methods (USDA, 1998).

Crop requirements

A requirement table for irrigated wheat is established using the structure of the FAO framework for land evaluation. Both previously established requirement tables (Sys and Debaveye, 1991) and conditions proper to Ziaran area were considered. The crop requirements in terms of land characteristics are presented in Table 2.

Land suitability evaluation based on fuzzy set methodology

Conventional methods of soil classification and evaluation ignore the continuous nature of the soil and the fact that spatial changes occur gradually over distance. They therefore classify soils in exactly definable, mutually exclusive classes. The concept of fuzzy sets is most easily understood as a generalization of the conventional sets which are known in mathematically terms as 'crisp' sets. The conventional set theory or Boolean algebra allows only binary membership (true or false) to a set. Fuzzy set theory allows partial membership to a set. The land suitability evaluation using fuzzy set method is performed in three successive steps. These steps involve determination of membership functions and membership values for a land unit, establishment of a weight matrix and calculation of the final matrix of land suitability. For each characteristic and for each suitability class membership functions are established. They express the degree to which a value of a land characteristic belongs to a suitability class. If a value of a land characteristic does entirely or absolutely not belong to the considered class, the membership value is 1 or 0 respectively. If the value of a land characteristic to some extent belongs to the considered class an intermediate membership value is determined along a general shape functions obtained from the sigmoid (Torbert et al., 2008; Keshavarzi et al., 2010) and Kandel (Sarmadian et al., 2009) membership functions. For a given land unit, the membership values for the different land

Table 3. Pair-wise comparison matrix

Criteria	Gravel (%)	Soil depth (cm)	Gypsum (%)	Texture (class)	OC (%)	EC (dSm^{-1})	ESP	Slope (%)	Climate (index)
Gravel (%)	1.00	6.00	5.00	2.00	2.00	3.00	3.00	4.00	3.00
Soil depth (cm)	0.17	1.00	0.33	0.20	0.16	0.20	0.25	0.16	0.50
Gypsum (%)	0.20	3.00	1.00	0.25	0.16	0.20	0.25	0.50	2.00
Texture (class)	0.50	5.00	4.00	1.00	0.33	2.00	3.00	4.00	3.00
OC (%)	0.50	6.00	6.00	3.00	1.00	2.00	3.00	5.00	3.00
EC (dSm^{-1})	0.33	5.00	5.00	0.50	0.50	1.00	2.00	3.00	4.00
ESP	0.33	4.00	4.00	0.33	0.33	0.50	1.00	2.00	2.00
Slope (%)	0.25	6.00	2.00	0.25	0.20	0.33	0.50	1.00	2.00
Climate (index)	0.33	2.00	0.50	0.33	0.33	0.25	0.50	0.50	1.00

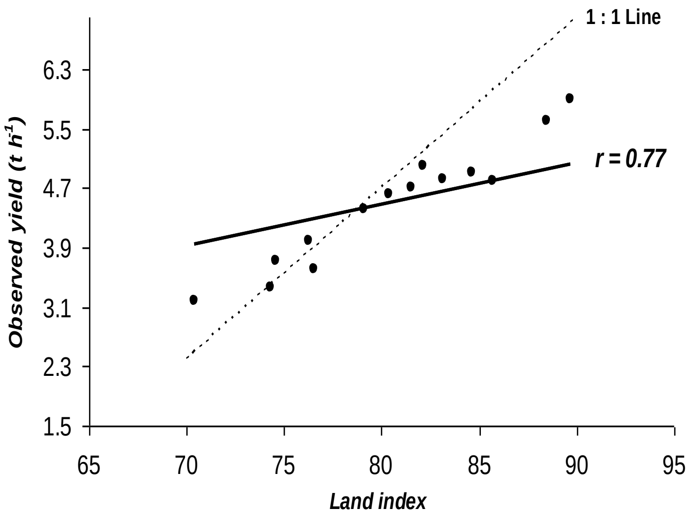

Fig 3. Linear regression between land suitability indices and observed irrigated wheat yield in fuzzy approach in Ziaran area

characteristics and suitability classes are determined using the membership functions (Sarmadian et al., 2009). The membership values are subsequently arranged in a matrix R (called characteristic matrix). The weighting parameters represent the relative importance of the suitability of each factor in relation to the other factors contributing for the suitability. Weighting parameters for land evaluation can be obtained based on experience, on statistical analysis or through an Analytic Hierarchy Process (Sanchez, 2007). AHP can be used as a consensus building tool in situations involving a committee or group decision-making (Saaty, 2003). AHP uses a hierarchy of factors where each general factor is subdivided or composed of several contributing sub factors. The later, a combination of experience and a mathematical process, was chosen due to its relative simplicity, the characteristics of the data and because it allows assigning different levels of importance to the different parameters involved in land suitability. Land characteristics have a different impact on crop performance. Their relative importance with regard to crop yield can be expressed by a weight factor. Via AHP the weight of each effective land characteristic in irrigated wheat yield was calculated and put in weights matrix (W). The AHP is characterized by pair-wise comparisons among decision elements for generation of relative matrix. In this method, pair-wise comparisons are considered as inputs and relative weights are as outputs. The Saaty scale (2003) was used for generation of pair-wise comparison matrix which relatively rates priorities for two criteria. The criteria priorities are defined according to expert's judgments. To determine the final land suitability class in each land unit, a multiple operator (combination) was used. The final matrix of land suitability was calculated after multiplying the characteristic matrix in each land unit by weights matrix (Keshavarzi et al., 2010). In order to calculate land index, the sum of components of land suitability matrix is set to one (standardized) and the new components of matrix are multiplied by average of indices of land suitability classes, respectively, based on Sarmadian et al. (2009) and Keshavarzi et al. (2010).

Table 4. Normalized pair-wise comparison matrix with criteria weights

Criteria	Gravel (%)	Soil depth (cm)	Gypsum (%)	Texture (class)	OC (%)	EC (dSm^{-1})	ESP	Slope (%)	Climate (index)	Weight
Gravel (%)	0.276	0.158	0.180	0.254	0.397	0.316	0.222	0.198	0.146	0.239
Soil depth (cm)	0.046	0.026	0.012	0.025	0.033	0.021	0.019	0.008	0.024	0.024
Gypsum (%)	0.055	0.079	0.036	0.032	0.033	0.021	0.019	0.025	0.098	0.044
Texture (class)	0.138	0.132	0.144	0.127	0.066	0.211	0.222	0.198	0.146	0.154
OC (%)	0.138	0.158	0.216	0.381	0.199	0.211	0.222	0.248	0.146	0.213
EC (dSm^{-1})	0.092	0.132	0.180	0.064	0.099	0.105	0.148	0.149	0.195	0.129
ESP	0.092	0.105	0.144	0.042	0.066	0.053	0.074	0.099	0.098	0.086
Slope (%)	0.069	0.158	0.072	0.032	0.040	0.035	0.037	0.050	0.098	0.066
Climate (index)	0.092	0.053	0.018	0.042	0.066	0.026	0.037	0.025	0.049	0.045

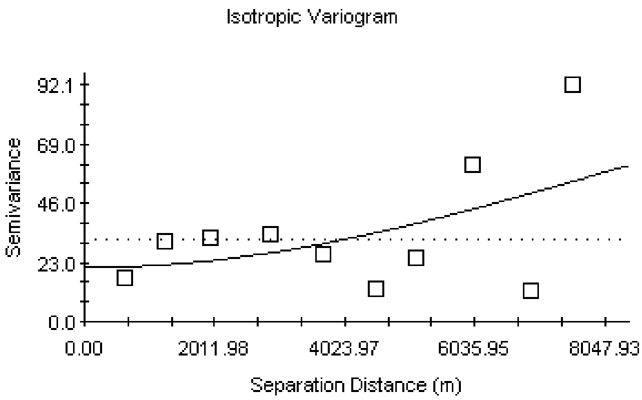

Fig 4. Omni-directional variogram related to fuzzy land index using block kriging method

Spatial prediction method

Geostatistics analysis methods are based upon the assumption that spatial variations in any continuous attribute are often too irregular to be modeled by a simple, smooth mathematical function. Instead the variation can be better described by a stochastic surface, known as a regionalized variable. Such variables apply to environmental properties such as soil types, variations in atmospheric pressure, elevation above sea level, and distributions of continuous demographic indicators (Wagner Lourenco et al., 2010). The experimental variogram measures the average degree of dissimilarity between unsampled values and a nearby data value and thus can depict autocorrelation at various distances. The value of the experimental variogram for a separation distance of h (referred to as the lag) is half the average squared difference between the value at z(xi) and the value at z(xi+h) (Robinson and Metternicht, 2006; Sarmadian et al., 2010):

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

Where: N(h) is the number of data pairs within a given class of distance and direction. If the values at z(xi) and z(xi+h) are auto correlated the result of Eq.(1) will be small, relative to an uncorrelated pair of points. From analysis of the experimental variogram, a suitable model is then fitted, usually by weighted least squares, and the parameters (e.g. range, nugget and sill) are then used in the kriging procedure. Spatial interpolation of land suitability indices was carried out by kriging (Braimoh and

Table 5. Results of statistical analysis on fuzzy land index

parameter	Min	Max	Mean	Std	Kurtosis	Skewness	CV (%)
Fuzzy land index	70.36	89.65	80.47	5.63	- 0.706	- 0.49	6.99

Table 6. Best-fitted variogram models of fuzzy land index

Model	Nugget (C_0)	Sill ($C+C_0$)	Range effect (km)	$C_0/C+C_0$ (%)	RSS
Gaussian	21.1	123.2	20.71	17.12	4.03
Spherical	15.9	82.8	21.1	19.2	4.32
Exponential	16.2	113.4	55.74	14.28	4.37

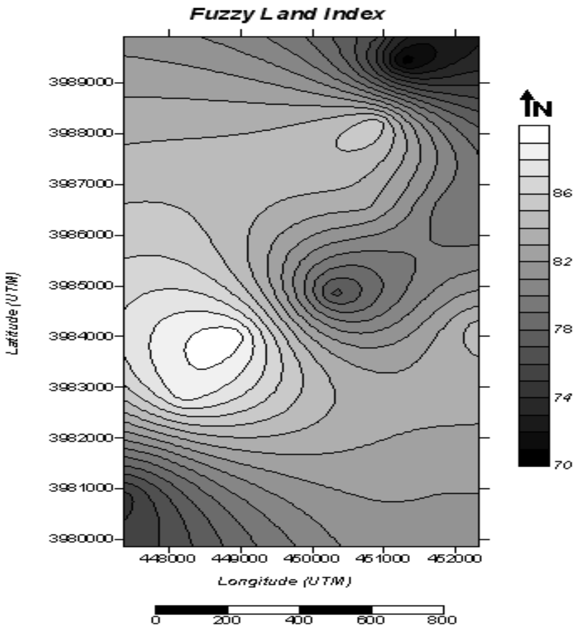

Fig 5. Land suitability index map

Stein, 2004). Ordinary point kriging provides the best linear unbiased predictor at point locations under the assumption that the mean of the quantity being predicted is constant, whereas ordinary block kriging provides average predictions of land suitability for areas of land. In kriging, the first step is to describe the spatial structure of the land suitability index using the variogram (Braimoh and Stein, 2004). Second, parameter estimates of the variogram were used to predict land suitability. Land suitability indices were predicted for block sizes of 2 km × 2 km being the maximum distance between two profiles in two neighbor land units in study area. Figure 2 represents the application procedure.

Conclusion

In this study, a spatially-based model of land suitability analysis was employed for mapping of spatial variability of fuzzy land suitability index using kriging method. This work demonstrated that fuzzy set method can be successfully combined with geostatistics technique to analyze data. The approach investigated in this study does not incorporate management decision. The output of the evaluation is simply a land suitability index map with suitability for wheat crop ranging from 0 to 100. Use of the land for wheat or any other crop remains a management decision. Similarly, the fact that an area has a relatively high suitability index does not automatically imply that high yields would be obtained if, for instance, the timing of planting or fertilizer application was wrong. A basic assumption of block kriging used in this study is that the mean of land index is constant over the area. There are situations, however, where such intrinsic stationary assumption may not be met (e.g., when an area has distinct physiographic regions that affect agricultural land suitability). In such situations, other techniques of interpolation such as kriging with external drift, which incorporates global trend estimation as part of the solution, would be more appropriate. Major limitations to wheat production are gravel and organic carbon. Emphasis should be placed on soil management techniques that conserve organic matter and enhance nutrient and soil water-holding capacity.

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