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ORIGINAL ARTICLE

Modeling land suitability evaluation for wheat production by parametric and TOPSIS approaches using GIS, northeast of Iran

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Abstract Land evaluation is the process of predicting land use potential on the basis of its attributes. In the present study, the qualitative land suitability evaluation by parametric and TOPSIS models was investigated for irrigated wheat crop based on FAO land evaluation frameworks (FAO 1976a, b, 1983, 1985) and the proposed methods by Sys et al. (1991b) and Hwang and Yoon (1981) in Joveyn plain, Northeast of Iran. Some 26 land units were studied at the study area by a precise soil survey and their morphological and physicochemical properties. The climatic and land qualities/characteristics for wheat crop were determined using the tables of soil and crop requirements developed by Sys et al. (1993). An interpolation function was used to map values to scores in terms of land qualities/characteristics for the land utilization type and the evaluation was carried out according to parametric and TOPSIS models. Our results indicated that the most limiting factor for wheat cultivation in the study area was soil fertility properties. The values of land indexes by parametric model ranged from 62.71 in some parts in east and west to 87.24 in the middle parts of the study area, which categorized the plain from moderate (S2) to high (S1) suitable classes. The TOPSIS preference values for wheat cultivation in the study area varied between 0.438 and 0.916 which categorized from moderate to very high classes for wheat production. The coefficient of determination between the parametric land index values and the corresponding TOPSIS preference values revealed a high correlation ($R^2 = 0.961$) between two models. The correlation coefficient (R^2) between the parametric land indexes and TOPSIS preference values with the observed wheat yield varied between 0.943 and 0.861, respectively, which verify the validation of both models in estimating land suitability for irrigated wheat production in the study area.

Keywords Land suitability · Evaluation · Model · Parametric · TOPSIS · GIS · Wheat

Introduction

It is clear that there is an urgent need to match land resource and land use in the most effective and logical way to continue sustainable production and to meet the needs of society while conserving fragile ecosystems (FAO 1993). Making effective decisions regarding agricultural land suitability problems are vital to achieve optimum land productivity and to ensure environmental sustainability (Kurtener et al. 2004). There are many approaches which are widely implemented in land evaluation such as: the USDA land capability classification (1961) and the FAO framework for land evaluation (1976a, b, 1985). Some of these techniques have used in developing countries, but the information which used is often not linked to local knowledge and local conditions. Land suitability evaluation is a powerful tool to support decision-making in land use planning; it deals with the assessment of the (most likely) response of land when used for specified purposes; it requires the execution and interpretation of surveys of climate, soil, vegetation and other aspects of land in terms of the requirements of alternative forms of land use. Land evaluation is carried out to estimate the suitability of land for a specific use

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such as arable farming or irrigated agriculture. Land evaluation can be carried out on the basis of biophysical parameters and/or socio-economic conditions of an area (FAO 1976a, b). Biophysical factors tend to remain stable, whereas socio-economic factors that are affected by social, economic and political performances (Dent and Young 1981; Triantafilis et al. 2001). Thus, physical land suitability evaluation is a prerequisite for land-use planning and development (Sys 1985; Van Ranst et al. 1996). It provides information on the constraints and opportunities for the use of the land and therefore guides decisions on optimal utilization of land resources (FAO 1984). The FAO (1976a, b) defines land evaluation as "a process of assessment of land performance when the land is used for specified purposes". A qualitative land evaluation takes into account two key elements, the soil qualities/characteristics and the crop requirements (FAO 1976a, b). The latter refers to "a set of land characteristics that can determine the production and management conditions of a kind of land use". The outcome of the suitability assessment for a particular crop which is the final result of a land assessment depends on whether the land characteristics match with the crop requirements. Land suitability assessment can be regarded as a specific case of land evaluation: it is an appraisal of land characteristics in terms of their suitability for a specific use (FAO 1976a, b). The basic concept behind land suitability evaluation is that suitability for a specific and sustainable use of the land is the synthetic result of complex relationships between different land environmental qualities (e.g., climate, soil characteristics and slope). Suitability for a specific use is therefore evaluated by matching requirements for that use with characteristics and qualities of land components. Land suitability is usually expressed by a hierarchical system organized into orders and classes (FAO 1976a, 1976b). Crucial to the estimation of land suitability is the matching of land characteristics with the requirements of envisaged land utilization types. Land evaluation results from a complex interaction of physical, chemical and bioclimatic processes and evaluation models are reliable enough to predict accurately the behavior of land. The methodology adopted based on FAO guidelines on land evaluation involves most aspects of climatic, soil requirements and land terrains (including soil physical properties, soil fertility and chemical properties, soil salinity and alkalinity, topography, erosion hazard and wetness) for each crop (Sys et al. 1991a, b, 1993). The parametric model is considered as a transitional phase between qualitative methods, which are entirely based on empirical expert judgments and standard mathematical models that would be the real quantitative systems. In parametric model different classes of land suitability are defined as completely separate and discrete groups and are separated from each other by distinguished and consistent range. Decision making issue in evaluating land suitability is very complex and complicated because of several decision indicators and criteria. These necessities leads to use of multivariate criteria decision making aimed at selection of the most appropriate crop among current crops. TOPSIS is the most famous multi criteria decision making (MCDM) model described by Hwang and Yoon (1981) for the first time. TOPSIS implies techniques such as AHP used to analyze a set of criteria providing decision makers with the priorities, or weights, of these criteria. The MCDM models such as TOPSIS have been employed with success in the land evaluation technique (Prakash 2003). TOPSIS orders a number of alternatives on the base of their separation from the ideal point and it employs a number of the distance matrix equations to produce the best alternatives (Malczewski 1999). It implies techniques used to analyze a set of criteria providing decision makers with the priorities, or weights, of these criteria. In TOPSIS model, the basic solution method is defining positive and negative ideal (non-ideal) solution (Biorani and Ghofran 2009). Positive ideal solution includes the best available value of parameters while the non-ideal one is made of the worst available value of parameters. Finally, the best answer has both the shortest distance from the ideal solution and the longest from the non-ideal. Simplicity, rationality, comprehensibility, good computational efficiency and ability to measure the relative performance for each alternative in a simple mathematical form are some of the advantages of TOPSIS model (Roszkowska 2011). The availability of GIS and multi-criteria decision analysis (MCDM) methods allow combining knowledge derived from different sources to support land use planning and management (Malczewski 1999). The plain of Joveyn is one of the main growing areas for wheat production in north east of Iran. Hence, the necessity of study on land suitability for production of these crops and their cultivation priority to achieve production sustainability is of great importance in this plain. The aim of the present study is to evaluate land suitability for wheat production based on parametric and TOPSIS models and the comparison of the results obtained from both models with the observed yield in Joveyn plain, Khorasan-Razavi province, northeast of Iran.

Materials and methods

General characteristics of the study area

The present study was conducted in Joveyn plain, Khorasan-e-Razavi Province, Northeast Iran (Fig. 1). The study area is located between latitude 35°28′51″N to 35°47′45″N

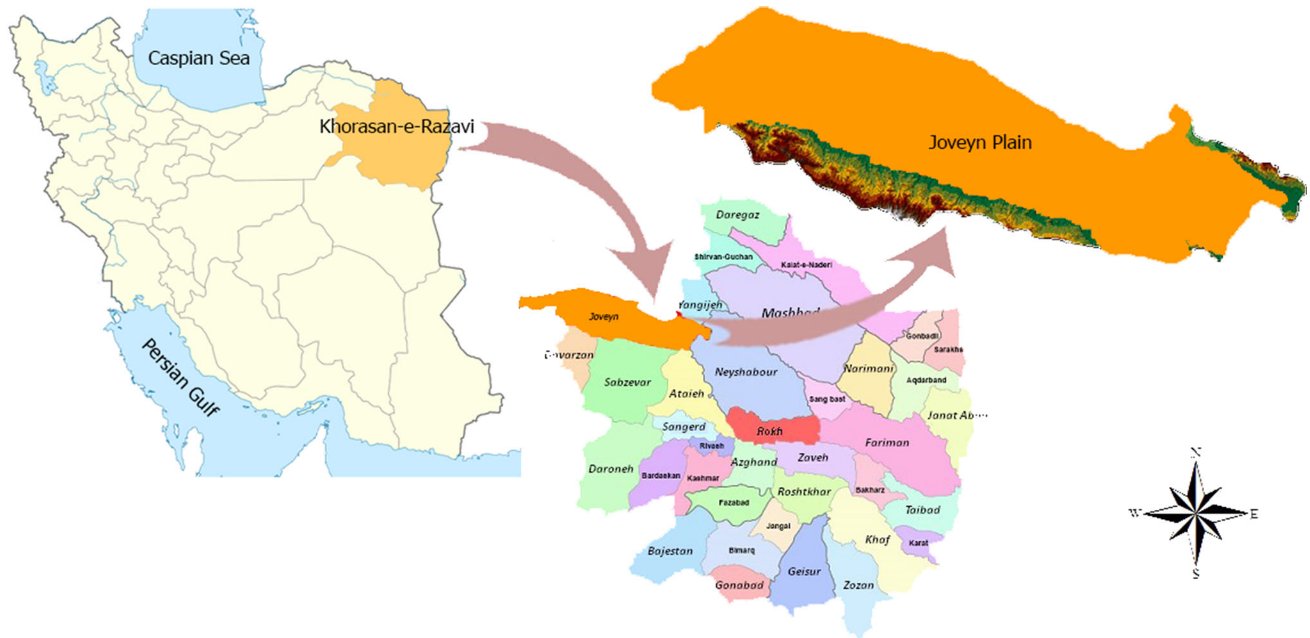

Fig. 1 The Geographical location of the study area

and longitude 58°34′49″E to 59°35′39″E including lands less than 2933 m asl. The general physiographic trend of the plain extends in a west-east direction with a maximum length of 92 km. The total surface of the study area comprises 4184.45 km^2. The elevation values of the study area vary between 1386 m and 1901 m asl, with an average of 1643.5 m asl. The main land use practice in the study area is irrigated farming. The climate of the study area is semi-arid with mean annual precipitation of 267.7 mm and means annual temperature of 14.3 °C (Fig. 1).

Parametric model

The process of evaluation is based on the FAO qualitative land evaluation system (FAO 1976a, b, 1983, 1985), which compares climatic conditions and land qualities/characteristics including topography, erosion hazard, wetness, soil physical properties, soil fertility and chemical properties, soil salinity and alkalinity with each specific crop requirements developed by Sys et al. (1991a, b, 1993). Based on morphological and physical/chemical properties of soil profiles some 11 land units were identified in the study area. For determining the mean values of soil physical, chemical and terrain parameters for the upper 60 cm of soil depth, the profile was subdivided into two equal sections and weighting factors of 1.75 and 1.25 were attributed for each section, respectively. A qualitative land suitability evaluation indicates the degree of suitability for specific land use, without respect to economic conditions. It emphasizes the relatively permanent aspects of suitability, such as climate and soil qualities/characteristics, rather than changeable ones, such as prices. The parametric land evaluation consists in numerical rating of different limitation levels of land characteristics according to a numerical scale between the maximum (normalized as 100 %) and the minimum value. Finally, the climatic index, as well as the land index, is calculated from these individual ratings. On this basis, Boolean classification was implemented in a way that for classified (qualitative) values (e.g. soil texture/structure = SL) the higher score of the class is given (e.g. 85) while, for continues (quantitative) values a linear interpolation function used to assign a score. The data provided from a soil survey are often continuous data and therefore it is necessary to apply a classification scheme that assigns scores to individual land qualities/characteristics. This scheme is based on linear interpolation functions that map value intervals to score intervals. If the observed value is x and it falls into the interval $[a,b]$ it needs to get a score y that falls into the interval $[c,d]$. The formula to calculate y is:

$$y = a + \frac{(b-a)(x-c)}{(d-c)}. \tag{1}$$

Each class-determining factor is first matched individually. Critical limits indicate how suitable a land unit is for a given land utilization type (LUT) in terms of that factor. For example, if one of the class determining factors for the LUT irrigated wheat is soil texture and the critical limits are to be represented in terms of soil texture corresponds tS1, S2, S3, N1 and N2 suitability levels. The soil texture recorded for each land unit will fall within one of these five ranges and the appropriate one is selected as the factor rating. In combining the factor ratings of several individual factors in order to decide the appropriate land suitability class to assign, the possibility of interactions should be taken into account. In a broad interpretation of the meaning of the word interaction it can be readily appreciated that many factors interact in the resultant land index which is the integral of their effects.

Climate evaluation

Climate data related to different stages of wheat growth were taken from thirty years of meteorological data of the region (1981–2010) and the climatic requirements of the crop were extracted from the table developed by Sys et al. (1993). Based on crop climatic requirements, the climate index (*CI*), climatic rate (*CR*) was determined as implemented factors in estimating land index (Table 1).

Estimating land suitability index

The proposed method is a parametric approach developed by Bagherzadeh (Bagherzadeh and Paymard 2015) to estimate the land suitability index. On this basis the land index of each land unit is calculated by multiplying geometrical mean value of the scores given to each land quality/characteristic and climate rate in the interaction of the square root values of scores according to the following formula:

Table 1 Climatic requirements and characteristics for wheat cultivation in the study area

Climate characteristics	Value
Precipitation of growing cycle (mm)	100.25
Monthly rainfall vegetative stage (mm)	14.79
Monthly rainfall Flowering stage (mm)	30
Monthly rainfall ripening stage (mm)	2.9
Mean temp. of the growing cycle (°C)	19.01
Mean temp. of the vegetative cycle (°C)	15.61
Mean temp. of the flowering cycle (°C)	11.69
Mean temp. of the ripening cycle (°C)	28.95
Average daily min temp, coldest month combined with	5.64
Average daily max temp, coldest month combined with	17.75
Climate index	54.38
Climate rate	89.79
Climate class	S1

$$LI = \prod_{i=1}^{n} x_i^{\left(\frac{1}{n}\right)} \times \sqrt[n]{\frac{\prod_{i=1}^{n} x_i}{100^n}}, \tag{2}$$

where, *LI* is the land index, *X*, is the score given to each land quality/characteristic, *n*, is the number of land qualities/characteristics.

Land suitability zonation

An interpolation technique using the ArcGIS ver.10.2.2 helped in managing the spatial data and visualizing the land index results in both models for preparing the final land suitability evaluation maps.

TOPSIS model

The technique for order preference by similarity to ideal solution (TOPSIS) proposed by Hwang and Yoon (1981) is one of the well-known methods for classical MCDM. The underlying logic of TOPSIS is to define the ideal solution and negative ideal solution. The ideal solution is the solution that maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution is the solution that maximizes the cost criteria and minimizes the benefit criteria. In short, the ideal solution consists of all of best values attainable of criteria, whereas the negative ideal solution is composed of all worst values attainable of criteria. The optimal alternative is the one which has the shortest distance from the ideal solution and the farthest distance from the negative ideal solution.

Problem solving process using TOPSIS model

TOPSIS model includes eight processes which are described in the following parts (Olson 2003).

1. Establishing data matrix based on alternative *n* and indicator *k*: generally, in TOPSIS model, matrix $n \times m$ with m alternative and n criteria is evaluated. In this algorithm, it is supposed that each indicator and criterion in decision making matrix has steady increasing and decreasing utility.

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}. \tag{3}$$

2. Standardizing data and preparing normalized matrix (matrix R) by Eq. (4):

Since it is possible that quantitative amount of criteria and indicators don't have equal unit, the dimensions of their units should be omitted. Thus, all amounts of entries of decision making matrix should be changed into dimensionless amount with following formula:

$$R_{IJ} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}. \quad (4)$$

3. Determining weights for whole indicators (wj): In the present study the AHP approach was used to calculate the amount of (wj). The AHP developed by Saaty (1990) considers a one-level weighting system through a pair wise comparison matrix between the parameters as described by Saaty (1990, 1994) and Saaty and Vargas (2001). The method employs an underlying nine-point recording scale to rate the relative preference on a one-to-one basis of each criteria (Malczewski 1999). For better map presentation purposes, the scale assigns a linguistic expression to each corresponding numerical value (Table 2). When using this approach, it is commonly accepted that taking numerical values and assigning them such linguistic expressions that translate into an imprecise terminology creates a vast area of ambiguity about the results. In most landslide hazard assessments, however, the state of knowledge about all event-controlling parameters is simply imperfect anyway. The numerical values are quantified translations useful for calculating factor weights and the validity of the numerical values may best be judged by the factor weights and the consistency of the calculation process (Ayalew et al. 2004). Pair-wise comparison, however, is subjective and the quality of the results is highly dependent on the expert's judgment. The weights of factors are calculated from the pair-wise comparison matrix undertaking specific values and vectors calculation. The sum of criteria weights should be equal to 1. It has been demonstrated that the specific vector corresponding to the largest specific value of the matrix provides the relative priorities of the factors, i.e., if one factor has preference; its specific vector component is larger than that of the other. The components of the specific vector sum to unity. Thus, a vector of weights is obtained, which reflects the relative importance of the various factors from the matrix of paired comparisons. The complete pair-wise comparison matrix contains many multiple paths by which the relative importance of factors can be assessed; therefore, it is also possible to determine the degree of consistency that has been used in developing the judgments. In the construction of the matrix of paired comparisons, the consistency of the judgments should be revealed because this matrix is a consistent matrix. The results of the pair-wise

Table 2 The Saaty scale (2004) was used for generation of pairwise comparison matrix

Intensity of importance	Definition
1	Equal importance
2	Equal to moderate importance
3	Moderate importance
4	Moderate to strong importance
5	Equally preferred
6	Strong to very strong importance
7	Very strong importance
8	Very to extremely strong
9	Extreme importance

Table 3 Pair-wise comparison matrix for calculating factor weights

Parameters	Soil texture	ECe	ESP	$CaCO_3$	Gravel	Soil depth	OC	pH	Climate	Slope	Drainage	Flooding	Gypsum	Weight
Soil texture	1													0.244
ECe	0.50	1												0.188
ESP	0.50	0.50	1											0.129
$CaCO_3$	0.33	0.33	0.50	1										0.097
Gravel	0.33	0.33	0.50	0.50	1									0.075
Soil depth	0.25	0.25	0.33	0.33	0.50	1								0.055
OC	0.25	0.25	0.33	0.33	0.50	0.50	1							0.048
pH	0.20	0.20	0.25	0.25	0.33	0.50	0.50	1						0.037
Climate	0.20	0.20	0.25	0.25	0.33	0.33	0.50	0.50	1					0.034
Slope	0.17	0.17	0.20	0.20	0.25	0.33	0.33	0.50	0.50	1				0.027
Drainage	0.17	0.17	0.20	0.20	0.25	0.25	0.33	0.33	0.50	0.50	1			0.025
Flooding	0.14	0.14	0.17	0.17	0.20	0.20	0.25	0.33	0.33	0.50	0.50	1		0.021
Gypsum	0.14	0.14	0.17	0.17	0.20	0.20	0.25	0.25	0.33	0.33	0.50	0.50	1	0.020

Table 4 The values of land indexes, land suitability classes/subclasses, the preference values and classes by parametric and TOPSIS models for wheat production in the study area

Land unit	Parametric model		TOPSIS model	
	Land index	Class	Preferences value	Class
1	71.31	$S2_f$	0.794	VH
2	75.12	S1	0.507	H
3	79.79	S1	0.828	VH
4	81.90	S1	0.858	VH
5	69.74	$S2_f$	0.483	M
6	70.32	$S2_f$	0.635	H
7	84.96	S1	0.780	VH
8	82.31	S1	0.875	VH
9	84.25	S1	0.898	VH
10	84.97	S1	0.899	VH
11	81.78	S1	0.858	VH
12	78.77	S1	0.734	H
13	79.55	S1	0.820	VH
14	85.81	S1	0.887	VH
15	87.36	S1	0.916	VH
16	62.71	$S2_f$	0.507	H
17	68.26	$S2_f$	0.486	M
18	72.67	$S2_f$	0.501	H
19	68.85	$S2_f$	0.440	M
20	73.61	$S2_f$	0.536	H
21	68.04	$S2_f$	0.438	M
22	78.47	S1	0.794	VH
23	75.43	S1	0.715	H
24	73.31	$S2_f$	0.502	H
25	82.65	S1	0.848	VH
26	74.50	$S2_f$	0.482	M

Table 5 Land suitability classes according to land index, the area and the percent of each suitability class for wheat production in the study area

Land suitability class	Land index	Area (km^2)	%
Parametric model			
Highly suitable (S1)	75–100	1080.5	25.82
Moderately suitable (S2)	50–75	3103.96	74.17
Marginally suitable (S3)	25–50	0	0
Marginally not suitable (N1)	12.5–25	0	0
Permanently unsuitable (N2)	0–12.5	0	0
Total		4184.45	100

comparison matrix and the factor weights are shown in Table 3. In AHP method, an index of consistency, known as the consistency ratio (*CR*), is a ratio between the matrix's consistency index and random index. *CR* is used to indicate the probability that the matrix judgments were randomly generated (Malczewski 1999).

$$CR = \frac{CI}{RI} \tag{5}$$

Where, *RI* is the average of the resulting consistency index depending on the order of the matrix given by Malczewski (1999) and *CI* is the consistency index and can be expressed as

$$CI = \frac{\lambda\max - \mathrm{n}}{n-1}. \tag{6}$$

where, λmax is the largest or principal specific value of the matrix and can be easily calculated from the matrix, and n is the order of the matrix. *CR* ranges from 0 to 1. A *CR* close to 1 indicates the probability that the matrix's rating was randomly generated. A *CR* of 0.10 or less is a reasonable level of consistency (Malczewski 1999). A *CR* above 0.1 requires revision of the judgments in the matrix. In this case, the *CR* of the matrix of paired comparisons between the 13 influential factors in our land suitability assessment is 0.035 which seems logic. Once a satisfactory *CR* is obtained, the resultant weights are applied (Table 3). The weights should add up to a sum of 1.0, as the linear weighted combination calculation requires.

$$\sum_{j=1}^{n} w_j = 1. \tag{7}$$

4. Creating dimensionless weighted matrix (*V*) to implement vector *W* as an input for algorithm:

In order that the amounts of entries in matrix *R* gain equal value, sum of weights of parameter (*wj*) are multiplied to the column of this matrix one by one. The acquired matrix is normalized and weighted matrix which is shown by sign (*V*).

$$V_{ij} = R_{ij} \times W_{m\times n} = \begin{bmatrix} V_{11} & \dots & V_{1j} & \dots & V_{1n} \\ \vdots & & \vdots & & \vdots \\ V_{m1} & \dots & V_{mj} & \dots & V_{mn} \end{bmatrix}. \tag{8}$$

5. Determining positive ideal (A^+) and negative ideal (A^-) and calculating distance size of *i*-alternative with ideals by Eqs. (9) and (10), respectively:

$$d_{i+} = distance\ of\ i - alternative\ from\ positive\ ideal = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^+)^2}; \quad i = 1, 2, \ldots, m. \tag{9}$$

$$d_{i-} = distance\ of\ i - alternative\ from\ negative\ ideal = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^-)^2}; \quad i = 1, 2, \ldots, m. \tag{10}$$

6. Calculating relative closeness for *i*-alternative (A_i) i to ideal solution using Eq. (11):

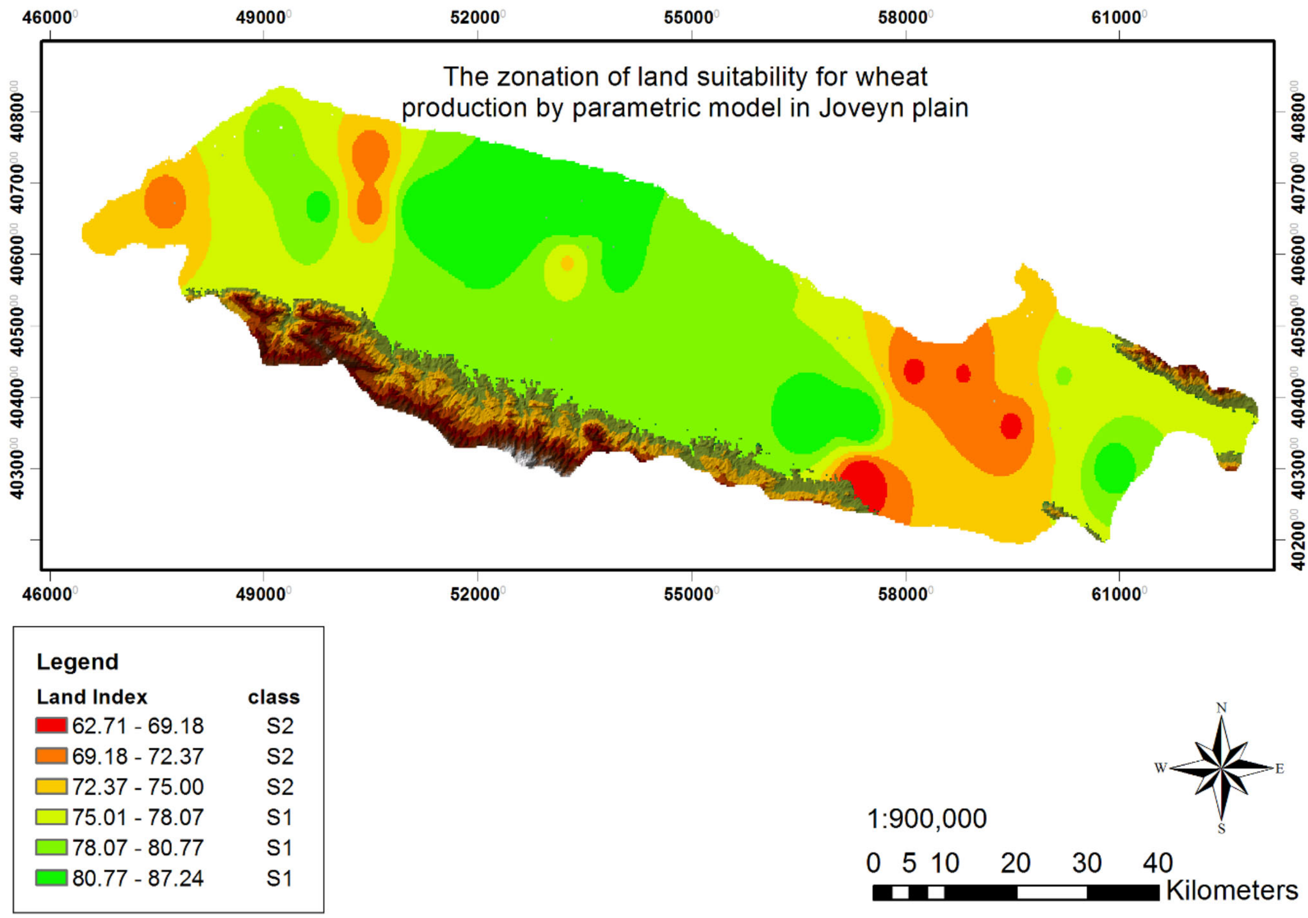

Fig. 2 The zonation of land suitability for wheat production by parametric model in Joveyn plain

$$cl_{i+} = \frac{d_{i-}}{d_{i+} + d_{i-}}; \quad 0 \leq cl_{i+} \leq 1; \quad i = 1, 2, \ldots, m \tag{11}$$

7. As you can see, if $Ai = A^{+}$, then $\mathrm{d}_{i+} = 1$ and $cl_{i-} = 0$, on the contrary if $A_i = A^{-}$, then $d_{i+} = 1$ and $cl_{i-} = 0$. In sum, the more alternative A_i is closer to ideal solution, the more value of cl_{i+} is closer to unit.

8. Ranking alternatives based on descending order of cl_{i+}: This amount is fluctuating between 0 and 1. Thus, $cl_{i+} = 1$ represents the highest rank and $cl_{i+} = 0$ the lowest rank.

Results and discussion

Parametric model in land suitability evaluation

Suitability is largely a matter of producing yield with relatively low inputs. There are two stages in finding the land suited to a specific crop. The first stage focuses on being aware of the requirements of the crop, or alternatively what soil and site attributes adversely influence the crop. The second stage is to identify and delineate the land with the desirable attributes. In the present study, the specific soil and climate requirements for irrigated wheat were determined based on Sys et al. guidelines (Sys et al. 1991a, b, 1993). There was an optimal climatic condition in most parts of the study area with an average climate rate of 89.80 which made the region highly suitable (S1 class) for irrigated wheat crop (Table 1). The values of land indexes based on parametric model varied between 62.71 and 87.36 with an average of 76.79 (Table 4). The land suitability classes for wheat were categorized into high suitable class of S1 and moderate suitable class of S2. The produced map of land suitability for wheat revealed that 74.18 % (3103.96 km^2) of the surface area were high suitable, while the values of moderate suitable class of S2 comprised 25.82 % (1080.50 km^2) for wheat production (Table 5). The most important limiting factors among land qualities/characteristics for wheat in the study area were soil fertility properties especially the soil organic carbon. The high suitability class of S1 was mainly distributed in the mid parts of the plain, while the east part of the study area and some scattered parts in west exhibited moderate suitability for irrigated wheat (Fig. 2).

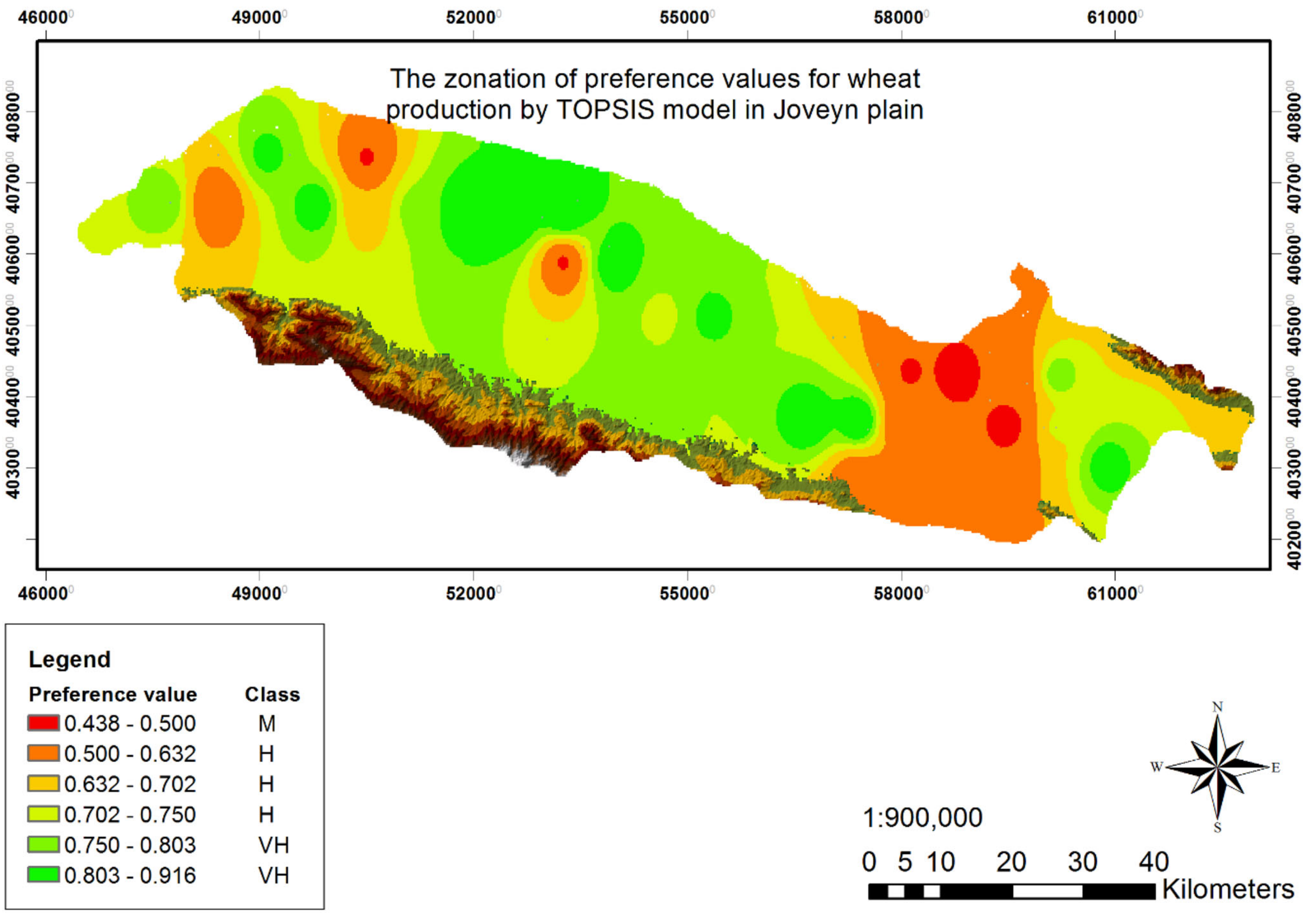

Fig. 3 The zonation of land suitability for wheat productions by TOPSIS model in Joveyn plain

Table 6 Preference classes according to preference values, the area and the percent of each preference class for wheat production in the study area

Preference class	Value	Area (km^2)	%
TOPSIS model			
Very high (VH)	0.75–1.00	2229.24	53.27
High (H)	0.50–0.75	1903.97	45.5
Moderate (M)	0.25–0.50	51.24	1.22
Low (L)	0.125–0.25	0	0
Very low (VL)	0–0.125	0	0
Total		4184.45	100

TOPSIS model in land suitability evaluation

The preference values among 26 land units in the study area ranged from 0.438 to 0.916 with an average of 0.693 (Table 4) and (Fig. 3). The produced map of TOPSIS values showed that 53.27 % (2229.24 km^2) of the study area has very high preference for wheat cultivation, while 45.5 % (1903.97 km^2) and 1.22 % (51.24 km^2) exhibited high and moderate preferences, respectively (Table 6). The geographic distribution of preference classes for wheat in the study area revealed that the areas with moderate preference expanded mainly in the east and scattered parts in the middle and west of the plain, while very high and high preferences for wheat production were dominated in the rest of the plain (Fig. 4). The land index values from parametric and the preference values by TOPSIS model were compared by calculating the coefficient of determination (R^2) defined by Nash and Sutcliffe (1970) which is calculated as follow:

$$R^2 = 1 - \frac{\left[\sum_{i=1}^{n}(P\ value_{TOPSIS} - LI_{parametric})^2\right]}{\left[\sum_{i=1}^{n}(P\ value_{TOPSIS}) - (\overline{LI}_{parametric})\right]^2} \quad (12)$$

where: P value and $LI_{parametric}$ are computed values of sample i, based on TOPSIS and parametric models, respectively. The coefficient of determination (R^2) estimated from the above formula for our study area was $R^2 = 0.961$ which shows a high correlation between the observed land index values and the preference values obtained from two models.

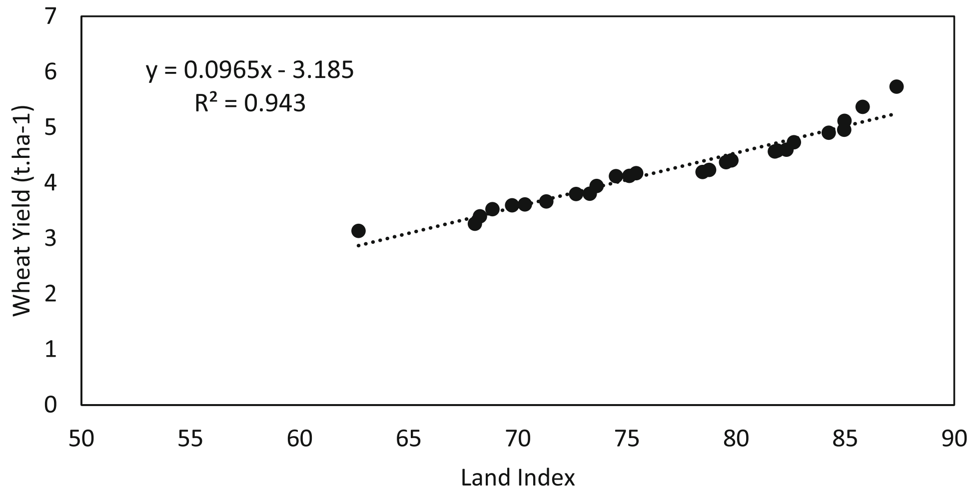

Fig. 4 Linear regression between the observed wheat yield and land index values by parametric model in Joveyn plain

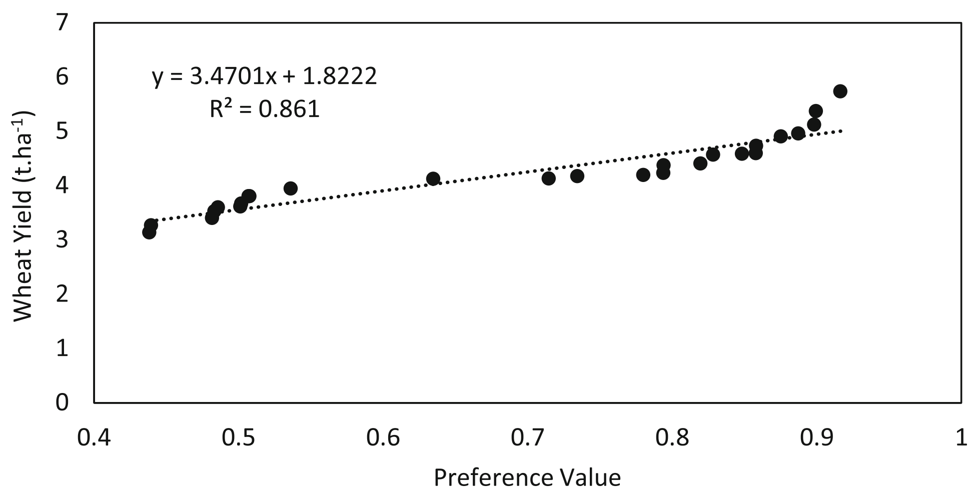

Fig. 5 Linear regression between the observed wheat yield and TOPSIS preference values in Joveyn plain

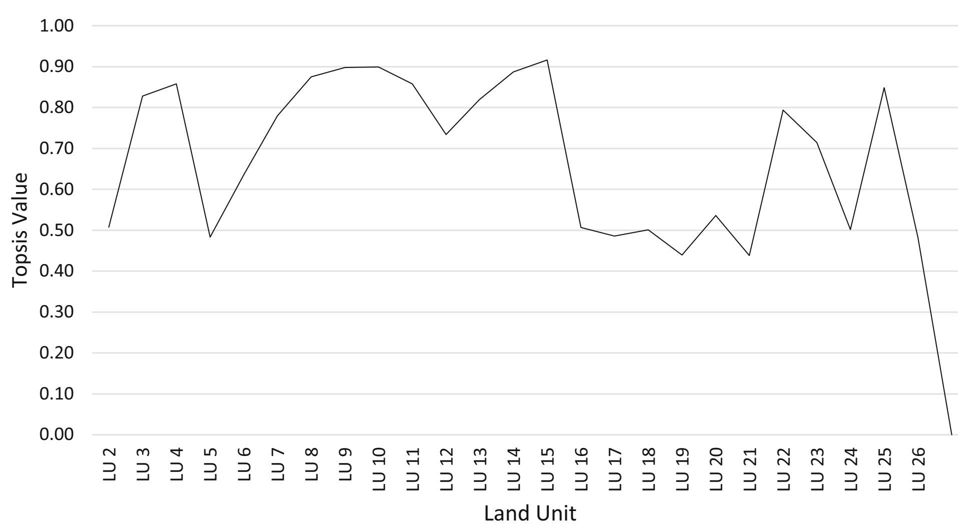

Fig. 6 TOPSIS preference values among 26 land units of the study area

Model validation

Comparing the land index values and preference values by parametric and TOPSIS models with the observed wheat yield in each land unit revealed high correlation between the land indexes and preference values in both models with irrigated wheat yield in the study area. The values of correlation coefficient (R^2) varied between 0.861 and 0.943 by TOPSIS and parametric models which verify the validation of both models in estimating land suitability for wheat production in Joveyn plain (Figs. 5, 6). A comparison between our results with the findings of other researchers (Tang et al. 1991, 1992; Van Ranst et al. 1996; Sanchez 2007; Joss et al. 2008; Keshavarzi and Sarmadian 2009; Bagherzadeh and Mansouri Daneshvar 2011) revealed that both models have enough accuracy and capability for land evaluation. The results of our study showed that both models declare land units variations clearly based on land qualities/characteristics and can determine the accurate variations among the land units. Hence, it is an efficient for managers to make decision easily while they are faced to several complicated parameters.

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References

Ayalew L, Yamagishi H, Ugawa N (2004) Landslide susceptibility mapping using GIS-based weighted linear combination, the case in Tsugawa area of Agano river, Niigata Prefecture, Japan. Landslide 1:73–81

Bagherzadeh A, Mansouri Daneshvar MRM (2011) Physical land suitability evaluation for specific cereal crops using GIS at Mashhad Plain, Northeast of Iran. Front Agric China 5(4):90–100

Bagherzadeh A, Paymard P (2015) Assessment of land capability for different irrigation systems by parametric and fuzzy approaches in the Mashhad Plain, Northeast Iran. Soil Water Res 10(2):90–98

Biorani H, Ghofran A (2009) Determining and using technique for order preference by similarity ideal solution (TOPSIS) for ranking of civic region based on crime. Detective 2:109–128 **(in Persian)**

Dent D, Young A (1981) Soil survey and land evaluation. E & FN Spon, reprint 1993. [A standard handbook on soil survey and land evaluation]

FAO (1976a) A framework for land evaluation. Food and Agricultural Organization of the Unite Nations, Rome

FAO (1976b) A framework for land evaluation. FAO Soil Bulletin 32, Rome

FAO (1983) Guidelines: land evaluation for rainfed agriculture. FAO Soils Bulletin, No. 52, FAO, Rome

FAO (1984) Guidelines: land evaluation for rainfed agriculture. FAO Soils Bulletin 52, Rome

FAO (1985) Guideline: land evaluation for irrigated agriculture. FAO Soils Bulletin, No. 55. Rome

FAO (1993) Guideline for land use planning. FAO Development Series No: 1, FAO, Rome, p 96

Hwang CL, Yoon K (1981) Multiple attribute decision making; methods and applications. Springer-Verlag, Heidelberg

Joss BN, Hall RJ, Sidders DM, Keddy TJ (2008) Fuzzy-logic modeling of land suitability for hybrid poplar across the Prairie Provinces of Canada. Earth Environ Sci 141:79–96

Keshavarzi A, Sarmadian F (2009) Investigation of fuzzy set theory's efficiency in land suitability assessment for irrigated wheat in Qazvin province using Analytic hierarchy process (AHP) and multivariate regression methods. In: Proceedings of 'Pedometrics 2009' conference, August 26–28, Beijing, China

Kurtener D, Krueger-Shvetsova E, Dubitskaia I (2004) Quality estimation of data collection. UDMS. UDMS Press, Giorggia-Venice, pp 9101–9109

Malczewski J (1999) GIS and multi-criteria decision analysis. Wiley, New York, p 392

Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models, part I: a discussion of principles. J Hydrol 10(3):282–290

Olson DL (2003) Comparison of weights in TOPSIS models. Math Comput Model 40:721–727

Prakash TN (2003) Land suitability analysis for agricultural crops: a fuzzy multicriteria decision making approach. M.Sc. Thesis, International Institute for Geo-Information Science and Earth Observation, Enschede, The Netherlands

Roszkowska E (2011) Multi-criteria decision making models by applying the TOPSIS method to crisp and interval data. In: Trzaskalik T, Wachowicz T (ed) Multiple criteria decision making. The Publisher of the University of Economics in Katowice, p 343–363

Saaty TL (1990) How to make a decision: the analytic hierarchy process. Eur J Oper Res 48:9–26

Saaty TL (1994) Fundamentals of decision making and priority theory with the AHP, RWS publications, Pittsburg

Saaty TL (2004) Mathematical Methods of Operations Research. Dover Publications, Mineola, p 415–447

Saaty TL, Vargas LG (2001) Models, methods, concepts and applications of the analytic hierarchy process. Kluwer, Dordrecht

Sanchez JF (2007) Applicability of knowledge-based and fuzzy theory-oriented approaches to land suitability for upland rice and rubber. M.Sc. Thesis ITC, The Netherlands

Sys C (1985) Land evaluation, parts I, II,III. ITC Lecture Notes, University of Ghent, Belgium, p 343

Sys C, Van Ranst E, Debaveye IJ (1991a) Land evaluation. Part I: principles in land evaluation and crop production calculations. General Administration for Development Cooperation, Agricultural Publication-No. 7, Brussels, Belgium, p 274

Sys C, Van Ranst E, Debaveye IJ (1991b) Land evaluation. Part II: methods in land evaluation. General Administration for Development Cooperation, Agricultural Publication-No. 7, Brussels, Belgium, p 247

Sys C, Van Ranst E, Debaveye IJ, Beernaert F (1993) Land evaluation. Part III: crop requirements. General Administration for Development Cooperation, Agricultural Publication-No. 7, Brussels, Belgium, p 199

Tang H, Debaveye J, Ruan D, Van Ranst E (1991) Land suitability classification based on fuzzy set theory. Pedologie 3:277–290

Tang H, Van Ranst E, Sys C (1992) An approach to predict land production potential for irrigated and rainfed winter wheat in Pinan County, China. Soil Technol 5:213–224

Triantafilis J, Ward WT, McBratney AB (2001) Land suitability assessment in the Namoi Valley of Australia, using a continuous model. Amst J Soil Res 39:273–290

USDA (1961) Land capability classification. In: Klingbiel AA, Montgomery PH (eds) Soil conservation. Agric Handbook No. 210, USDA, Washington

Van Ranst E, Tang H, Groenemans R, Sinthurahat S (1996) Application of fuzzy logic to land suitability for rubber production in Peninsular Thailand. Geoderma 70:1–19