CrossMark

ORIGINAL ARTICLE

Land suitability modeling by parametric-based neural networks and fuzzy methods for soybean production in a semi-arid region

Ali Bagherzadeh[1] · Elnaz Ghadiri[1] · Ali Reza Souhani Darban[1] · Amin Gholizadeh[1]

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 using parametric learning neural networks and fuzzy models was investigated for irrigated soybean production based on FAO land evaluation frameworks (FAO 1976, 1983, 1985) and the proposed methods by Sys et al. (1991c) and Hwang and Yoon (1981) in Neyshabour plain, Northeast of Iran. Some 41 land units were studied at the study area by a precise soil survey and their morphological and physico-chemical properties. The Climatic and land qualities/characteristics for soybean crop were determined using the tables of soil and crop requirements developed by Sys et al. (1993). An interpolation function in GIS was used to map values to scores in terms of land qualities/characteristics for the land utilization type. Our results indicated that the most limiting factor for soybean cultivation in the study area was soil fertility properties. The values of land indexes by neural networks model ranged from 29.77 in some parts in west and middle to 57.45 in the north west and east parts of the study area, which categorized the plain from marginally suitable (S3) to moderately suitable (S2) classes. The land index values by fuzzy model varied between 16.10 and 47.80 which classified from marginally not suitable (N1) to marginally suitable (S3) classes. The coefficient of determination between the neural network land index values and the corresponding fuzzy values revealed a high correlation ($R^2 = 0.966$) between two models. The exponential regression coefficient (R^2) between the land indexes of neural networks and fuzzy models with the observed soybean yield in the study area varied between 0.610 and 0.514 respectively, which revealed higher performance of neural networks in predicting land suitability for irrigated soybean production in the study area.

Keywords Land evaluation · Suitability · Neural networks · Fuzzy logic · Soybean · Yield

✉ Ali Bagherzadeh
  abagherzadeh@mshdiau.ac.ir

[1] Department of Agriculture, Islamic Azad University-Mashhad Branch, Emamyeh Boulevard, P.O. Box: 91735-413, Mashhad, Iran

Introduction

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 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 1976). 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, qualitative 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 (1976) defines land evaluation as "a process of assessment of land performance

Springer

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 1976). 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 1976). 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 1976). The parametric approach 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 approach different classes of land suitability are defined as completely separate and discrete groups and are separated from each other by distinguished and consistent range. The non-certainty in the output results obtained by parametric approach can solve by evolutionary learning and the nonlinear mapping ability of the neural networks. Artificial neural networks (ANN) are a form of artificial intelligence, which by means of their architecture attempt to simulate the biological structure of the human brain and nervous system (Zurada 1992). A neural network consists of simple synchronous processing elements, called neurons, which are inspired by biological nerve system (Malinova and Guo 2004). The mathematical model of a neural network comprises of a set of simple functions linked together by weights. The network consists of a set of input units x, output units y and hidden units z, which link the inputs to outputs. The learning algorithm of neural networks used the values obtained by parametric approach. Through evolutionary learning from samples a neural network adapts its connection weights to approximate the desired output. Then, successfully trained neural networks can accomplish the suitability analysis task. Neural networks can identify subtle patterns in input training data, which may be missed by conventional statistical analysis. In contrast to statistical regression models, neural networks do not require knowledge of the functional relationships between the input and the output variables. Moreover, neural networks are nonlinear, and therefore

may handle very complex data patterns, which make mathematical modeling unattainable. Another advantage of neural networks is that all kinds of data-continuous, near-continuous, and categorical or binary can be input without violating model assumptions, as well as the ability to model multi-output phenomena. Decision making issue in evaluating land suitability is very complex and complicated because of several decision indicators and criteria. Fuzzy set methodologies have been proposed as a method for overcoming problems related to vagueness in definition and other uncertainties. The use of fuzzy set methodologies in land suitability evaluation allows imprecise representations of vague, incomplete and uncertain information. Fuzzy land evaluations define continuous suitability classes rather than "true" or "false" as in the Boolean model (e.g. Burrough 1989; Sicat et al. 2005; Ziadat 2007; Keshavarzi et al. 2010). Fuzzy set methodologies have the potential to provide better land evaluations compared to Boolean approaches because they are able to accommodate attribute values and properties which are close to category boundaries. The fuzzy methods are able to address and explore the uncertainties associated with land resources, especially if they are integrated with fuzzy set models (Xiang et al. 1992; Ceballos-Silva and Lopez-Blanco 2003; Prakash 2003; Guerrero and Moreno 2007; Chaddad et al. 2009). However fuzzy methods are still relatively unknown in land suitability evaluations for agricultural crops. Fuzzy sets theory for the first time defined by Zadeh (1965) in order to quantitative defining and determining of some classes that are expressed vaguely such as "very important" and so on. In fuzzy thinking, determination of specific border is difficult and belonging of various elements to various concepts and issues are relative. In fuzzy theory, the membership was not two-valued, but it can allocate the range of numbers from zero to one. A function that expresses degree of membership is called membership function. In the present study a Gaussian combination membership function was used. Fuzzy model has been used by many researchers in land suitability evaluation (Tang et al. 1991; Van Ranst et al. 1996; Keshavarzi and Sarmadian 2009). Most of the researchers, have been compared the results of this evaluation with other conventional methods such as maximum limitation, parametric and multiple regression methods in order to predicting the yield of production. Fritz and See (2005) studied the comparison of land cover maps using fuzzy agreement. The spatial fuzzy agreement between the two land cover products is provided. The results showed that fuzzy agreement can be used to improve the overall confidence in a land cover product. Tang et al. (1991) used fuzzy method for evaluation of Hamen lands in Liaoning province in China in order to cultivating corn. These researchers were obtained the final matrix of suitability with constituting weight

matrix and land characteristics matrix and multiplication of them and finally were calculated the land index. In this study, they were used multiple regression to determination of weights. The aim of the present study is to evaluate land suitability for soybean production in a semi-arid region by Parametric-based neural networks and fuzzy models and comparing land index values of both models with the observed yield of the crop to validate the accuracy of the models in practice.

Materials and methods

General characteristics of the study area

The present study was conducted in Neyshabour plain, Khorasan-e-Razavi Province, Northeast Iran (Fig. 1). The study area is located between latitude 35°41′N to 36°39′N and longitude 58°13′E to 59°30′E including lands less than 2933 m asl. The general physiographic trend of the plain
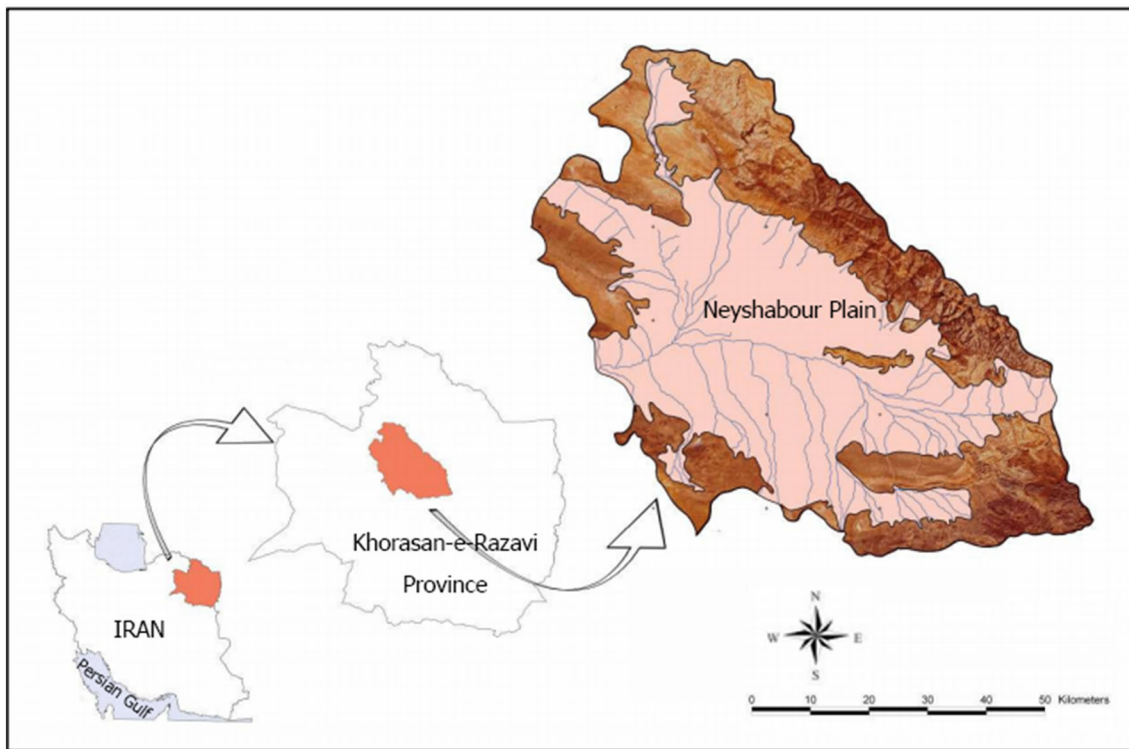

Fig. 1 The Geographical location of the study area (Neyshabour plain)

Table 1 The values of climate characteristics and the degree of limitation for Soybean production in the study area based on Sys et al. (1993)

Climate characteristics	Value	Degree of limitation
Precipitation of the first month (May)	20.70	16.38
Precipitation of the second month (June)	4.90	22.55
Precipitation of the third month (July)	1.00	24.50
Precipitation of the forth month (August)	0.00	60.00
Precipitation of growing cycle	26.60	21.31
Mean temp. of growing cycle	23.28	98.19
Mean min temp. of growing cycle	14.65	91.63
Relative humidity of develop stage (second month)	32.00	46.67
Relative humidity of maturation stage (forth month)	29.00	93.33
n/N at developing stage (second month)	0.77	82.64
n/N at maturation stage (forth month)	0.85	97.46
Climate index (CI)		23.71
Climate rate (CR)		37.939
Climate class		S3

extends in a NW–SE direction. The total surface of the study area comprises 5060 km^2. The elevation values of the study area vary between 1100 and 1700 m asl, with an average of 1400 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 247.4 mm and the mean annual temperature of 13.9 °C.

Parametric approach

The process of evaluation is based on the FAO qualitative land evaluation system (FAO 1976, 1983, 1985), which applies climatic conditions and land qualities/characteristics including topography, flooding hazard, drainage

Fig. 2 Artificial neural network neuron (w_0 is a threshold)

condition, soil texture, gravel percent, soil depth, calcium carbonate, gypsum, organic carbon, pH, soil salinity and alkalinity requirements for soybean production (Sys et al. 1991a, b, 1993). Based on morphological and physical/chemical properties of soil profiles some 41 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 the above and below sections, respectively (Sys et al. 1991c). 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. Applying parametric learning neural networks in land evaluation consists of numerical rating of different limitation levels of land characteristics according to a numerical scale between the maximum (normalized as 100) and the minimum value of zero. 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
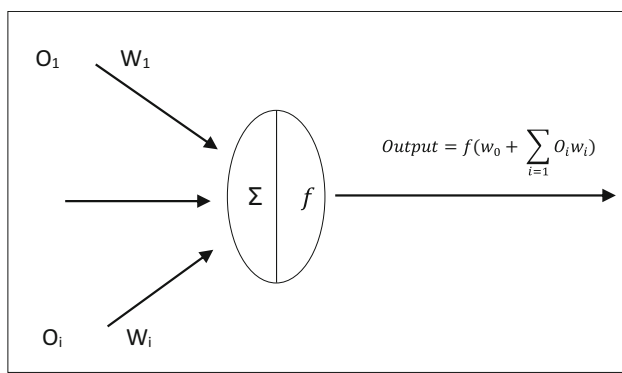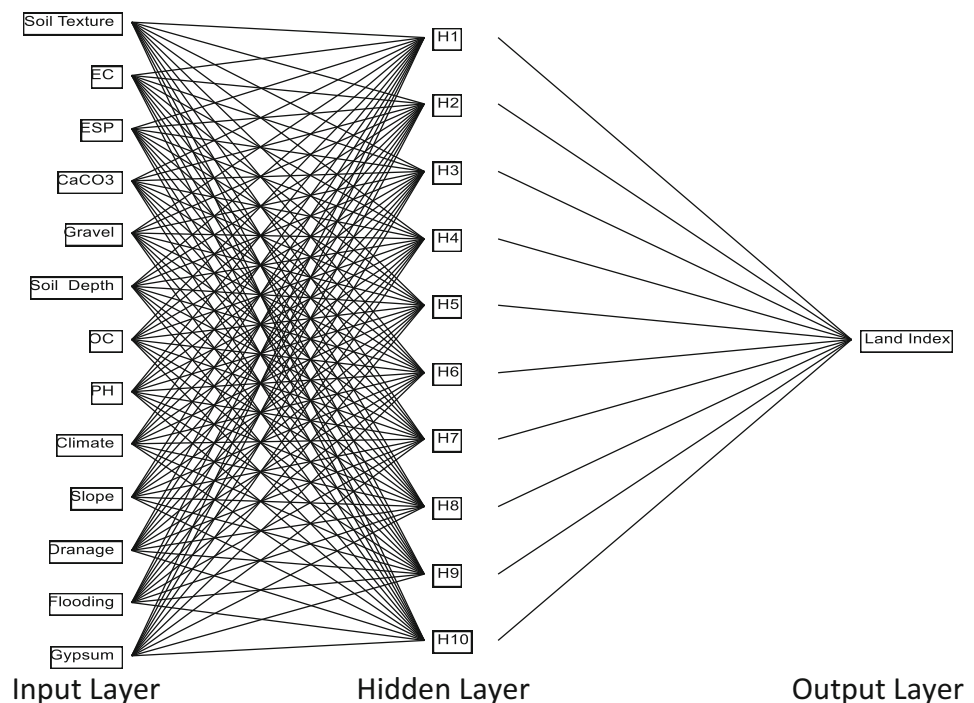

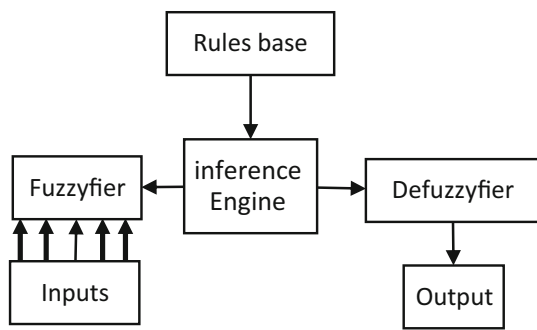**Fig. 3** The diagram of neural networks and its components
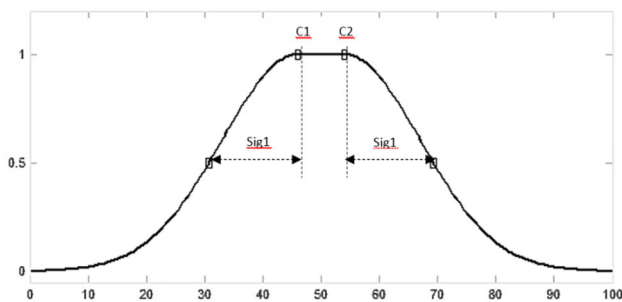
Fig. 4 A block diagram of the fuzzy system

Fig. 5 Gaussian combination membership function (Gauss2mf)

Table 2 Land suitability classes according to land index (Sys et al. 1991c)

Class	Intensity of limitation	Land index
S1	Highly suitable	75–100
S2	Moderately suitable	50–75
S3	Marginally suitable	25–50
N1	Marginally not suitable	12.5–25
N2	Permanently unsuitable	0–12.5

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 soybean is soil texture and the critical limits are to be represented in terms of soil texture corresponds to S1, 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 soybean growth were taken from 30 years of meteorological data of the region (1981–2010) and the climatic requirements of the crop were extracted from 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 and Paymard (2015) to estimate the land suitability index. On this basis the land index of each land

Table 3 The statistical values for degrees of limitation of soil qualities/characteristics in depth of 0–60 cm at the study area

	Min	Max	Mean	Median	SD	Variance	CV	Skewness
Slope	85.0	100.0	95.7	95.0	4.7	48.5	0.0	−1.3
Flooding	48.8	100.0	56.5	60.0	11.4	6.3	0.2	2.8
Drainage	66.3	97.5	94.1	97.5	7.0	85.2	0.1	−3.5
Soil texture	66.4	93.5	91.0	88.5	4.7	21.8	0.1	−3.4
Gravel	90.0	97.5	92.8	92.5	2.5	21.3	0.0	0.4
Gypsum	72.5	97.5	85.9	90.0	9.3	127.3	0.1	−0.7
OC	44.6	76.3	52.3	51.0	5.7	31.3	0.1	2.1
ESP	40.0	99.7	82.1	92.0	21.4	444.7	0.3	−1.2
pH	23.3	73.5	49.5	53.1	10.7	111.7	0.2	−0.7
CaCO$_3$	15.5	95.6	73.0	76.4	18.2	323.5	0.2	−1.5
EC	12.6	99.4	77.3	95.8	34.8	1178.1	0.4	−0.9

Table 4 The values of land indexes and land suitability classes by neural networks and fuzzy models for Soybean production in the study area

Land unit	Neural networks model		Fuzzy model	
	Land index	Class	Land index	Class
1	39.36	S3	18.1	N1
2	54.58	S2	44.6	S3
3	51.85	S2	47.6	S3
4	50.62	S3	46.8	S3
5	50.13	S2	46.8	S3
6	52.05	S2	43.8	S3
7	48.22	S3	43.0	S3
8	55.78	S2	42.6	S3
9	48.93	S2	28.5	S3
10	38.90	S3	41.3	S3
11	55.13	S2	41.7	S3
12	55.23	S2	41.7	S3
13	51.96	S2	44.4	S3
14	40.19	S2	27.7	S3
15	48.80	S3	47.8	S3
16	53.24	S3	46.4	S3
17	53.70	S2	46.1	S3
18	43.06	S2	28.8	S3
19	33.85	S3	16.1	N1
20	51.84	S2	45.9	S3
21	52.85	S2	42.0	S3
22	51.08	S3	43.0	S3
23	42.17	N1	43.7	S3
24	55.79	S2	46.5	S3
25	56.03	S2	45.6	S3
26	48.14	S2	28.0	S3
27	41.90	S2	25.3	S3
28	52.38	S2	47.1	S3
29	31.81	S3	16.8	N1
30	57.45	S2	46.8	S3
31	50.61	S3	47.1	S3
32	55.65	S2	47.5	S3
33	50.14	S3	36.8	S3
34	53.02	S2	47.1	S3
35	46.77	S3	31.1	S3
36	29.77	N1	16.7	N1
37	48.58	S3	45.1	S3
38	43.36	S2	18.0	N1
39	33.16	S3	16.8	N1
40	55.07	S3	44.4	S3
41	36.72	S3	18.7	N1

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:

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

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

Neural networks modeling

The neural network model is derived from a simulation of the human brain. The basic computation unit in a neural network is a neuron. A neuron performs the simple weighted summation and nonlinear mapping (Fig. 2), where $w0$ is a threshold and f is usually a sigmoid function: i.e.,

$$f(z) = \frac{1}{1 + e^{-z}} \quad (3)$$

A neural network has many neurons. The way neurons connect determines the structure of a neural network. A type of neural network called multilayer perceptron (MP), or feed forward network, consists of a sequence of layers of neurons with full connections between successive layers. Two layers of MP have connections to the outside world: the input and output layer. There are one or more hidden layers between the input and output layer. Information sequentially passes through the input, hidden, and output layers. A feed forward network with one or more hidden layers can form any shape of decision boundaries or approximate any continuous function, given sufficient hidden neurons (De Villers and Barnard 1992; Kreinovich and Sirisaengtaskin 1993). A neural network usually has two distinctive phases: learning and recall. Currently, the most popular learning algorithm for feed-forward network is back-propagation (BP) (Rumelhart and Hinton 1986). We will refer to a feed-forward network using a BP learning algorithm as a BP network in this paper. With the BP algorithm, a set of training samples with the desired output is required. It is a procedure which iteratively adjusts the weights of the connections in the gradient descent direction so as to minimize a measure of the difference between the actual output vector of the network and the desired output vector. The difference is usually measured by the error function:

$$E = \frac{1}{2} \sum_{c} \sum_{j} (y_{j.c} - d_{j.c})^2 \quad (4)$$

where, c is an index over cases (input–output pairs), j is an index over output units, y is the actual state of the output unit, and d is its desired state. The simplest version of gradient descent is to change each weight by an amount proportional to the accumulated $\partial E/\partial w$: i.e.,

Table 5 Land suitability classes, land indexes, the surface area and the percent of each suitability class by neural networks and fuzzy models in the study area

Land suitability class	Land index	Neural networks model		Fuzzy model	
		Area (km^2)	%	Area (km^2)	%
Highly suitable (S1)	75–100	0	0	0	0
Moderately suitable (S2)	50–75	1440.92	26.48	0	0
Marginally suitable (S3)	25–50	3618.65	73.52	4804.54	94.96
Marginally not suitable (N1)	12.5–25	0	0	255.03	5.04
Permanently unsuitable (N2)	0–12.5	0	0	0	0
Total		5059.57	100.00	5059.57	100.00

$$\Delta w = -\frac{\eta \partial E}{\partial w} \tag{5}$$

where, η is the learning rate.

A neural network's generalization ability, or the power to handle unseen data, is crucial. The generalization ability can be measured by a set of testing samples in the recall phase. If a trained neural network generalizes well, it can be safely used to process the whole data set.

The schematic of the neural networks and its components in the present study has been illustrated in Fig. 3.

Fuzzy logic modeling

The Fuzzy set theory (Zadeh 1965) is a body of concepts and a technique that gives a form of mathematical precision to human thought processes that are imprecise and ambiguous in many ways. At the present study, we considered the fuzzy approach on the Singleton fuzzyfier, Centroid defuzzyfier and minimum Mamdani inference engine in MATLAB Ver. R2012a software. The fuzzy system has the following block diagram (Fig. 4). Accordingly, the application of the fuzzy set theory to determine the impact of land qualities for irrigated soybean comprises several steps:

- Defining the inputs and output of fuzzy system;
- Determination of membership functions;
- Determination of membership values;
- Determination of fuzzy If and Then rules;
- Defuzzyfication of all membership values and determination of land index for each land unit.

In this study the membership function was defined as Gaussian combination membership function as follows:

Syntax: y = gauss2mf (x, [sig1 c1 sig2 c2]) $\tag{6}$

The Gaussian function depends on two parameters sig and c as given by:

$$f(x; \sigma, c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{7}$$

The function gauss2mf is a combination of two of these two parameters. The first function, specified by sig1 and c1, determines the shape of the left-most curve. The second function specified by sig2 and c2 determines the shape of the right-most curve. Whenever c1 < c2, the gauss2mf function reaches a maximum value of 1. Otherwise, the maximum value is less than one. The parameters are listed in the order: [sig1, c1, sig2, c2] (Fig. 5).
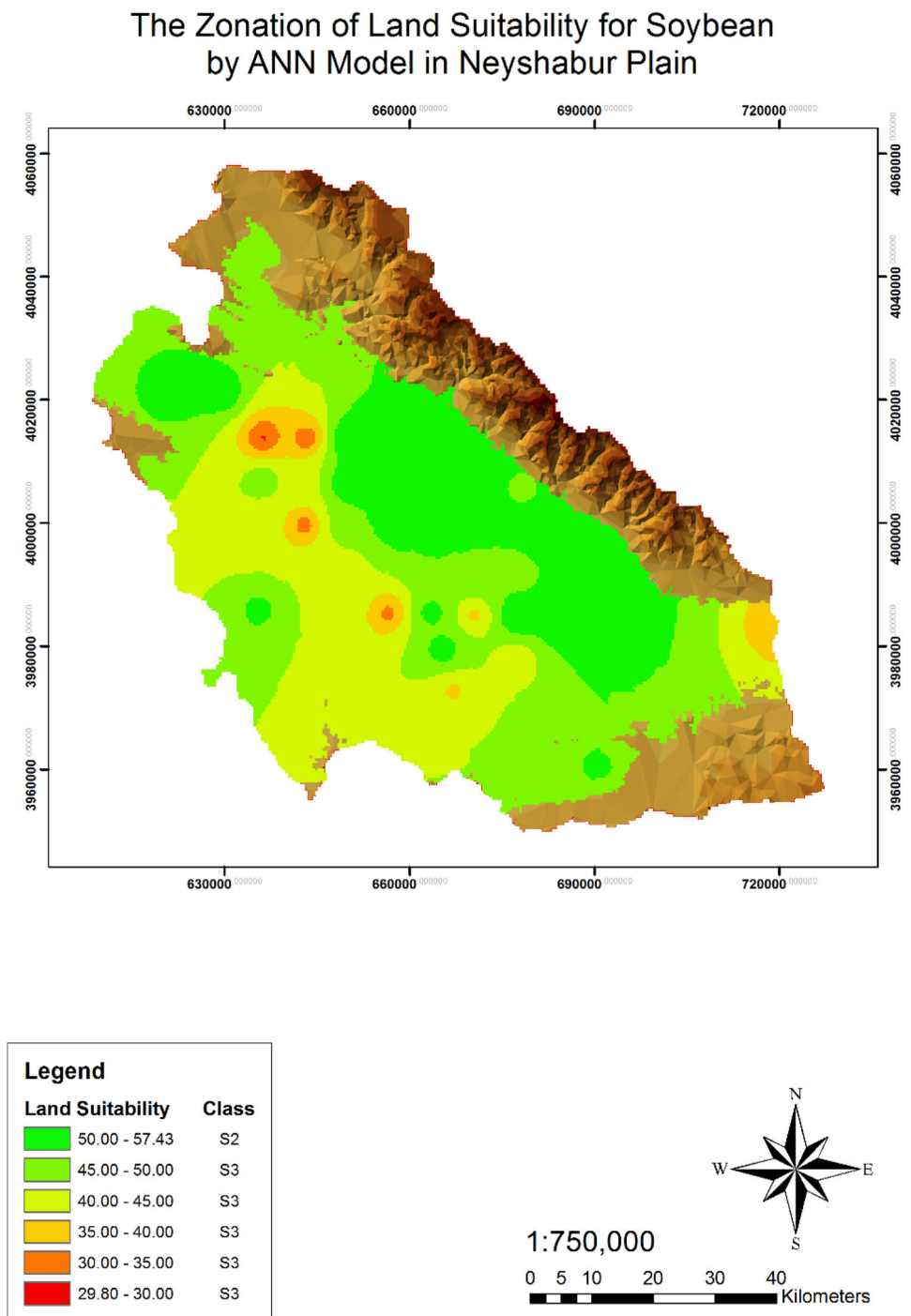
The zonation of land suitability

An interpolation technique using the ArcGIS ver.10.3 helped in managing the spatial data and visualizing the land index values using parametric learning neural networks and fuzzy models for preparing the final land suitability evaluation maps for both models. According to Sys et al. (1991c) the land suitability classes, the intensity of limitation and the land index ranges are demonstrated in Table 2.

Results and discussion

Neural networks 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 soybean were determined based on Sys et al., guidelines (1991a, b, 1993). There was a relatively low climate rate ranged from 37.0 to 38.0 in most parts of the study area which characterized the region marginally suitable (S3 class) for irrigated soybean production (Table 1). The statistical values for degrees of limitation of each soil quality/characteristic in depth of 0–60 cm at the study area indicated higher standard
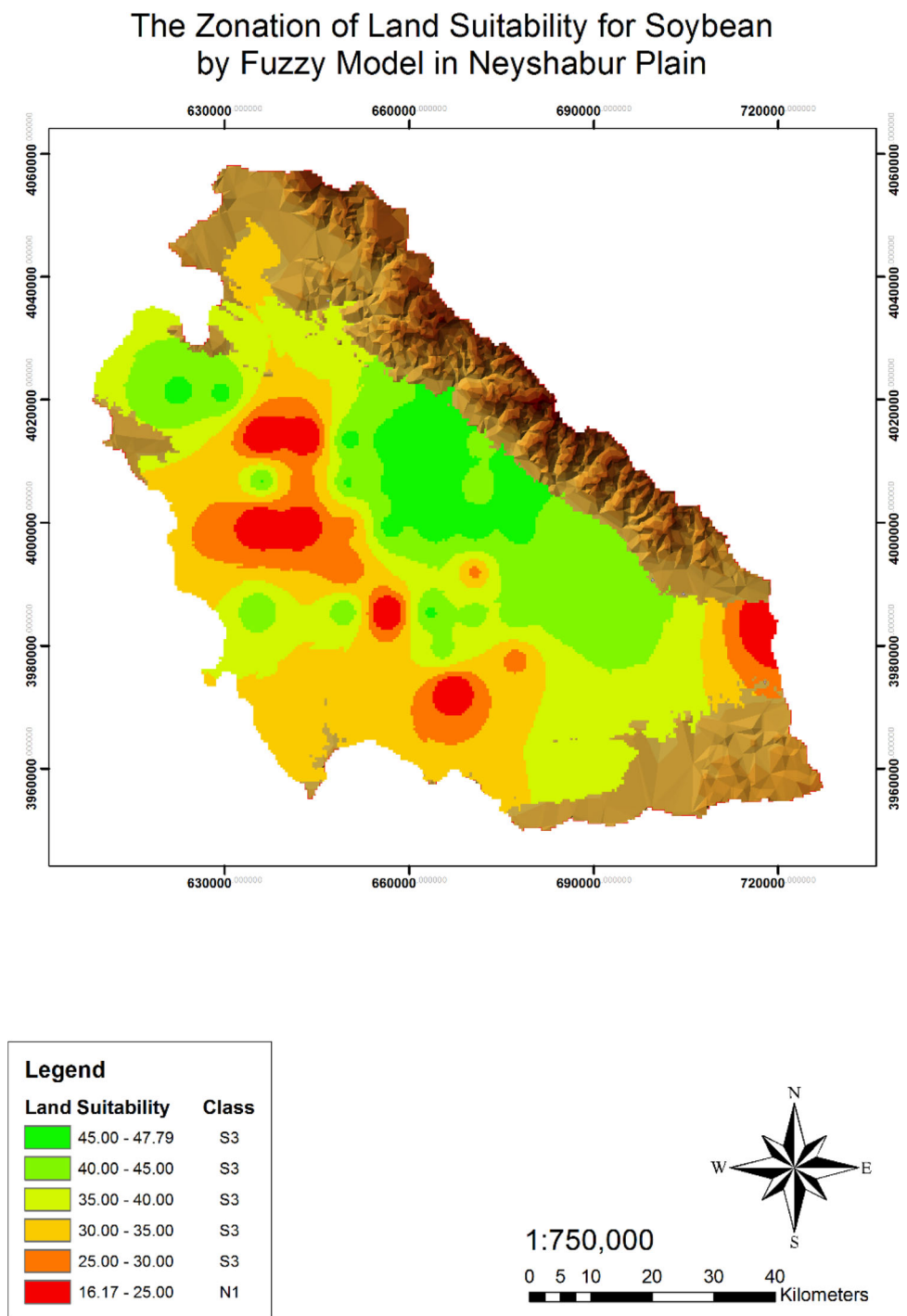
Fig. 6 The zonation of land suitability for Soybean production by neural networks model in Neyshabour plain

The Zonation of Land Suitability for Soybean by ANN Model in Neyshabur Plain

Legend

Land Suitability   Class

	Land Suitability	Class
(green)	50.00 - 57.43	S2
(light green)	45.00 - 50.00	S3
(yellow-green)	40.00 - 45.00	S3
(yellow)	35.00 - 40.00	S3
(orange)	30.00 - 35.00	S3
(red)	29.80 - 30.00	S3

1:750,000

0 5 10   20   30   40
Kilometers

deviation and coefficient of variation for soil salinity and alkalinity, which affect the land index variations by both models more effectively than other soil parameters (Table 3). The values of land indexes using parametric learning neural networks varied between 29.77 and 57.45 with an average of 48.05 (Table 4). The land suitability classes for soybean were categorized into marginally suitable of S3 and moderate suitable class of S2. The zonation

map of land suitability revealed that 73.52 % (3618.65 km^2) of the surface area were marginally suitable and 26.48 % (1440.92 km^2) were moderate suitable for soybean production (Table 5). The most important limiting factors for soybean production in the study area were climate conditions, soil pH and soil organic carbon. The moderate suitability class of S2 was mainly distributed in west and north parts of the plain, while the middle and

Fig. 7 The zonation of land suitability for Soybean productions by Fuzzy model in Neyshabour plain

The Zonation of Land Suitability for Soybean by Fuzzy Model in Neyshabur Plain

Legend

Land Suitability   Class

45.00 - 47.79   S3
40.00 - 45.00   S3
35.00 - 40.00   S3
30.00 - 35.00   S3
25.00 - 30.00   S3
16.17 - 25.00   N1

1:750,000
0 5 10   20   30   40
Kilometers

east parts of the study area exhibited marginal suitability for irrigated soybean production (Fig. 6).

Fuzzy model in land suitability evaluation

Land suitability analysis deals with many factors that are continuous in nature, like soil characteristics, and climatic parameters. Using parametric approach makes it impossible to model such a vagueness and imprecision of environmental factors. Fuzzy logic aids in most precise representation of such imprecise, incomplete and vague information. The values of land indexes based on fuzzy model altered from 16.10 to 47.80, which categorized the region into marginally not suitable class of N1 to marginally suitable class of S3 (Table 4). The major limitations for soybean cultivation were found to be climate
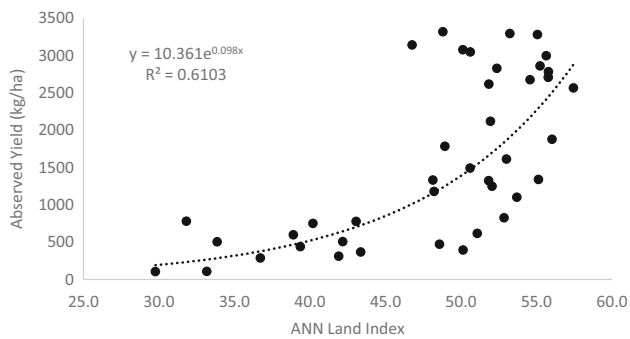
Fig. 8 Exponential regression between the observed yield of Soybean and the land index values by parametric-based neural networks model in Neyshabour plain
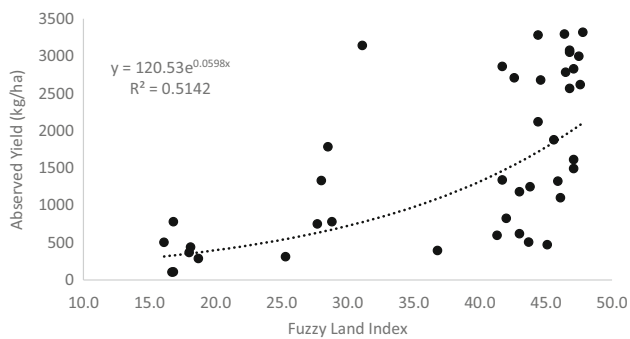

Fig. 9 Exponential regression between the observed yield of Soybean and the Fuzzy preference values in Neyshabour plain

conditions, soil pH and soil organic carbon. Hence, emphasis should be placed on soil management techniques that conserve organic matter and enhance nutrient and water-holding capacity of the soil. The produced maps of land suitability by fuzzy logic approach showed that 255.03 km^2 equal 5.04 % of the study area has marginally not suitability and 4804.54 km^2 equal 94.96 % of the plain has marginally suitability for soybean production (Table 5). The marginal suitability class of S3 was distributed all over the plain, while scattered parts in south, southeast and middle of the plain exhibited marginal not suitability for irrigated soybean production (Fig. 7).

Model validation

The land index values from neural networks and fuzzy models were compared by calculating the coefficient of determination (R^2) defined by Nash and Sutcliffe (1970) which is calculated as follow:

$$R^2 = 1 - \frac{\left[\sum_{i=1}^{n}(LI_{fuzzy} - LI_{ANN})^2\right]}{\left[\sum_{i=1}^{n}(LI_{fuzzy} - \overline{LI}_{ANN})\right]^2} \quad (8)$$

where: LI_{fuzzy} and $LI_{parametric}$ are computed values of sample i, based on the fuzzy system and parametric

model, respectively, and $LI_{parametric}$ is the mean of measured values. The coefficient of determination (R^2) estimated from the above formula for our study was $R^2 = 0.966$ which shows a high correlation between the estimated land index values from both models. The values of regression coefficient (R^2) between the estimated land index values by both models with the observed soybean yield in each land unit varied between 0.610 and 0.514 for neural networks and fuzzy approaches, respectively, which indicate similar trend of both models in estimating land suitability for soybean production in the study area (Figs. 8, 9).

References

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

Burrough PA (1989) Fuzzy mathematical methods for soil survey and land suitability. J Soil Sci 40:477–492

Ceballos-Silva A, Lopez-Blanco J (2003) Delineation of suitable areas for crops using a multi-criteria evaluation approach and land use/cover mapping: a case study in Central Mexico. Agric Syst 77:117–136

Chaddad F, Senesi SI, Palau H, Vilella F (2009) The emergence of hybrid forms in Argentina's grain production sector. International Food & Agribusiness Management Association World Food & Agribusiness Symposium 19, Budapest, Hungary, June 20–21, 2009

De Villers J, Barnard E (1992) Backpropagation neural nets with one and two hidden layers. IEEE Trans Neural Netw 4(1):136–141

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

Fritz S, See L (2005) Comparison of land cover maps using fuzzy agreement. Int J GIS 19:787–807

Guerrero JA, Moreno G (2007) Optimizing fuzzy logic programs by unfolding, aggregation and folding. In: Proceedings of 8th international workshop on rule-based programming (RULE'07), Paris, France. June 29. University of Paris

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

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: Proc 'Pedometrics 2009' Conf, August 26–28, Beijing, China

Keshavarzi A, Sarmadian F, Heidari A, Omid M (2010) Land suitability evaluation using fuzzy continuous classification (a case study: Ziaran region). Mod Appl Sci 4:72–81

Kreinovich V, Sirisaengtaskin O (1993) 3-Layer neural networks are universal approximators or functionals and for control strategies. Neural Parallel Sci Comput 1(3):325–346

Malinova T, Guo ZX (2004) Artificial neural network modeling of hydrogen storage properties of Mg-based alloys. Mater Sci Eng 365:219–227

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

Prakash TN (2003) Land suitability analysis for agricultural crops: a fuzzy multicriteria decision making approach. Msc. Thesis, International Institute for Geo-InformationScience and Earth Observation Enschede, The Netherland

Rumelhart DE, Hinton GE (1986) Learning representation by back-propagation errors. Nature 323(6088):533–536

Sicat RS, Carranza EJM, Nidumolu UB (2005) Fuzzy modeling of farmers' knowledge for land suitability classification. Agric Syst 83:49–75

Sys C (1985) Land evaluation, parts I, II, III. ITC lecture notes, University of Ghent, Belgium

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

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

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

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

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

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

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

Xiang WN, Gross M, Fabos JG, MacDougall EB (1992) A fuzzy group multicriteria decision making model and its application to land-use planning. Environ Plan B 19:61–84

Zadeh LA (1965) Fuzzy sets. Inf Control 8:338–353

Ziadat FM (2007) Land suitability classification using different sources of information: soil maps and predicted soil attributes in Jordan. Geoderma 140:73–80

Zurada JM (1992) Introduction to artificial neural systems. West, St. Paul