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Modeling of yield and rating of land characteristics for corn based on artificial neural network and regression models in southern Iran

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Abstract

This study was conducted to rate the land characteristics of corn in hot areas based on artificial neural networks and regression models. For this purpose, 63 corn fields were selected in southern Iran. In each farm, a pedon was excavated, described and sampled. A questionnaire was completed for each farm. A stepwise regression model was used to study the relationship between land characteristics and corn yield. A characteristic-function curve was used to rate the land characteristics. Finally, crop requirements were prepared by artificial neural network and regression models and verified by comparing the actual and predicted performance levels. The results of regression analysis showed that soil salinity, exchangeable sodium percentage, sand, clay, phosphorous, gypsum and potassium recorded the highest effect on yield and according to the artificial neural network, the exchangeable sodium percentage, soil salinity, soil texture and cation exchange capacity are the most important. Based on regression and artificial neural network methods, the threshold limit and break even production for soil salinity were 4, 2.5, 12, and 10 dS m^{-1}, respectively, but for exchangeable sodium percentage the values were 18, 14, 35, and 30, respectively. The coefficient of determination (R^2) between the actual and predicted yield based on the regression model was 0.88, but it was 0.945 (training data) and 0.837 (testing data) for the artificial neural network. Also, the results of the verification of the prepared crop requirements tables showed that the correlation of determination between the land index and the yield in the regression method was 0.78 but it was 0.81 for the artificial neural network, these results are acceptable in both methods.

Keywords*:* Critical production; Crop requirements; Land suitability; Corn; Threshold limit; Very hot region

1. Introduction

In recent years, corn is widely cultivated in different parts of Iran but it appears that corn is the second most important plant cultivated in hot and very hot regions of Iran including Orzouyeh, Soghan, Jiroft, Kahnouj and Manojan in Kerman province,Saravan and Iranshahr in Sistan and Baluchestan province and Hajiabad, Ashkara, Fareghan, Tarom and Tashkoyeyeh in Hormozgan province. In these areas, corn is generally cultivated after wheat (Agricultural Statistics, 2016). According to agro-climate zoning (ACZ) through UNESCO, these areas are dry with mild winter and very hot summers (Ghaffari *et al.*, 2015). According to FAO, in 2014, 184 million hectares of land was used for the cultivation of corn and it yielded 1016.74 million tons (FAO, 2015). In 2014-2015, the area used for the cultivation of corn in Iran was 166000 hectares, which contributed to 1.46% of the total crop products and 2.03% of the total grain yield. The first to fifth ranks of corn production belonged to Khuzestan, Fars, Kermanshah, southern Kerman and Kerman, respectively. These areas

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encompassed 67.63% of harvested corn in Iran (Agricultural Statistics, 2016).

The relationship between land use and land unit is determined by land suitability studies. This classification underlies sustainable agricultural development. This evaluation system determines compliance criteria, compliance of land with plant, climatic requirements and a specific type of productivity (Ayoubi and Jalalian, 2006). The preparation and correction of crop requirements tables is the key to land suitability studies. It should be noted that this crop can be cultivated in most areas with different soil properties but the crop yield would not be desirable and profitable. This may lead to loss of capital, soil and water resources (Zeinadini, 2015).Therefore, it is essential to prepare and revise corn requirements tables based on soil properties in these areas and classify land suitability (Zeinadini and Moghimi, 2008).

Modeling is one of the most important solutions that gives an accurate estimate of corn yield and rating of land characteristics using a scientific method (Mohammadi, 2006; Alvarez, 2009). For this purpose, several methods have been proposed such as regression models, artificial neural network (ANN), Analytic Hierarchy Process Analysis (AHP), fuzzy logic and decision trees.

In their study, Olalieh and Osiname (2010) evaluated four rice cultivars to determine the relationship between soil properties and rice yield in four different climates in Nigeria. ANOVA tables were prepared and soil properties having a significant relationship (high correlation) with rice yield in different climates were determined. The regression equations revealed that in all climates, there was a correlation between three soil properties (acidity, available phosphorus and sand percent) with yield. The correlation coefficients varied from 36.5to 63%.

Mandal and Venugopalan (2005) assessed the classification of corn land suitability in vertisols in India. In this area, two soil types were identified as Typic Haplusterts and Vertic Haplustepts. The results revealed the suitability of Vertic Haplustepts soils for corn cultivation. In this study, tables of crop requirements of corn were prepared and revised based on soil properties. Thereafter, the classification was performed based on the FAO land suitability evaluation (Sys *et al*., 1991). In recent decades, ANN models and adaptive neuro-fuzzy inferences system (ANFIS) have been widely used in environmental sciences and agriculture including land suitability evaluation. ANFIS aims to model the relationship between land properties and production rate (Abraham, 2005; Jang, 1993). Yagmayian and Samadzadeh (2015) used multilayer perceptron (MLP) artificial neural network with back propagation algorithm to predict the qualitative class of alfalfa land suitability in Noush Abad in Kashan. Information about the soil and climatic requirements were determined as input while qualitative suitability was regarded as the output to the model. The FAO model was also used to compare and measure the power of ANN. The results showed that an ANN model with higher coefficient of determination ($R^2 = 0.78$) and less root mean square error (RMSE = 0.036) is more effective than the FAO method (Sys *et al*., 1991) in predicting and estimating the qualitative land suitability class. Yazdchi *et al*. (2010) used multi-criteria decision making (MCDA) methods based on analytic hierarchy process analysis (AHP) as well as ecological and environmental requirements for the cultivation of saffron in Marand town. They showed that this method is effective in assessing land suitability for saffron cultivation.

Safa *et al*. (2015) conducted several studies to present a model for the prediction of wheat yield using synthetic networks in 40 farms in Canterbury in New Zealand. The final model could estimate wheat production using direct and indirect factors. From a total of 140 examined parameters, six major factors (slope, bulk density, water holding capacity, clay percentage, available phosphorus and organic carbon) were selected and the final model could suitably predict wheat production (error margin of ± 9 %).

Tables of crop requirements are not in details in different sources and should be calibrated and updated for each area (Edoardo and Costantino, 2009). Unfortunately, this issue is neglected most times. In many cases, land suitability studies were conducted according to those tables. This point should be noted, especially in the case of plants cultivated in a wide range of climatic and soil properties because yield and output are not desirable and profitable in many cases and could result to loss of capital and misuse of soil and water resources (Moghimi, 2002). It should be noted that soils with different characteristics can be used for corn cultivation. However, studies should be conducted to determine whether corn cultivation in that type of soil is profitable and suitable based on sustainable agriculture and optimal use of natural resources. Since an increase in the area under cultivation regardless of climatic and land properties has decreased yield in some areas, it is necessary to prepare and revise tables of corn requirements and classify land suitability, this will prevent the loss of natural resources (especially soil and water) and the wasting of time and capital (Licht, 2015). In this regard, it appears that new computational methods such as ANN can better measure natural complex conditions and give better estimates, since these methods are not linear (Emamqoli *et al.*, 2015). Therefore, the main purpose of the present study is to prepare a table of crop requirements based on the FAO framework (FAO, 1976) for southern regions of Iran, using ANN and regression models.

2. Materials and Methods

Firstly, corn farms with different soil properties and crop yield were selected according to soil maps (Semi-detailed soil surveys of Soghan, Shahmaran, Vakil abad, Chahnarenj, Faryab, Ashkara, Tarom and Iranshahr with 1:20000 scale), satellite images (google earth) and laboratory results and field survey. Accordingly, 63corn farms in Shahmaran, Soghan, Vakil abad,Chahnarenj and Faryab plains in Kerman province,Ashkara and Tarom in Hormozgan province and Iranshahr in Sistan and Baluchestan province were selected (Zeinadiniand and Moghimi, 2008) (Fig1).

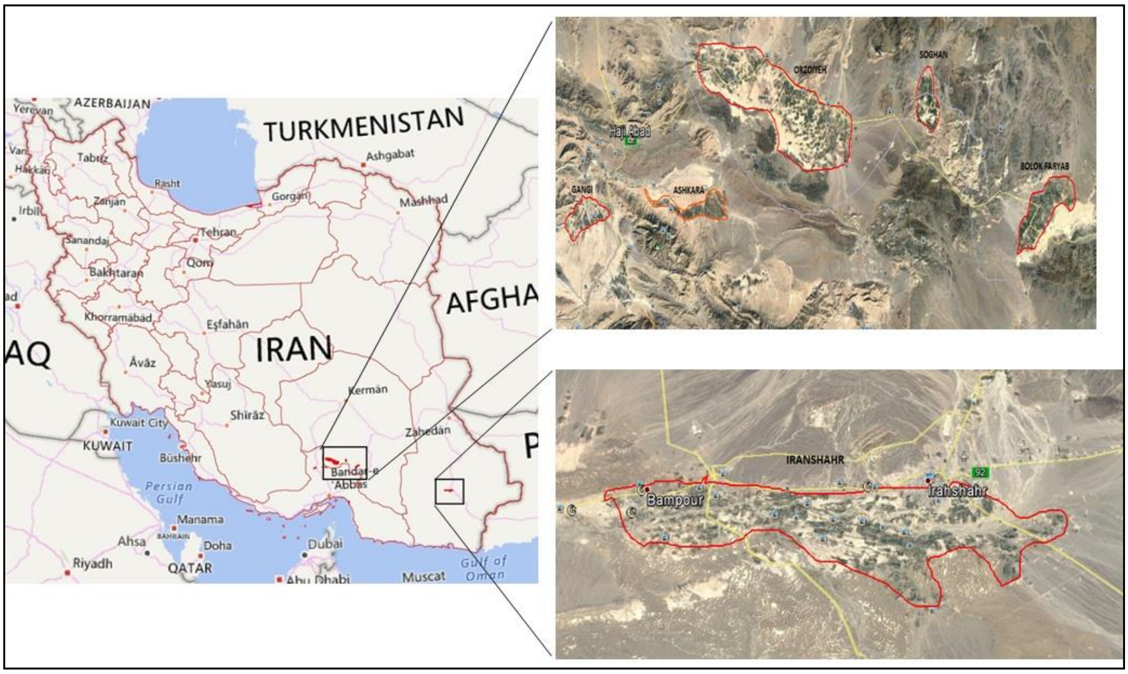

Fig. 1. Location of the study areas

In each farm, a pedon was excavated, described, and sampled (FAO, 1991). After transferring the soil samples to laboratory, physical and chemical analyses such aselectrical conductivity (EC) (Roads, 1996), pH (Richards, 1954), soil texture(Gee and Bauder, 1986), organic carbon (OC) (Nelsen and Samner, 1982), gypsum and calcium carbonate equivalent (Leopert and Suarez, 1996), available phosphorus (Olsen, 1980), available potassium (Panus and Guatheyrou, 2007), cation exchange capacity (CEC) (Sumner and Miller, 1996) and exchangeable sodium percentage (ESP) (Roads, 1996) were carried out on all of them according to standard methods. Besides, a special management and economic questionnaire was prepared for each farm. In these questionnaires, such information as geographical coordinates, yield, irrigation intervals, variable and constant costs in a crop year (plowing and disc, fertilization, spraying, irrigation, pruning, harvest, cost, labor, etc.) were recorded. In each farm, preliminary information on use of different inputs, yield and cultivars were also identified. After analysis of soil samples and collection of required data, all physical and chemical parameters were analyzed in different regions (Zare Chahuki, 2010).

Mean weight was calculated with the depth correction index for some parameters including salinity, clay, sand, gypsum and calcium carbonate equivalent to determine the relationship of land properties and yield (Sys *et al.*, 1991). Accordingly, databases were built. Such soil properties as salinity, acidity, clay, sand, silt, gypsum, calcium carbonate equivalent, surface and subsurface pebbles, absorbable phosphorus and potassium and ESP were determined as independent variables and yield as a dependent variable in each pedon.

2.1. Regression method

SPSS software was used to determine the regression relationships. Different regression methods were tested. The best regression equation was selected by examining different regression equations. Finally, stepwise regression delivered more satisfactory results (Rezaei and Soltani, 1998). Simple regression relationships were identified between yield and each property. The curve between yield and each parameter was plotted and slope of each line was determined that indicated the trend of variations in yield per unit increase or decrease in each parameter. Effective and important parameters in yield were determined (properties with R^2=0.3).

Yield-property curve was used to rating different characteristics. The boundary between the suitable class (S) and unsuitable class (N) from the point of break even production (yield component: value of the output is approximately equal to current costs in a crop year. If the yield is less than critical production, cultivation of the product is not profitable. Break-even yield or critical production is used in land suitability studies of boundary of suitable classes (S3) with unsuitable classes (N). Variable costs and product value were calculated and break-even yield in 2016 was determined for rating of corn land properties). Value of the boundary is between suitable and unsuitable classes (S with N) (Zeinadini, 2014). The boundary between S1 and S2 (threshold limit (the limit that either decreases or increases yield if the parameter exceeds it) or critical level (value of the parameter or the soil property; yield or growth is decreased if the parameter is less than critical level)) is drawn from 85% maximum yield perpendicular to the curve and perpendicular to the property. Similarly, the boundary between S2 and S3 from 60% maximum yield and the boundary between N1 and N2 from25% maximum yield are determined using the curve between yield and changes in each parameter (FAO, 1976) (for example Fig.2 shows rating of ESP for corn). For example, at the yield of 4000 Kg ha^{-1} (S1S2 boundary) a line from the Y axis (yield) is horizontally drawn to cut the regression line. Then another line is vertically drawn from there (cross point) to the X axis (i.e. ESP). This point on the X axis shows the boundary between S1 and S2 for the related property (i.e. ESP, here)

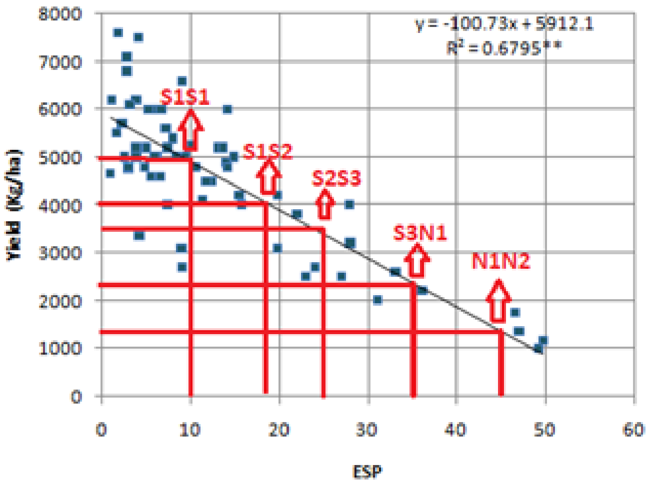

Fig. 2. Rating of ESP for corn

Finally, rating of land properties were performed to prepare tables of crop requirements of crop in very hot regions in Iran based on regression method.

2.2. Artificial neural network model

ANNs are flexible computing networks that can describe complex nonlinear relationships between given variables (Jang, 1991). The ANN models require three categories of training, validation and testing data. Training data is used to find the relationship between observed inputs and outputs. Validation data is used to control and supervise correct learning of the network. Testing data is used to evaluate the proposed network performance. Certainly, only two categories of training and testing data were used in most studies for design of ANN (Sarmadian andTaghizadeh Mehrjardi, 2008). Multilayer perceptron was selected as the ANN model in this study. The model was developed using training data. Properties of important lands for corn production were determined as the inputs and the amount of production was determined as the output. Structure of the ANN(number of layers, the number of neurons in each layer and transitional functions)was determined through trial and error. The best model was developed using the training data. Then, the developed model was tested using testing data (Safa *et al.*, 2015; Nowruz, 2008).In this research, 70% and 30% of total data were used for training and testing of the model, respectively. Soil properties were obtained as the same of the regression relationships. These properties were soil salinity, ESP, pH, clay, sand, gypsum, calcium carbonate equivalent (CCE), topsoil and subsoil gravel. These properties were determined as inputs and yield was determined as output. The MLP network was used in order to train the ANN. Fig.3 shows a schematic structure of the employed ANN.

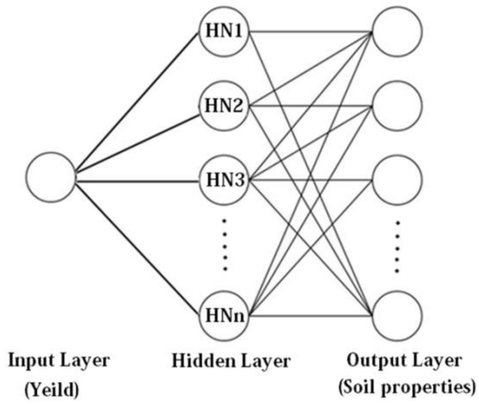

Fig. 3. Structure of the employed ANN model

The learning process involved changes in weights of different layers during the training period to the extent that the difference between actual data (for testing data) and predicted data will be minimized. Finally, more than 200000 different networks were designed. The aim of each training algorithm was decrease in root mean square error (RMSE) and increase in R^2. The best ANN was an MLP1-5-1 which means an MLP including one input (yield), one hidden layer with 5 nodes (units) and 12 outputs (soil properties). Finally, rating of effective and important land properties was determined. The best sensitivity analysis network was selected to evaluate the effect of different parameters on yield. Similar to regression method, numerical values of soil properties were determined by taking into account numerical value of yield for the boundary between suitability classes.

3. Results and Discussion

The results showed that yield has a significant correlation with ESP, soil salinity, sand and clay content. The relationship of ESP and soil salinity with yield was negative but sand content had a non-linear and variable relationship with yield (when sand percentage between 0-35: yield increase, sand percentage 35-60: yield fixed and sand percentage more than 60: yield decrease). Zeinadini and Moghimi (2008) identified the most important parameters in corn yield in Orezouyeh area, Kerman province, and in Hajiabad, Hormozgan province. They confirmed the above results. Yield increased as the sand increased by 55% but yield decreased with further increase in sand content. The same trend was observed in clay. Yield increased by increasing clay up to20% but yield decreased with further increase in clay content (Zeinadini, 2014). Accordingly, available phosphorus, pH, gypsum, available potassium and CCE were effective in corn yield. Available phosphorus and available potassium had a positive effect on yield. Gypsum and CCE had a negative effect on yield. pH had a variable and non-linear relationship with yield. For comparison of results, estimation of yield from regression relationships using selected independent variables in stepwise regression models was given as input and the actual yield was given as output. The chart was drawn (Fig. 4). Fig. 5shows the scatter plot of regression predicted yield versus actual yield (19 test samples).The charts and Table 1 show RMSE and R^2 values for multivariate regression and actual yield.

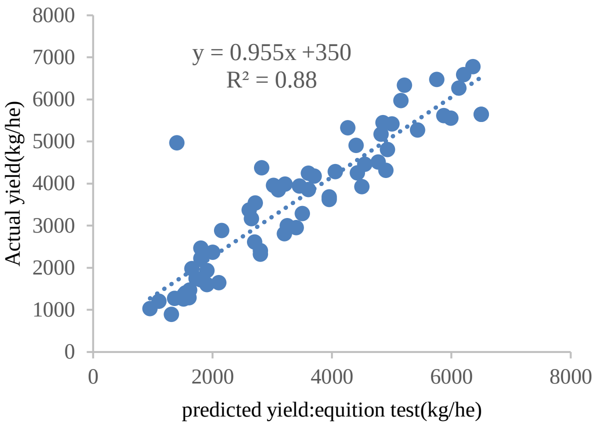

Fig. 4. The scatter plot of regression predicted yield versus actual yield (training)

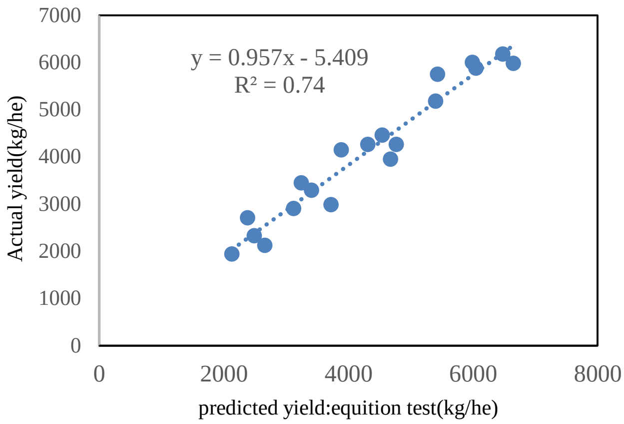

Fig. 5. The scatter plot of regression predicted yield versus actual yield (testing)

Table 1. RMSE and R^2 values for MLR relationships

RMSE	R^2	Number of data	Kind of data
900.15	0.88	44	Training data
860.31	0.74	19	Testing data

In order to evaluate and compare performance of ANN, estimated yield was drawn versus actual yield as a curve. The best line passing through the data was fitted to the model. The results of the best network for training and testing data are shown in Figs.6and 7.

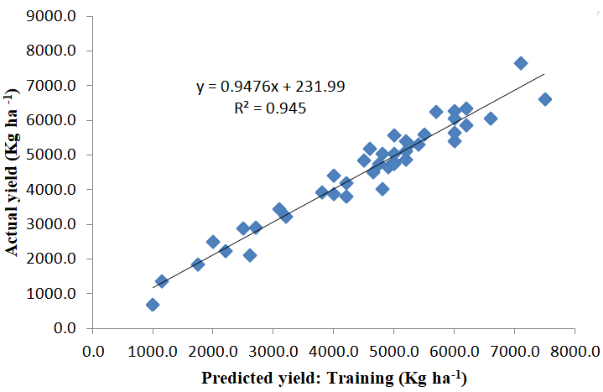

Fig. 6. The scatter plot of predicted yield versus actual yield (training)

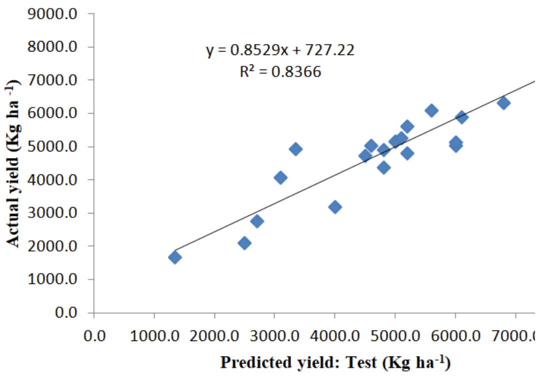

Fig. 7. The scatter plot of predicted yield versus actual yield (testing)

Comparison of Figs. 4 to 7shows that the ANN model more accurately estimates the corn yield. However, the results of regression are also acceptable. In order to evaluate and compare the performance of ANN, the yield estimated by ANN was drawn versus actual yield and the best line passing through the data was fitted to the model. R^2 in the ANN is 0.945 for training, which is larger than R^2 in the regression method (0.88). This is because nonlinear relationships between phenomena are considered in ANN (Sarmadian, 2010).Table 2 shows ANN RMSE and R^2 in ANN.

Table 2. ANN RMSE and R^2 in ANN

RMSE	R^2	Number Of Data	Model
353.41	0.945	44	training
622.20	0.837	19	testing

* All R^2 values are significant at 99% level.

Sensitivity analysis results are presented in Fig. 8. Four properties include EC, silt, ESP, sand and CEC are the most importance factors in corn yield.

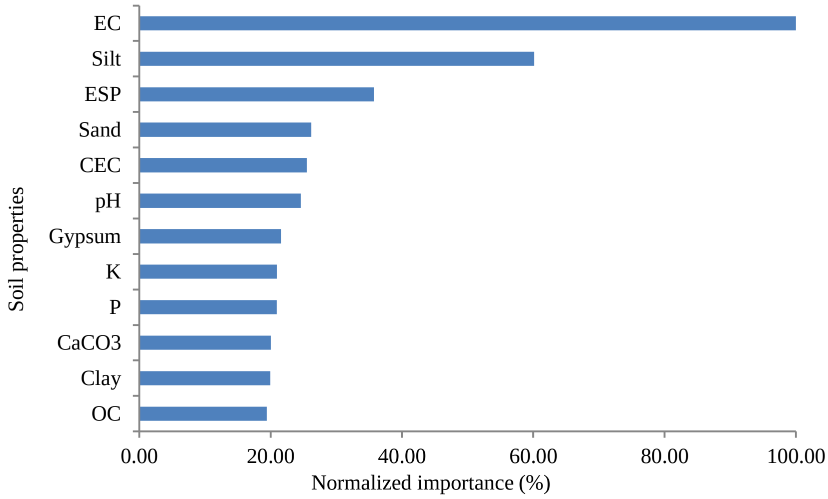

Fig. 8. Sensitivity analysis based on ANN for some parameters

The results showed that ANN can be a suitable alternative to conventional regression models in modeling yield and determining crop requirements since it considers nonlinear relationships between the parameters and increases accuracy of predicted estimates (Eskandari *et al.*, 2015). Statistical parameters listed in the above tables (Tables 1and 2), R^2 and RMSE values obtained from two MLR and ANN models show that ANN is superior to multivariate regression method. The results also confirm the nonlinear relationship between parameters and yield.

Rating of land properties for preparing crop requirements of corn in very hot areas in Iran was made based on the FAO framework (FAO, 1976). Tables 3 and 4 show classification of properties of main lands based on MLR and ANN models.

Table 3. Rating of land characteristics for corn in southern Iran based on MLR model

Land characteristic	Class, degree of limitation and rating scale					
	S_1		S_2	S_3	N_1	N_2
	0	1	2	3	4	
	100 95	85	60	40 25	0	
Physical soil characteristics						
Texture/ Struct.	SiC, SiCL, Si, SiL	L, SCL	SL,LfS, LS	fS, LcS, CL	-	Sa -C
Coarse fragments (vol%)	0-3	3-15	15-35	35-55	>55	-
Soil depth (cm)	>90	90-70	70-50	50-40	40-15	<15
$CaCO_3$ (%)	0-6	6-15	15-30	30-45	45-55-	>55
Gypsum(%)	0-2	2-4	4-10	10-20	20-25	>25
Soil fertility characteristics (f)						
Apparent CEC (cmol (+)/kg clay)	>24	24-16	<16(-)	<16(+)	-	-
pH H_2O	6.9-7.2	7.2-7.8	7.8-8.2	8.2-8.5	>8.5	
Organic carbon(%)	>0.1	0.1-0.5	0.5-0.3	.>0.3	-	-
Salinity and Alkalinity (n)						
ECe(dSm^{-1})	0-2	2-4	4-9	9.12	12-18	>18
ESP	0-10	10-18	18-25	25-35	35-45	>45

Tables of crop requirements are not presented in details by SYS *et al.* (1991). Comparison of rating of land characteristics reveal some land properties such as soil salinity, ESP, gypsum and CCE based on the regression method. The predicted values in this method are larger than those presented in SYS *et al.* (1991) tables. Estimated values of regression and ANN are introduced for properties of very hot areas in Iran but the SYS *et al.* (1991) tables are not for specific areas and are introduced for all climates (Ritung, 2007). Rating of properties of corn lands for physical, chemical and fertility properties is made based on regression and ANN. Rating of land properties for corn some areas in southern Iran was made based on regression method. The results showed that the rates were almost similar but not identical (Zeinadiniand and Moghimi, 2008).

Table 4. Rating of land characteristics for corn in Southern Iran (ANN)

Land characteristic	Class, degree of limitation and rating scale					
	S_1		S_2	S_3	N_1	N_2
	0	1	2	3	4	
	100 95	85	60	40 25	0	
Physical soil characteristics(s)						
Texture/ Struct.	SiC, SiCL, Si, SiL	L, SCL	SL,LfS, LS	fS, LcS, CL	Sa -C	
Coarse fragments (vol%)	0-5	5-15	15-30	30-50	>50	-
Soil depth (cm)	>90	90-75	75-50	50-40	40-20	<20
$CaCO_3$ (%)	0-21	21-23	23-32	32-40	40-50	>50
Gypsum(%)	0-1.6	1.6-3.5	3.5-8.5	8.5-15	15-18	>18
Soil fertility characteristics (f)						
Apparent CEC (cmol (+)/kg clay)	>24	24-16	<16(-)	<16(+)	-	-
pH H_2O	6.9-7.9	7.9-8.1	8.1-8.2	8.2-8.5	8.5-8.7	8.7
Organic carbon(%)	>0.1	0.1-0.5	0.5-0.3	.>0.3	-	-
Salinity and Alkalinity (n)						
ECe(dSm^{-1})	0-1	1-2.5	2.5-6	6-.10	10-19.5	>19.5
ESP	0-8	8-14	14-22	22-30	30-41	>41

Comparison of rating of land characteristics according to the above methods show that values of classes for each parameter are similar but not identical. Most of estimated values in the regression method are greater than ANN. The highest correlation belonged to high suitable classes and the least correlation belonged to not suitable classes. Studies have shown that rating of land characteristics and prediction of yield are more satisfactory using ANN compared to regression. Similar studies have also been conducted using ANN (Safa *et al.*, 2015; Nowroozi *et al.*, 2008; Eskandari *et al.*, 2015; Yaghmian and Samadzadeh, 2015; Sarmadian and Taghizadeh Mehrjardi, 2008; Sarmadian and Keshavarzi, 2010; Alvarez, 2009) and regression (Zeinadini, 2014; Zeinadiniand andMoghimi, 2008; Pettapiec, 1995; Olaleye, 2010).

In order to verify rating of land characteristics based on regression methods and ANN, parametric land suitability approach for 15 pedons located in corn fields was evaluated. Then, the coefficient of determination (R^2) between actual yield and land index (parametric approach) was determined. The results were analyzed.

Analysis of the results showed that the coefficient of determination of the land index with yield in regression method was 78% and in ANN was 81%, which were acceptable for rating. The results of land suitability evaluation indicated that the classes with actual yield are categorized in one unique class. Studies have shown that threshold limit, critical level and critical production (break-even production) are determined for some parameters for corn in very hot areas in Iran (Table 5).

Table 5. Threshold limit, critical level and break-even production for some important parameters for corn

critical production (break-even production)		threshold limit/ critical level		UNIT	Land Characteristics
regression	ANN	regression	ANN		
12	10	4	2.5	dSm^{-1}	EC
35	30	18	14	-	ESP
20	15	4	3.5	%	Gypsum
45	40	23	23	%	CCE
40	40	75	70	cm	Soil Depth
12	11	19	17.6	$mgkg^{-1}$	available phosphorus
195	190	270	250	$mgkg^{-1}$	available potassium
>1		>1.5		m	Ground Water Level

Threshold limit or critical level and critical production (break-even production) based on regression methods and ANN show that values of each parameter are not much different and are almost the same. However, the values estimated by the regression method are greater than ANN. Soil salinity threshold limits based on regression and ANN are 4 and 2.5 dSm^{-1}, respectively. Accordingly, 49% and 72% of soil salinity of the farms are greater than the threshold limit. Moreover, 21% and 23% of soil salinity of the fields are greater than the critical production based on regression and ANN. It should be noted that mean soil salinity of the soil in all farms is greater than the threshold limit. Therefore, this parameter is one of the main factors restricting production of crop in studied areas. It also contributes to non-suitable of corn production in some areas. Studies have shown that ESP also has a significant effect on yield and this parameter is greater than the threshold limit in 26% and 38% farms based on regression and ANN. Mean ESP is13, which is less than threshold limit. In addition, ESP is greater than break-even production in 7.6% and 12.3% of studied farms.

Gypsum ($CaSO_4.2H_2O$) negatively affects the yield and 60% of the fields are free of gypsum and 40% contain different amounts of gypsum. Gypsum is greater than threshold limit in 33% and 27% of total farms and greater than critical production in 6% and 9% of total farms based on regression methods and ANN.

Available phosphorus and available potassium are two important soil properties with positive effects on corn yield. Available phosphorus content is greater than critical level in 40% and 30% based on ANN and regression methods. Mean available phosphorus of the soil is 15.3 $mgkg^{-1}$. This element is less than break-even production in 38% and 34% of the farms based on ANN and regression method. Mean available potassium content of the farms is 224 $mgkg^{-1}$ and this element is less than break-even production in 31% and 27.6% of the farms.

4. Conclusion

The results showed that soil salinity and ESP have the highest negative effect and available phosphorus and potassium have positive effects on corn yield. Therefore, these parameters should be considered in management of the soils under cultivation. The results of rating land characteristics were satisfactory according to the regression method and ANN, although ANN method delivers more accurate results. In regression models, a weak correlation between two dependent variables always does not indicate that these two variables are not related to each other. In some cases, there may be a non-linear correlation between two variables, which cannot be measured by linear correlation coefficient. Since, it is essential to study land properties and land suitability studies for optimal use of production resources, especially in arid and semi-arid regions, it is suggested to optimize or modify the existing tables of crop requirements based on the local situation. Therefore, land suitability studies can be used to prepare modified tables for crop requirements.

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