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Soil and Topographic Attributes Affecting Rainfed Wheat Yield in a Semi-arid region of Iran

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ABSTRACT: The effects of topography and soil properties, as the most important parameters influencing crop production, need to be identified and considered in rainfed agricultural management. The objective of this research was to investigate the impact of topographic and soil properties on rainfed wheat yield, comparing Regression and Artificial Neural Networks methods, in Sisab region, North Khorasan province, Iran. Surface soil samples and wheat yield data were taken from 97 plots of 1×1 meter in a region with about 800 hectares area, and employing Digital Elevation Model and soil physical and chemical properties. Primary and secondary topographic attributes were also measured. The results showed that in comparison to MLR, ANN methods could provide better prediction of yield components. The multilayer perceptron model with 16-20-1 layout predicted 92% of the variance of wheat yield, while MLR models could explain about 40-43%. Based on the results of the sensitivity analysis of ANN models, gravel, soil organic matter and calcium carbonate equivalent from soil characteristics and surface curvature, topographic wetness index and elevation from topographic attributes were the main factors affecting yield variations.

Keywords: Artificial neural network, digital elevation model, modelling, sensitivity analysis, topographic properties.

INTRODUCTION

Determination of such factors affecting yield variations is crucial for improving agricultural productivity. On a local scale, soil and topographic properties are the main factors for maintaining a successful rainfed agriculture. Topography, one of the major soil forming factors, controls various soil properties (Florinsky *et al,* 2002). Variations in soil properties such as water redistribution, soil temperature, soil organic matter (SOM), nutrients availability and soil texture influence crop growth, especially in hilly areas (Dinaburga *et al,* 2010). A thorough understanding of the effects of soil properties on the performance of the strategic cereal crops in the semi-arid and arid regions provides valuable information for enhancing agricultural productivity (Ayoubi *et al,* 2009).

Modelling is a technique applied for better understanding of the relationships between soil, climate, and topographic properties and quality and quantity of agricultural products. It is also a reliable procedure to distinguish effective factors for crop growth and yield. Prediction of yield quantity can provide accurate information on the factors responsible for suitable growing of crops and it can help farmers and decision makers to select proper management options and minimize production risk. Multiple Linear Regression (MLR) (Jiang and Thelen, 2004), Principle Component Analysis (PCA) (Ayoubi *et al,* 2009), Factor Analysis (FA) (Kasper *et al,* 2003), Regression Tree (RT) (Park *et al,* 2005) and Artificial Neural Network (ANN) (Kaul *et al,* 2005; Green *et al,* 2007 and Norouzi *et al,* 2009) are commonly used methods for modelling yield components and recognizing factors that affect them.

Artificial neural networks (ANNs) constitute an information-processing paradigm that is inspired by biological nervous systems (Haykin,1994). The key element of this paradigm is the novel structure of the information processing system. It consists of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. An ANN is commonly divided into three or more layers: an input layer, a hidden layer(s), and an output layer. Each layer of the ANN is linked by weights determined by a learning algorithm. Green *et al* (2007) demonstrated the utility of ANN with topographic attributes that contain implicit soil and water information for estimating spatial patterns of rainfed wheat yield in the northeast of Colorado, USA.. Norouzi *et al* (2009) used the ANN in order to identify the most important topographic and soil attributes in undulating hillslope of western Iran, and found out that the ANN models could explain 89-95% of the total variability in wheat biomass, grain yield and grain protein content.. To predict the biomass and grain yield of barley from soil properties in the arid region of northern Iran, Ayoubi and Sahrawat (2011) designed ANN models and compared their performances with the earlier-tested statistical models based on multivariate regression.

Results showed that ANN models gave higher R2 and lower RMSE demonstrating that ANN is a more powerful tool than multivariate regression. Soares *et al* (2014) investigated the potential of using the culture's characteristics in predicting production responses by applying ANNs and MLR in banana plants cv. Tropical, and reported that the neural network is more accurate in forecasting the weight of the bunch than MLR (mean prediction error = 1.40, mean square deviation = 2.29 and R2 = 0.91).

Economically, wheat is an important crop cultivated in arid and semi-arid regions of Iran. Hence, it is essential to identify the soil and water limitations of this strategic product. Due to relatively suitable climatic conditions, North Khorasan province is one of the main regions with rainfed crop productions located in the northeastern of Iran. In this province, 49% of the irrigated and 56% of the rainfed agricultural areas have been allocated to wheat cultivation, producing about 16% of total irrigated and nearly 48% of total rainfed productions of the country (Ministry of Jihad-e-Agricultutre, 2011). Despite the importance of wheat in this part of Iran, to the best of our knowledge, no research has yet been made to identify factors affecting rainfed wheat yield. Therefore, the objective of this study was to find out the most important soil and topographic attributes which affect yield variations in Sisab, North Khorasan province, Iran and ultimately, compare the capability of ANN and MLR models.

MATERIALS AND METHODS

A. Description of the Study Area

An area of 800 hectares located at 57 36 to 57 40 E and 37 23 to 37 27 N in the rainfed cultivated lands of Sisab region, North Khorasan province, was selected (Fig. 1). Average elevation, mean annual temperature, and precipitation are 1278 m, 12.2 C, and 250 mm, respectively. Study area comprised of cretaceous orbitolinia limestone hilly lands that has been allocated to wheat and barley cultivation. Seedbed preparations included chisel plowing, each fall before planting of the crop. Fertilizer management consisted of the application of 60-20-40 kg (N-P-K) in the fall. Rainfed wheat (cv. Azar 2) growing period starts about the first week of October and after approximately 260 days of the growing season, finishes late in June. More than 85% of mean annual precipitation occurs during the growing period. Based on De Martonne index, the climate of the study region is semi-arid.

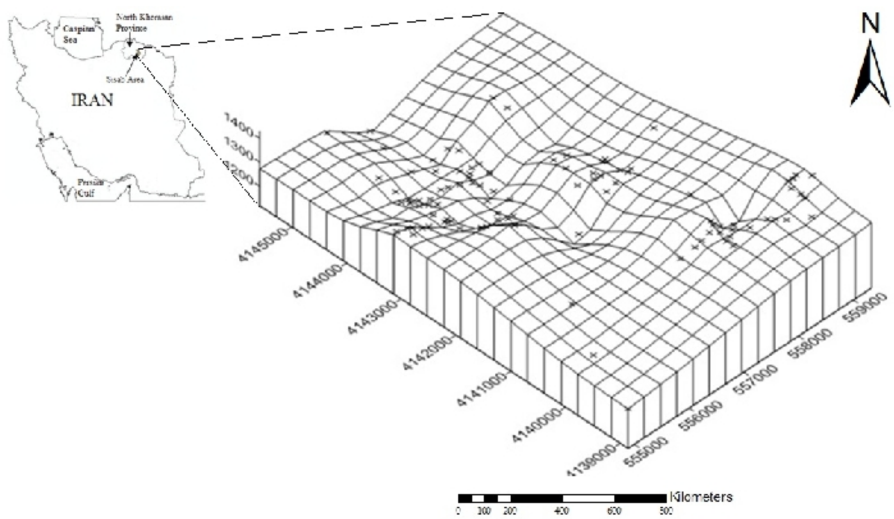

Fig. 1. Location of study area in northeastern Iran, showing the Sisab region and sampling points on a schematic three-dimensional topographic map.

B. Field and Laboratory Analyses

Wheat and soil samples were collected in July 2010 from 97 randomly selected 1×1 meters plots, as representative of different landscape positions. All of aboveground parts of wheat in each plot were harvested for measuring total and grain yield. At each plot, a composite soil sample was prepared from a depth of 0-30 cm for laboratory analyses. The air-dried soil samples were passed through a 2-mm sieve to remove gravel, roots, and large organic residues for selected chemical and physical measurements. Particle size distribution was measured using the hydrometer method (Gee and Bauder, 1986). Calcium carbonate equivalent (CCE) was also measured by Bernard's calcimeter method (Black *et al,* 1965). Soil organic matter (SOM) was determined using a wet combustion method (Nelson and Sommers, 1982) and total nitrogen (TN) was measured by the Kjeldhal method (Bremner and Mulvaney, 1982).

Available potassium (Kav) was measured using 1N ammonium acetate as the extractant (Richards, 1954) and available phosphorus (Pav) was measured as described by Olsen and Sommers (1982) . Soil pH was measured using a 1:2 soil/water ratio by a pH electrode (Maclean, 1982) and electrical conductivity (EC) was determined using an electrical conductivitymeter (Rhoades,1982).

C. Calculating Topographic Attributes

A 30 m cell size digital elevation model (DEM) was used to calculate the primary and secondary topographic indices. The primary derivatives including elevation, slope angle, aspect and mean curvature were extracted directly from DEM (Computation method is according to Hengl *et al* (2003) procedure) and the secondary derivatives were calculated from combination of the primary, applying both ArcGIS and ILWIS software.

Topographic wetness index (TWI), stream power index (SPI) and sediment transport index (STI) are the three hydrologically-based compound topographic indices that own the potential use for predicting the spatial distribution of soil properties and soil-specific crop management. Topographic wetness index has been used to characterize the spatial distribution of surface saturated zones and soil water content in different parts of landscapes. Greater and smaller values of TWI represent wetter and drier zones, respectively. Stream power index (SPI) is an expression of the erosive power of overland flows and is related closely to TWI. Zones with greater SPI values are more sensitive to erosion. Sediment transport index (STI) points out erosion and sedimentation procedures and mainly shows the effect of slope on erosion. This index is similar to the length-slope factor in the USLE, but is mainly applicable to three-dimensional landscapes (Wilson and Gallant, 2000)

D. MLR modelling

Pearson correlation matrix was established among soil and topographic parameters and rainfed wheat yield components. Stepwise MLR analysis was made using SPSS software to determine linear relationship between the studied attributes and the yield components. Soil and topographic features were considered as the independent variables and wheat yield components as the dependent ones. Kolmogorov-Smirnov (K-S) test was used for examining significance level of normalization of each variable. The variable with K-S values smaller than 0.05 were not normal, so it was necessary to make them normalize before MLR modelling.

E. ANN Modelling

For neural network analysis, the multilayer perceptron (MLP) with back-propagation learning rule was applied, which is the most commonly used neural network structure in ecological modelling and soil science (Boco *et al,* 2010; Tracy *et al,* 2011; Tajik *et al,* 2012 and Besalatpour *et al,* 2013). A total of 97 data sets were divided into three data sets for learning (61 data), validation (18 data), and testing (18 data) processes. The network was designed with 16 parameters (soil and topographic characteristics) as the input pattern and the yield components were used as the output pattern. Two networks were designed for estimation of total and grain yield, separately. The numbers of neurons were determined by trial and error and finally the model with the lowest RMSE, and the highest coefficient of determination (R2) was selected as the best-fit model. In this study, ANN models were performed using MATLAB software package (MATLAB version 7.6 with neural network toolbox). To avoid reduction in network speed and accuracy and to make data values equal, it was necessary to normalize input data. Hence, normalization was done so that obtained mean of the data series was 0.5 (Kumar *et al,* 2002). The following equation was used for normalizing data:

$$x_n = 0.5\left[\frac{x-\bar{x}}{x_{\max}-x_{\min}}\right]+0.5 \quad \ldots\text{(i)}$$

where x_n represents normalized value, x denotes actual value, represents mean value, x_{min} denotes minimum value and x_{max} is maximum value of parameter.

The performances of the developed models were evaluated using various standard statistical performance evaluation criteria. The statistical measures used in this study included the root mean square error (RMSE), and correlation coefficient (R2) between the measured and the predicted yield values. The RMSE and R2statistics are defined as:

$$RMSE = \sqrt{\frac{1}{n}\left[\sum_{i=1}^{n}\left(Z^{*}-Z\right)^{2}\right]} \quad \ldots\text{(ii)}$$

$$R^2 = 1-\frac{\sum_{i=1}^{n}[Z^{*}-Z]^2}{\sum_{i=1}^{n}[Z-\bar{Z}]^2} \qquad \ldots\text{(iii)}$$

where Z* and Z are the estimated and the actual values of observation respectively, is the mean of actual values, and n is the total number of observations.

In order to identify the most important soil and topographic characteristics affecting wheat yield components, sensitivity analysis was done using the Stat Soft method (Statsoft Inc, 2004). A relative sensitivity coefficient was calculated as the ratio of the total network error with and without the presence of the given variable. The higher this ratio, the greater the importance of the variable (Ayoubi and Sahrawat, 2011; Norouzi *et al,* 2009 and Miao *et al,* 20006).

RESULTS AND DISCUSSION

A. Descriptive statistics

The descriptive statistics of soil and topographic parameters and yield components are given in Table 1. Results of normalization by K-S test are presented in Table 1. Abnormal variables (K-S value < 0.05) became normal by logarithm function.

B. Relationship between Soil and Topographic Properties with Yield Components

The correlation coefficients of soil and topographic attributes with yield components are given in Table 2. Among soil properties, gravel and CCE have the highest negative correlation with yield components.

Table 1: Statistical parameters of rainfed wheat yield components and soil and topographic properties (n=97).

Parameter	Clay	Gravel	SOM	CCE	TN	Pav	Kav	EC	pH	Curvature	Elevation	Aspect	Slope	SPI	STI	TWI	Total Yield	Grain Yield
Unit	%				mg kg^{-1}			dS m^{-1}		m $^{-1}$	m	RAD	%				t ha^{-1}	
Mean	12.9	18.4	1.3	27.9	0.06	6.9	203.3	0.3	7.8	-0.05	1289.7	2.36	10.2	1940.9	84.1	10.3	5.98	1.82
Max	21.1	29.0	2.7	49.4	0.12	22.7	712.5	0.6	8.1	0.67	1429.0	6.25	26.4	27731.3	492.8	17	10.55	3.17
Min	8.0	9.0	0.7	13.4	0.03	2.6	108.0	0.2	7.5	-1.33	1114.0	0.02	2.5	18.1	1.3	6.6	2.32	0.43
Range	13.1	20.0	2.0	36.0	0.09	20.1	604.5	0.4	0.6	2.0	315.0	6.23	23.9	27713.2	491.5	10.4	8.23	2.74
K-S value	0.055	0.317	0.030	0.076	0.093	0.018	0.004	0.003	0.343	0.059	0.501	0.004	0.385	0.000	0.002	0.004	0.688	0.887

CCE: Calcium Carbonate Equivalent, SOM: Soil Organic Matter, SPI: Stream Power Index, STI: Sediment Transport Index, TWI: Topographic Wetness Index, TN: Total Nitrogen, P_{ave}: Available Phosphorus, K_{ave}: Available Potassium

Table 2: Correlation coefficients between rainfed wheat yield components, soil properties and topographic attributes (n=97).

Parameter	Clay	Gravel	SOM	CCE	TN	Pav	Kav	EC	pH	SPI	STI	TWI	Curvature	Elevation	Aspect	Slope
Unit	%				mg kg^{-1}			dSm^{-1}					m^{-1}	m	RAD	%
Total Yield	0.28^{*}	-0.36^{**}	0.27^{*}	-0.45^{**}	-0.20^{*}	0.09	0.17	0.12	-0.24^{*}	0.15	-0.08	0.33^{**}	-0.26^{**}	-0.45^{**}	0.10	-0.23^{*}
Grain Yield	0.24^{*}	-0.3^{5**}	0.20^{*}	-0.42^{**}	-0.21^{*}	0.10	0.14	0.19	-0.26^{*}	0.18	-0.06	0.36^{**}	-0.24^{**}	-0.43^{**}	0.14	-0.19

**:Significant at 1 % probability level, *: Significant at 5 % probability level, CCE: Calcium Carbonate Equivalent, SOM: Soil Organic Matter, TN: Total Nitrogen, P_{ave}: Available Phosphorus, K_{ave}: Available Potassium, SPI: Stream Power Index, STI: Sediment Transport Index, TWI: Topographic Wetness Index

Calcium carbonate influences aggregate stability, improves infiltration capacity and accordingly decreases soil erodibility; but reversely, high amount of CCE decreases nutrient absorption capability especially micronutrients (Motallebi *et al,* 2011). It seems that high amount of CCE in the studied soils has left its effect on yield by reducing the availability of nutrients (Table 1). Gravel has a negative impact on water retention and supply of nutrients in soil. Masoni *et al* (2008) related similar negative correlation to dilution effect of gravel and decreasing the effective volume of soil. The highest correlations of yield components and topographic attributes belonged to elevation and TWI, but it was negative for elevation and positive for TWI. Difference in altitude creates various hydrological and thermal regimes. Several studies have reported that areas with lower elevation have more fertile soils and subsequently greater crop yield (Jiang and Thelen,2004; Kumhalova *et al,* 2008 and Souza *et al,* 2010)

The high positive correlation between yield and TWI in the current study indicates that water availability is one of the most important yield-affecting factors (Table 2). Si and Farrell (2004) indicated that TWI explained 46% of the total variation of wheat grain yield. In the east-central Mississippi, USA, Iqbal *et al* (2005)observed that TWI was positively correlated with cotton lint yield.

C. Modelling and Validation of Yield Prediction

Regression analysis equations and validation results of wheat yield components are shown in Table 3. The CCE and SOM out of soil properties and elevation, slope and TWI from topographic attributes contribute in the models. Therefore, MLR models explained 42.6% of total yield variation and 39.6% of total grain variation.

Table 3: Multiple linear regression (MLR) models for rainfed wheat yield components.

MLR Model	R^2	RMSE
Total Yield (t ha^{-1}) = 18.033 - 0.070 (CCE**) – 0.008 (Elev**) + 3.557 (SOM*) – 0.086 (Slope*)	0.426**	1.84
Grain Yield (t ha^{-1}) =5.321 - 0.003 (Elev**) + 1.588 (SOM**) + 0.086 (TWI*)	0.396**	0.56

**:Significant at 1 % probability level, *: Significant at 5 % probability level, CCE: Calcium Carbonate Equivalent, Elev: Elevation, SOM: Soil Organic Matter, TWI: Topographic Wetness Index

Parameters of the best structure for ANN model were derived in order to predict rainfed wheat yield components. Each model consists of 16 nodes within the input layer (soil and topographic properties) and 1 node in the output layer (yield component). Numbers of nodes in the hidden layer for total and grain yield components and optimum iteration were 20 and 1000, respectively; and hyperbolic tangent was the most efficient transfer function.

D. Comparing ANN and MLR Models

In order to evaluate and compare the performance of ANN and MLR models, rainfed wheat yield components values were predicted and plotted against observed values (Fig. 2). Values of R2 and RMSE for prediction of total yield by ANN model are 0.92 and 0.039 whereas for MLR models, they are 0.426 and 1.84, respectively. Similarly, for the grain yield, ANN model resulted in R2 and RMSE of 0.921 and 0.164 versus 0.396 and 0.56 for MLR models, respectively. Kaul *et al* (2005) observed that ANN models consistently resulted in more accurate yield predictions than MLR models. R2 and RMSEs for soybean yield prediction by ANN model were calculated as 0.81 and 214 in contrast to 0.46 and 312 for MLR model

High values of R2 and low values of RMSE mean a more accurate modelling. Comparing Figures 2 (a) and (b) indicates that ANN is more powerful than MLR model in predicting rainfed wheat yield components. Also, distribution of dots below the line X=Y in Fig. 2 represents an underestimation of MLR model. The inability of regression analysis to consider the complex nonlinear relationships between yield components and independent variables may be the main reason accounted for the failure of regression modelling. Park et al (2005) concluded that the linear models have the weakest capability for maize yield prediction modelling under different soil and land management practices, although ANN models are more efficient for predicting crop yield, mainly due to considering nonlinear relationships and having less sensitivity to errors in input data. In this study, the MLP model predicted 92% of the variance of wheat yield, while MLR models could explain approximately 40-43%.

More appropriate results of ANN compared to MLR is a proxy of the nonlinear relationships between the soil and topography variables and crop yield. By using the ANN models, 8 percent of the variability of wheat yield components remained unexplained. This could have been affected by other factors such as management practices and the availability of micronutrients, which were not quantified in the study. Results of Ayoubi and Sahrawat (2011) indicated that the ANN models could explain 93 and 89% of the total variability in barley biomass and grain yield, respectively.

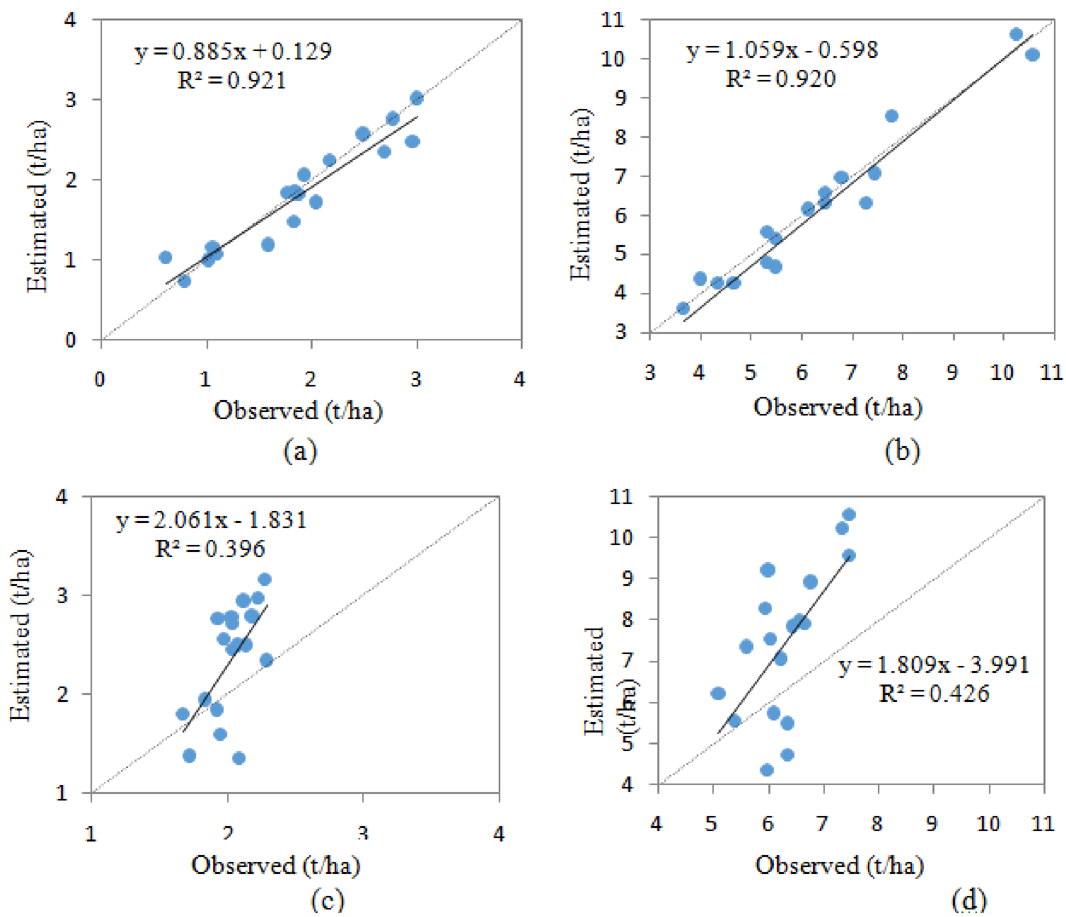

Fig. 2. Observed and estimated values for a) grain yield using artificial neural network, b) total yield using artificial neural network, c) grain yield using multiple linear regression, d) total yield using multiple linear regression.

E. Sensitivity Analysis Results and Effective Factors on Yield Components

Sensitivity analysis results for rainfed wheat yield components are given in Fig. 3. Of the topographic properties, surface curvature, TWI, and elevation; and from soil attributes, gravel percentage, SOM content and CCE were the most important parameters affecting yield components variability in the study region.

Surface curvature was identified as the most important parameter affecting wheat yield components in the Sisab region (Fig. 3). Landscape curvature influences concentration or diffusion of surface water flow. In other words, surface curvature indirectly represents soil moisture storage for crop growth (Dinaburga *et al*, 2010).

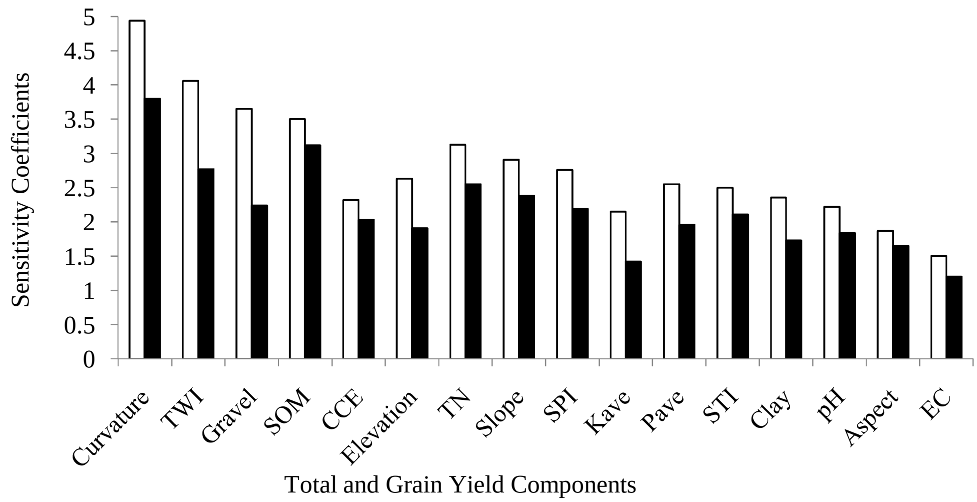

Fig. 3. Total (black bars) and grain (white bars) yield components of wheat sensitivity coefficients histogram; TWI: Topographic Wetness Index, SOM: Soil Organic Matter, CCE: Calcium Carbonate Equivalent, SPI: Stream Power Index, STI: Sediment Transport Index.

In the study area, it seems that the consistent factors related to landscape positions, mainly explain yield variability. According to sensitivity analysis results of ANN model, 4 out of 7 parameters including surface curvature, TWI, elevation, and slope which are considered as the topographic attributes are on the top ranks of sensitivity analysis (Fig. 3). It means that water movement, sedimentation, hydrological and erosional procedures have significant relationship with considerable amount of yield components variability in Sisab region. In other words, surface curvature and TWI, which are related to moisture distribution on the landscape surface and slope that affect the erosional processes, have been recognized as the most important factors influencing variability of yield components of rainfed wheat. Mehnatkesh et al (2013) showed that slope, TWI, catchment area, and STI are the most important variables of topography for explaining variability in soil depth, and consequently crop yields..

After analyzing the sensitivity of ANN model, Miao et al (2006) reported that cation-exchange capacity (CEC) and relative elevation were consistently identified among the top four most important soil and landscape factors for both corn yield and quality in a study performed at two field sites in Illinois. In this regard Ayoubi et al (2014) indicated that out of topographic properties, TWI and curvature had the greatest impact on the quality of wheat grain in the hilly regions of western Iran, proving our results regarding the importance of processes controlling soil water distribution.

CONCLUSION

Information on spatial variability in wheat yield is beneficial for developing site-specific management practices. This study was conducted to compare the ability of linear and nonlinear functions in order to predict wheat yield components from soil and topographic properties in Sisab region, Iran. The obtained results showed that the ANN models were more powerful tools than MLR to establish the relationships between the soil and topographic properties and wheat yield components. Sensitivity analysis for ANN models indicated that gravel percentage, SOM, and calcium carbonate from soil characteristics and surface curvature, TWI and elevation from topographic properties are the most important parameters affecting yield components. In general, yield variability have been influenced by five parameters including elevation, curvature, TWI, SOM and CCE; moreover, sensitivity analysis coefficients represented surface curvature as the main parameter for explaining yield variability in the study area. Finally, knowing the fact that water availability is the most crucial factor controlling crop yield in this region, the lands should be managed in a proper way to save the water available in the soil as long as possible.

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