ISSN (Print) : 0974-6846
Indian Journal of Science and Technology, *Vol 8(28), DOI: 10.17485/ijst/2015/v8i28/83328, October 2015* ISSN (Online) : 0974-5645

Predicting Cation Exchange Capacity by Artificial Neural Network and Multiple Linear Regression using Terrain and Soil Characteristics

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Abstract

This research was an attempt to investigate the capability of using attributes derived from digital elevation model together with easily/readily obtainable soil properties for estimating Cation Exchange Capacity (CEC) of soils. The study area was located in hilly lands of Lordegan region, west of Iran. Soil samples were collected from 130 points with 0-30 cm depth. Modeling was performed applying the artificial neural networks and regression pedotransfer functions and three models with different inputs (soil properties, topographic properties and both of them) were used. The results showed the efficacy of models when using soil and topographic attributes alone, do not have much difference, while utilization of both soil and topographic characteristics was improved the precision of models in both methods which was more sensible for neural networks. Moreover, the results of quantifying variables importance employing connection weight method were implied that four parameters comprising topographic wetness index, slope, surface curvature and aspect had the highest contribution in CEC variation in the study area. Furthermore, the results of current research support this idea that soil attributes are highly controlled by topographic properties and affected by water movement, hydrological and erosional processes and also microclimate variation caused by topographic features. Thus, topographic data could be used with high confidence in order to predict soil characteristics such as CEC in Lordegan region.

Keywords: CEC, Modeling, Sensitivity Analysis, Topographic Attributes

1. Introduction

Cation Exchange Capacity (CEC) is one of the most important chemical properties of soil that plays an influential role in adsorbing and releasing the majority of required plant nutrients and estimating potential risk of heavy metals. Moreover, CEC is a vital feature of soil in order to forecast its quality and capability for degrading some pollutants in environment[1], considered as an important soil attribute required in soil databases, and used as input in soil and environmental models[2]. Additionally, it is a solid index to determine the quality and productivity of soil, and its values depend on the amount of Organic Matter (OM), the percentage and the type of clay and soil conditions. Although it is possible to measure CEC directly, this measurement is erroneous, particularly in aridisols of Iran having high amounts of calcium and gypsum[3]. On the other hand, CEC measurement is time-consuming and costly. Hence, it seems crucial to use indirect methods needing less time and cost while having sufficient accuracy for estimating CEC from other easily-obtainable properties. One of these methods is developing pedotransfer functions (PTFs) that predict difficult-to-obtain attributes from easily-obtainable properties[4]. Recently, attempts were made to use new methods and techniques for modeling such functions, and utilizing artificial neural networks (ANNs) is a recent approach of PTFs modeling to encounter the uncertain and dynamic properties and vague relationships in natural systems (e.g. soil). Data of terrain attributes in mountainous regions are of easily-obtainable properties that could be used to estimate difficult-to-obtain features in regression-based soil

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PTFs or computational intelligence-based methods. In such regions there is a close relationship between soil and topographic properties and topography is often applied in soil studies comprising modeling and forecasting soil attributes, and highly affects other soil formation factors[5]. Obtaining easily and low variability with time, comparing to dynamic soil properties, are important advantages of topographic data. Consequently, there is an increasing interest in connecting soil attributes to topographic data[6]. In other words, knowing the patterns of soil properties distribution regarding landscape characteristics considered as an effective stage in order to improve the accuracy of predicting soil attributes[7].

Various researchers have been studied PTFs for relationship of CEC and easily-obtainable properties of soil like clay (%) and OM[3,8-12], however, even though terrain attributes calculations are more simple and cheaper, there is not much research allocated to use these properties for estimating CEC or improving available models. This study was an attempt to develop CEC modeling using not only easily-obtainable properties of soil, which used mostly in previous studies, but also the efficacy of terrain surface parameters solely or in cooperation with soil attributes. Moreover, performing sensitivity analysis of the best model, the most important effective parameters on CEC variances were introduced in the study area.

2. Materials and Methods

2.1 Description of the Study Area

The research site lies between the 49° 55' and 50° 34' east longitudes and the 30° 55' and 31° 26' north latitudes in Lordegan, Chaharmahal-Bakhtiari province, west of Iran (Figure 1). The area has about 1800 m of elevation above the sea level in the central Zagrous Mountain. The average yearly temperature and rainfall are 14.9°C and 500 mm, respectively with warm summers, cold winters and semi-humid climate[13].

Figure 1. Location of the study area, Lordegan in Chaharmahal-Bakhtiari province, west of Iran.

2.2 Soil Sampling and Laboratory Analysis

Sampling units were defined on the basis of landscape position in the hill slopes. A total of 130 surface (0-30 cm) soil samples were obtained. To reduce micro-variability, at each point three sub-samples were collected and made into one composite sample. Prior to analyses, the soil was air-dried and ground to pass through a 2-mm sieve for removing stones, roots, and large organic residues to prepare for chemical and physical measurements. Particle size distribution was measured using the hydrometer method[14]. Soil organic matter (SOM) was determined using a wet combustion method[15]. Soil pH was measured in saturated paste using a pH electrode[16], and CEC was determined using 1N sodium acetate[17].

2.3 Digital Terrain Modeling (DTM)

Digital elevation model (DEM) were created by using a 1:25000 topography map with 10 m elevation resolution. The raster format of DEM was produced utilizing interpolation algorithm in ILWIS software[18]. Topographic indices comprised of primary and secondary indices. Primary indices (elevation, slope, length of slope, aspect and mean curvature) were calculated directly from DEM with ILWIS and DIGEM softwares (http//:www.geogr.uni-goetingen.de/pg/saga/digem), and secondary index (topographic wetness index) was calculated from combinations of the primary indices. The topographic wetness index (TWI) is defined as the ratio of specific catchment area to slope gradient and indicates the spatial distribution of zone surface saturation and soil water content in landscape. It is calculated by Equation (1).

$$TWI = A_s / \tan \beta \tag{1}$$

Where A_s and β are specific catchment area and slope degree, respectively.

2.4 Descriptive Statistical Analysis

Descriptive statistics of the experimental data including mean, minimum, maximum, and skewness were determined using SPSS statistical software (IBM Com., Chicago, USA). Coefficient of Variation (CV) was calculated to estimate and explain the variability of the selected soil and topographic variables. Correlation coefficients were computed to define relationships between soil and terrain attributes with CEC using the SPSS.

2.5 Multiple Linear Regression (MLR)

Linear regression is one of the oldest statistical techniques, and has long been used in biological research[19]. The basic linear regression model has the following form:

$$Y = \propto + X_T \beta + \varepsilon \tag{2}$$

where Y denotes the dependent variable, α is a constant called the intercept, $X_T = (X_1,\ldots,X_n)$ is a vector of explanatory variables, $\beta = (\beta_1,\ldots,\beta_n)$ is the vector of regression coefficients (one for each explanatory variable) and ε represents randomly measured errors as well as any other variation not explained by the linear model. To determine the best linear regression model for estimating CEC in this study, 3 models were considered. The first one developed using solely soil properties (percentage of soil particles, OM and pH). Topographic attributes comprising elevation, slope degree, length of slope, aspect, surface curvature and TWI, were the inputs for the second model. All mentioned variables (topographic and soil features) were entered the last model, simultaneously. Moreover, prior to modeling, 85% of data (110 samples) were selected for modeling procedure and 15% (20 samples) for model testing.

One of the assumptions in multiple linear regression is not existing a collinear relation between independent variables. Variance inflation factor (VIF) is an index that uses for collinear determination was obtained. If there is no linear relationship between independent variables, VIF value will be one and the deviation of this factor from 1 reveals the tendency to collinearity. Having VIF values more than 10 for each variable show the multiple collinearity and it may be resulted in problems in estimations[20]. SPSS was used for developing multiple linear regression models.

2.6 ANN Modeling

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 modeling and soil science[11,21]. A total of 130 data sets were divided into three data sets for learning (90 data), validation (20 data), and testing (20 data) processes. Three models were considered for ANN modeling, similar to regression models design.

The number of neurons in MLP were determined by trial and error and finally the model with the lowest root mean square error (RMSE) and the highest coefficient of determination (R^2) 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 also to make data values equal, it is necessary to normalize input data. Hence, normalization was done so that the obtained mean value of the data series was 0.5[22]. The following equation was used for normalizing data:

$$x_n = 0.5\left[\frac{x - \bar{x}}{x_{\max} - x_{\min}}\right] + 0.5 \tag{3}$$

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

The performance of the developed models has been evaluated using various standard statistical performance evaluation criteria. The statistical measures used in this study were RMSE and R^2 (calculated between the measured and the predicted yield values) (equations 4 and 5).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z^* - Z_i)^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Z^* - Z_i)^2}{\sum_{i=1}^{n}(Z_i - Z_m)^2} \tag{5}$$

Where Z^* and Z_i are the estimated and actual values of observations, respectively, Z_m is the mean of actual values, and n denotes the total number of observations.

2.7 Sensitivity Analysis for Quantifying Variable Importance

Prediction accuracy is a major benefit of ANN models, but the ANN models of any physical processes are purely black box models, which do not explain the process being simulated and whose utility is limited, without information regarding the relative importance of the parameters in the system. The development of a method to couple input factors to meaningful outputs in ANN models is of critical importance[23]. The data employed for developing

ANN models do contain important information regarding the physical process being simulated[24].

A connection weight approach was used to evaluate the importance of inputs relative to output in ANNs. The connection weight method is to sum the products of the input-hidden and the hidden-output connection weights between each input neuron and output neuron for all input variables. The relative contributions of the inputs to the output are dependent on the magnitude and direction of the connection weights[25]. The larger the sum of the connection weights, the greater the importance of the variable. The relative importance of input variable i was determined through the following formula:

$$RI_i = \frac{\sum_{j=1}^{m} W_{ij} W_{jk}}{\sum_{i=1}^{n} \sum_{j=1}^{m} W_{ij} W_{jk}} \times 100 \qquad (6)$$

where: RI_i: relative importance of the variable i (I = 1, 2, 3, …, n) in the input layer on the output variable (%), j: index number of the hidden node (j =1, 2, 3, …, m), W_{ij}: connection weight between input variable i and hidden node j, W_{jk}: connection weight between hidden node j and the output node k.

The whole computation was repeated for each output neuron.

3. Results and Discussion

The descriptive statistics of soil and topographic properties (maximum, minimum, mean, coefficient of variation and skewness of all data) are given in Table 1 and 2.

Table 1. Summary of statistics for soil attributes in the study area (n=130)

CV (%)	Skewness	Mean	Max.	Min.	Unit	Soil Properties
23.41	0.89	25.39	58.48	12.64	%	Sand
15.12	−0.47	42.14	56.27	22.93	%	Silt
18.44	−0.51	32.42	46.09	17.5	%	Clay
36.58	−0.47	1.23	2.27	0.11	%	OM
2.34	−0.4	7.8	8.16	7.4	-	pH
25.33	−0.42	26.17	38.23	10.7	Cmol kg^{-1}	CEC

OM: Organic matter, CEC: Cation exchange capacity, CV: Coefficient of variation

Table 2. Summary of statistics for topographic attributes in the study area (n=130)

CV (%)	Skewness	Mean	Max.	Min.	Unit	Topographic Properties
11.36	0.65	1816	1884	1764	m	Elevation
39.63	0.73	16.43	40.1	4.8	%	Slope
42.05	0.98	11.7	28.81	2.22	m	Length of slope
36.25	−0.187	1.6	2.69	0.39	Rad	Aspect
61.87	−0.064	-0.016	0.03	−0.04	m^{-1}	Curvature
26.35	0.075	7.21	12.15	3.33	-	TWI

TWI: Topographic wetness index, CV: Coefficient of variation.

The skewness values, ranging from −1 to +1 confirmed that all the variables were normally distributed. Coefficient of Variation (CV) was calculated to describe the variance in selected variables. The CV values of soil properties ranged from 2.34 for soil pH to 36.58 for Organic Matter (OM) in the study area. The high value of OM in this research could be due to its dynamic nature and dependency on soil fertility, localized vegetation and water availability.

Correlation coefficient among CEC and soil and topographic properties are displayed in Table 3. From soil properties, OM (r = 0.67) and clay percentage (r = 0.55) had the highest positive correlation with CEC in Lordegan region. In addition, a significant negative correlation was obtained for CEC with sand percentage and pH. Amini et al. (3) and Memarian Fard and Beigi Harchagani[26] were reported significant correlation for CEC with clay percentage and OM. Xiao-rong et al.[27] in their research showed that CEC related negatively with pH and positively with OM. They reported that accumulation and degradation of OM could be resulted to releasing the organic and inorganic acids in soils and consequently decreasing the soil pH, wherever OM and CEC are rather high. The negative significant correlation between pH and CEC in this study explains based on the observed negative correlation of pH and OM (r = -0.38). The highest observed correlation between CEC and topographic attributes in the current study was attributed to elevation (r = -0.48) and TWI (r = 0.46), which seems that related to negative correlation of elevation with OM and clay percentage, along with positive correlation of TWI with these two variables (Table 3). There are a plenty of studies that reported positive correlation between TWI and soil OM[28-31]. The observed significant negative correlation between CEC and surface curvature in the study area implied the accumulation of clay and OM and accordingly increase in CEC in concave regions.

Negative correlation between degree and length of slope with CEC demonstrated more erosion in lengthy and steep slopes that resulted in decreasing soil CEC. Kravchenko and Bullock[32] reported significant negative correlation among CEC and slope, curvature and elevation. In Ongsomwang and Rattanakom[7] research, elevation, slope, aspect, curvature and TWI showed significant correlations with CEC in surface and subsurface soil. Johnson et al.[33] found that CEC correlated negatively with elevation and slope, while correlated positively with TWI. The CEC values were significantly greater in northern slopes comparing with the southern, in the study area, which positive correlation of OM and clay percentage with aspect supports it.

3.1 Regression Modeling Results

Prior to calculation of regression equation, it should be verified the assumption of coefficients significance for independent variables and interception, which was done utilizing the t test in this research. Based on p-values (<0.01) resulted from this test, it could be said with confidence of 99% that the mentioned coefficients are not zero and are equal to the estimated values in the Table 4.

Table 3. Pair wise correlation coefficients among CEC and soil and topographic attributes in the study site (n=130)

	pH	OM	Clay	Silt	Sand	TWI	Curvature	Aspect	LS	Slope	Elevation	CEC
pH	1											
OM	−0.38**	1										
Clay	−0.33**	0.75**	1									
Silt	−0.04	0.08	−0.01	1								
Sand	0.2*	−0.58**	−0.63**	−0.7**	1							
TWI	−0.17	0.48**	0.35**	−0.2*	−0.2*	1						
Curvature	0.27**	−0.44**	−0.36**	0. 1	0.2*	−0.58**	1					
Aspect	−0.18*	0.51**	0.2*	0.11	−0.21*	0.32**	−0.14	1				
LS	0.14	−0.47**	−0.3**	−0.06	0.26**	−0.56**	0.18	−0.16	1			
Slope	0.1	−0.5**	−0.32**	0.03	0.21*	−0.52**	0.2*	−0.21*	0.64**	1		
Elevation	0.15	−0.2*	−0.24**	−0.07	0.25**	−0.42	0.21*	−0.1	0.4**	0.21*	1	
CEC	−0.37**	0.67**	0.55**	0.03	−0.42**	0.46**	−0.44**	0.38**	−0.41**	−0.44**	−0.48**	1

**, *: Correlation is significant at the 0.01 and 0.05 level, respectively, OM: Organic matter, LS: Length of slope, TWI: Topographic wetness index, CEC: Cation exchange capacity

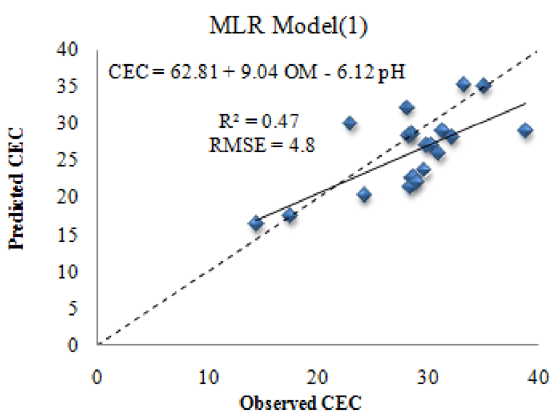
Table 4. Coefficients of regression relations and results of their significance test (n=110)

Model	Inputs	Function	Standardized Coefficients	Unstandardized Coefficients (Beta)	p-value	VIF
(1)	Soil attributes	Constant	62.81	-	0.002	-
		OM	9.04	0.61	0.000	1.12
		pH	−6.12	0.17	0.015	1.12
(2)	Topographic attributes	Constant	174.27	-	0.000	-
		Curvature	−179.97	−0.27	0.001	1.39
		Elevation	−0.08	−0.29	0.000	1.16
		Aspect	2.95	0.23	0.001	1.09
		Slope	−0.23	−0.22	0.003	1.27
(3)	Soil and topographic attributes	Constant	141.83	-	0.000	-
		OM	7.44	0.503	0.000	1.26
		Elevation	−0.07	−0.25	0.000	1.17
		Curvature	−148.21	0.22	0.001	1.34

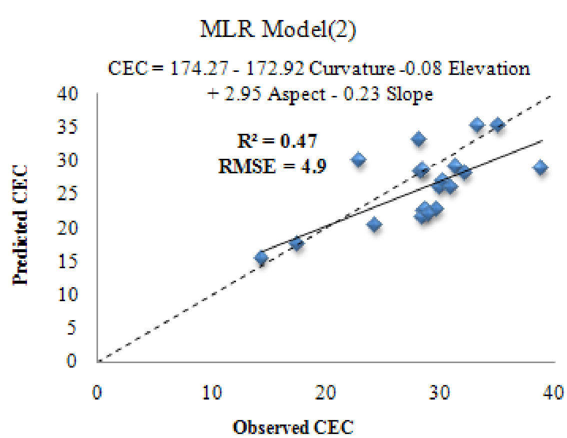
VIF: Variance inflation factor, OM: Organic matter

The VIF values in Table 4. represent that there is no collinearity between the independent variables. Unstandardized coefficients for regression influence (Beta) define the relative contribution of each independent variable in determining the independent variable variances. The high value of beta is, the more its contribution in predicting the dependent variable variations[34-36]. The values of beta in Table 4. show that OM in the first and third model and elevation in the second model are the most important factors for explaining the CEC variability. The scatter plots for measured values of CEC against its predicted values for the test data set are given in Figure 2. for the three MLR models. Regression models and the results of their validation (R^2 and RMSE values) are presented in Figure 2.

As it can be seen from Figure 2, 47% of CEC variability was explained by OM percentage and pH in regression model 1 and 47% by elevation, surface curvature, aspect and slope in regression model 2. The OM percentage out



(a)



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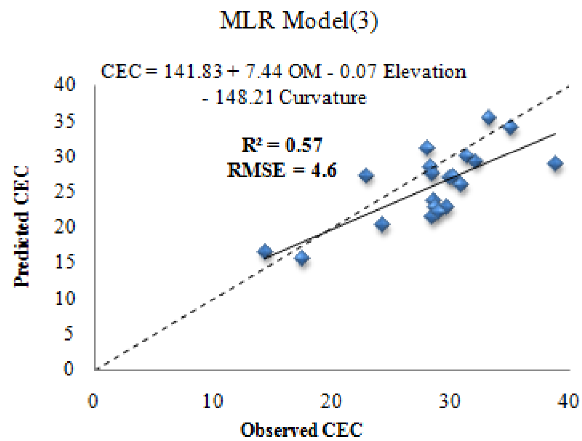


(c)

Figure 2. The scatter plots of measured versus predicted values of CEC for MLR models **(a)** soil attributes as input data, **(b)** topographic attributes as input data, **(c)** soil and topographic attributes as input data.

of soil properties and elevation and surface curvature from topographic attributes were contributed in the model 3. The simultaneous use of soil and topographic properties in this model was increased slightly the model accuracy, however, more than 40% of variances were not considered in this model ($R^2 = 0.57$) yet. This result supports the idea of using function fitting methods that are capable of explaining the complicated structure of natural systems such as soil in such conditions. Ongsomwang and Rattanakom[7] suggested regression models to estimate topsoil and subsoil CEC utilizing DEM variables, rainfall and normalized difference vegetation index. Their models were explained 77 to 85% of CEC variances.

3.2 Artificial Neural Network Model Results

The characteristics of the best structures for MLP network that could be used to predict CEC in the study area are presented in Table 5.

The first model comprised of 5 neurons (sand, silt, clay percentage, OM and pH), the second one has 6 neurons (elevation, aspect, slope length and degree, surface curvature and TWI), and the last model has all 11 variables in input layer. The optimum number of neurons in hidden layer for models 1, 2 and 3 were estimated 8, 10 and 15, respectively. Additionally, the most efficient activity function in hidden layer of the first and third models was sigmoid and in the second one was hyperbolic tangent.

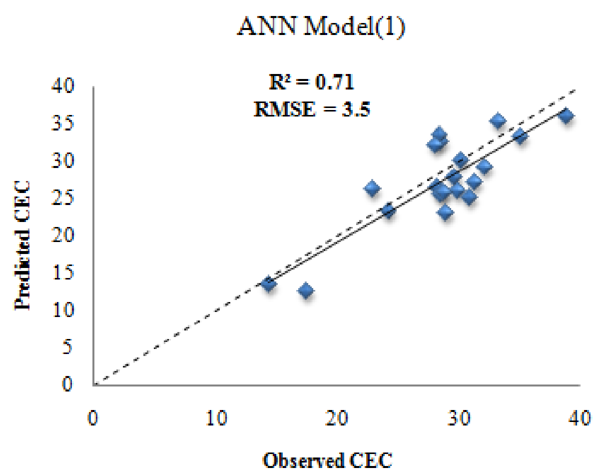
The scatter plots for measured values of CEC against its predicted values for the test dataset are given in Figure 3. for the three MLP networks, along with the results of models validating (R^2 and RMSE values).

According to results displayed in Figure 3, simultaneous application of soil and topographic properties in MLP network was improved noticeably the accuracy of CEC

Table 5. Characteristics of the best layout for MLP network

Model	NIL	NHL	NOL	HLF	OLF
(1)	5	8	1	Sigmoid	Linear
(2)	6	10	1	Hyperbolic tangent	Linear
(3)	11	15	1	Sigmoid	Linear

NIL: Number of neurons in input layer, NHL: Number of neurons in hidden layer, NOL: Number of neurons in output layer, HLF: Hidden layer function, OLF: Output layer function



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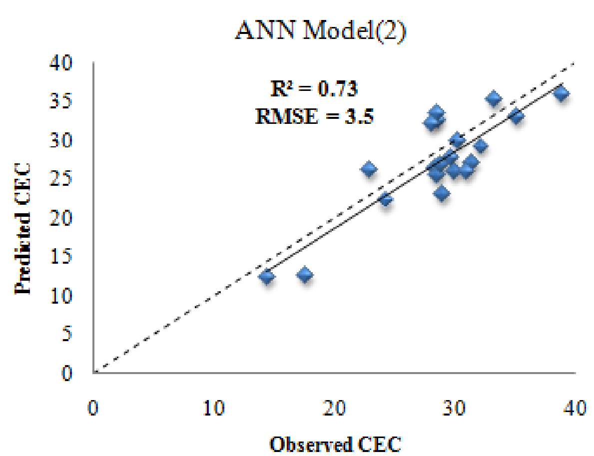

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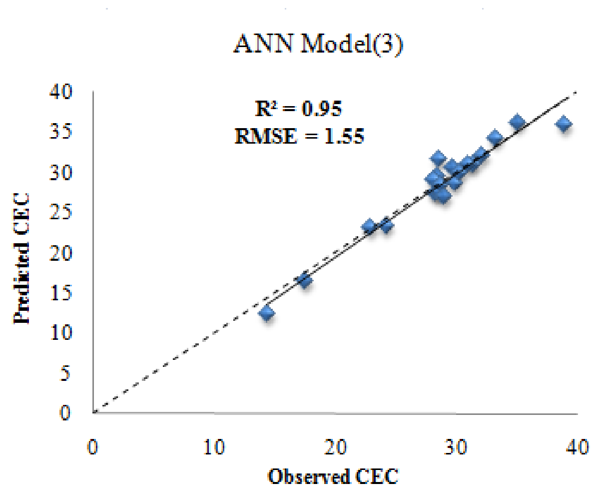

(c)

Figure 3. The scatter plots of measured versus predicted values of CEC for MLP models **(a)** soil attributes as input data, **(b)** topographic attributes as input data, **(c)** soil and topographic attributes as input data.

estimation (R^2 increased from nearly 70% for model 1 and 2 to 95% for model 3). Furthermore, RMSE in the third model is lower than half of that in the first and second models.

3.3 Comparing the Results of Regression Models and ANNs

Results presented in Table 6. indicate that MLP network is more powerful than MLR model for predicting CEC in the study area.

The efficacy of models 1 and 2 in each used methods (MLR and MLP) is not so different from the other one (Table 6). In other words, topographic attributes could be employed as precise as soil properties in order to estimate CEC. On the other hand, concurrent utilization of both soil and topographic characteristics (model 3) was improved the precision of models in both methods, which was more apparent for ANN and supports its better performance encountering complicated problems. To sum up, with increasing model inputs and consequently increasing the complexity of their relations, ANNs showed much better performance. Amini et al.[3] were estimated CEC in the central region of Iran using soil OM and clay contents. They used the ANN model and five other regression-based experimental models. Their results showed that MLP network with eight hidden neurons was able to predict CEC better than the regression

Table 6. Statistical parameters of used models for predicting CEC from soil and topographic attributes

Methods	Models	R^2	RMSE	Inputs
MLR	(1)	0.47	4.8	Soil attributes
	(2)	0.47	4.9	Topographic attributes
	(3)	0.57	4.6	Soil and topographic attributes
MLP	(1)	0.71	3.5	Soil attributes
	(2)	0.73	3.5	Topographic attributes
	(3)	0.95	1.55	Soil and topographic attributes

MLR: Multiple linear regression, MLP: Multilayer perceptron

PTFs. Tang et al.[21] applied radial basis function (RBF) neural networks to predict CEC and found out that neural networks are more accurate in estimating CEC compared with multivariate regression models. Memarian Fard and Beigi Harchagani[26] have reported that their MLP network with 4 input neurons (organic carbon, saturation moisture, clay and sand percentage) and 7 neurons in hidden layer was able to estimate CEC better than other neural networks and also regression models.

3.4 Sensitivity Analysis Results

Aimed at investigating the importance of employed data in the best model of estimating CEC (MLP third model), applied weights in this network were derived from MATLAB. These weights are kind of connection bridge between inputs and outputs. Then, the sensitivity of all input variables were calculated based on equation 6 (Figure 4).

As shown in Figure 4, TWI was the most important index in explaining CEC variation in the examined area. This index was used in a pile of research for estimating soil physical, chemical and hydrological properties in a spatial manner[28,30]. Furthermore, the results of Figure 4. implied that topographic attributes contribution in explaining CEC variances is more than soil factors for the study area. From six topographic components entered the model 3 of MLP, 4 variables including TWI, slope, surface curvature and aspect had the highest importance. In other words, TWI and curvature that correlate moisture distribution through the landscape, slope which relates to erosional processes, and aspect that affect microclimate distribution and the flux of solar radiation on landscape, were the most important factors influencing CEC variability in the study area. Moreover, OM, clay and silt percentages were the

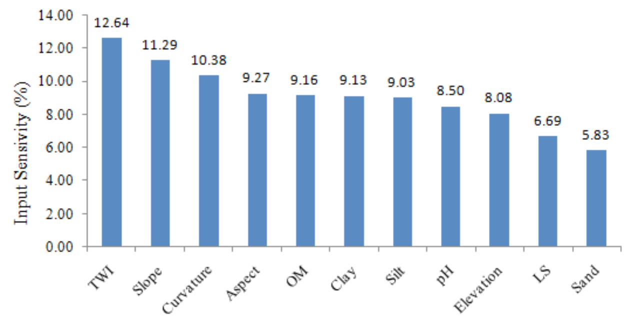

Figure 4. Results of quantifying the importance of input variables using connection weights method for the third model of MLP (TWI: Topographic wetness index, OM: Organic matter, LS: Length of slope).

most important soil properties affecting CEC variation in Lordegan region, which holds true for previous studies[3,26]. In addition, it could be attributed the effect of TWI, slope, surface curvature and aspect on CEC, to their close relationship with clay and OM percentage in soils of hilly region study area (Table 3). Schwanghart and Jarmer[31] were observed a positive trend in accumulating soil OM with respect to increase in TWI of lands with mild slope degree that were attributed to accumulation of water and soil fine particles in such regions. Similarly, the results of Pei et al.[30] study implied that out of topographic properties derived from DEM, TWI has allocated the highest correlation coefficient with soil organic carbon. In the same way, Guo et al.[29] were reported higher values of OM in regions which have mild slopes, more water storages and are more concave. It could be concluded that in the investigated region, soil attributes are highly controlled by topographic properties and also are influenced by water movement, hydrological and erosional processes, along with microclimate changes due to topography. Hence, topographic data would be used with high confidence to estimate soil characteristics such as CEC in the study area.

4. Conclusion

Aiming at modeling soil cation exchange capacity (CEC) using terrain attributes and easily/readily obtainable soil properties, a research was performed in some parts of hilly lands located in Lordegan, west of Iran. Soil attributes comprising texture, organic matter, pH and CEC of 130 surface soil samples were measured in the study area. Then, terrain attributes corresponding to each point were derived from digital elevation model with 10 meters accuracy. The artificial neural networks and regression pedotransfer functions were used for predicting CEC values. For this purpose, three models were developed in each method. The first model was employed solely soil properties as inputs, while the second one used topographic features and the last model utilized both characteristics simultaneously to estimate CEC. There was no noticeable difference between the efficacy of the first and second model using regression and neural network models. In other words, topographic properties were capable of predicting CEC as accurate as soil features. On the other end, the simultaneous use of both categories (soil and topographic attributes) was improved the accuracy, which was more sensible for neural network, and supports the superiority of neural network models encountering complicated problems. It means that increasing the model inputs and subsequently increasing the complexity of relations between used data, were resulted in much better performance of neural network model. Furthermore, the results of quantifying variables importance employing connection weight method implied that in neural network technique four parameters comprising topographic wetness index, slope, surface curvature and aspect had the highest contribution in CEC variation in the study area. The results of this research support this idea that topographic attributes comparing with soil features were more influential in explaining CEC variation in Lordegan region. Hence, it is a cost-effective and confident method to employ terrain attributes for estimating soil characteristics such as CEC in the investigated region.

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