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Estimating effects of terrain attributes on local soil organic carbon content in a semi-arid pastureland

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Abstract

Soil organic carbon (SOC) is a source or sink of *atmospheric* carbon and importance of it has been increasingly recognized in soil physical, chemical and biological characteristics. The objective of this study was to predict and evaluate the effects of topographic attributes on the soil organic carbon content at a hilly pastureland in Mereg watershed, Iran. In this research, topographic attributes include the primary factors such as elevation, slope, plan and profile curvature, transformed aspect and secondary factors such as slope-aspect combinative index, wetness index and stream power. Multiple linear regression (MLR) and radial basis function (RBF) artificial neural network were employed. The comparison of model evaluation criteria demonstrates that the RBF model (R=0.954, RMSE=0.087%) provides more accurate predictions of SOC than the MLR model(R=0.528, RMSE=0.349%). The RBF model, with 15 neurons in hidden layer and 2 spread value was applied successfully and exhibited the more reliable predictions than the MLR model. Results showed that, SOC content were mostly sensitive to the profile curvature, plan curvature, transformed aspect and slope percent.

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Introduction

The importance of the soil organic carbon(SOC) has been increasingly recognized in ecosystem budgets for this element (Ilvesniemi *et al.*, 2002). Soil organic carbon is extremely important in soil quality and health. SOC influences soil physical, chemical and biological characteristics such as water *retention*, aeration and workability, aggregate stability, nutrient retention and availability and nutrient cycling.

SOC is particularly important in semi-arid areas since it sustains soil fertility, increases soil moisture storage and mitigates droughts(Tiessen *et al.*, 1994).

SOC content is controlled by many factors such as climate, land use, management and topography. Many studies have revealed the relationship between SOC and topography (Moore *et al.*, 1993; Gessler *et al.*, 2000; Moorman *et al.*, 2004; Terra *et al.*, 2004; Papiernik *et al.*, 2007).

Topography is the key factor forming the soil cover in climatically and geologically homogenous areas. It has a significant influence on a great range of soil physical and chemical properties (Gerrard, 1981). In landscapes where topography is an important control on geomorphological, hydrological and/or biogeochemical processes, topographic features can be useful for partitioning the landscape into homogeneous units of soil organic carbon (Webster *et al.*, 2011)

Many different methods were used to predict relationship between soil properties. Whereas, the complex relationship between soil properties and topographic attribute has resulted in some study, in recent years, studies attempted to develop nonlinear models with artificial intelligence techniques such as artificial neural networks (ANNs) (Ingleby and Crowe, 2001; Somaratne *et al.*, 2005; Dai and Huang, 2006; Zhao *et al.*, 2010; Yilmaz and Kaynar, 2011; Besalatpour *et al.*, 2013; Guo *et al.*, 2013).

Since, in landscape scale with same parent material, climate regime and natural vegetation types, SOC content significantly controlled by variation in topographic attributes, This study was conducted to: (1) developing multiple linear regression (MLR) and radial basis function (RBF) neural network models to predict SOC variation under the influence of topographic attributes (2) investigation the predictive performance of the MLR and the RBF models and recognition the superior model in the study pastureland.

Materials and methods

Study area and data collection

The study was carried out in a pastureland site located in Mereg watershed, west of Iran (698930 to 699750mE and 3780020 to 3780730mN). The most abundant plant was *Astragalus sp.*. The soil moisture and temperature regimes were Xeric and Thermic, respectively, with 458 mm average annual rainfall and 14.1 °C mean annual temperature.

The soil samples were collected across gradient of topographic factors within a 100 m grid in systematic grid sampling pattern. The soil samples were taken from 31 topsoil (0-30 cm) points. Location of the study area and soil sampling points are shown in Fig.1.

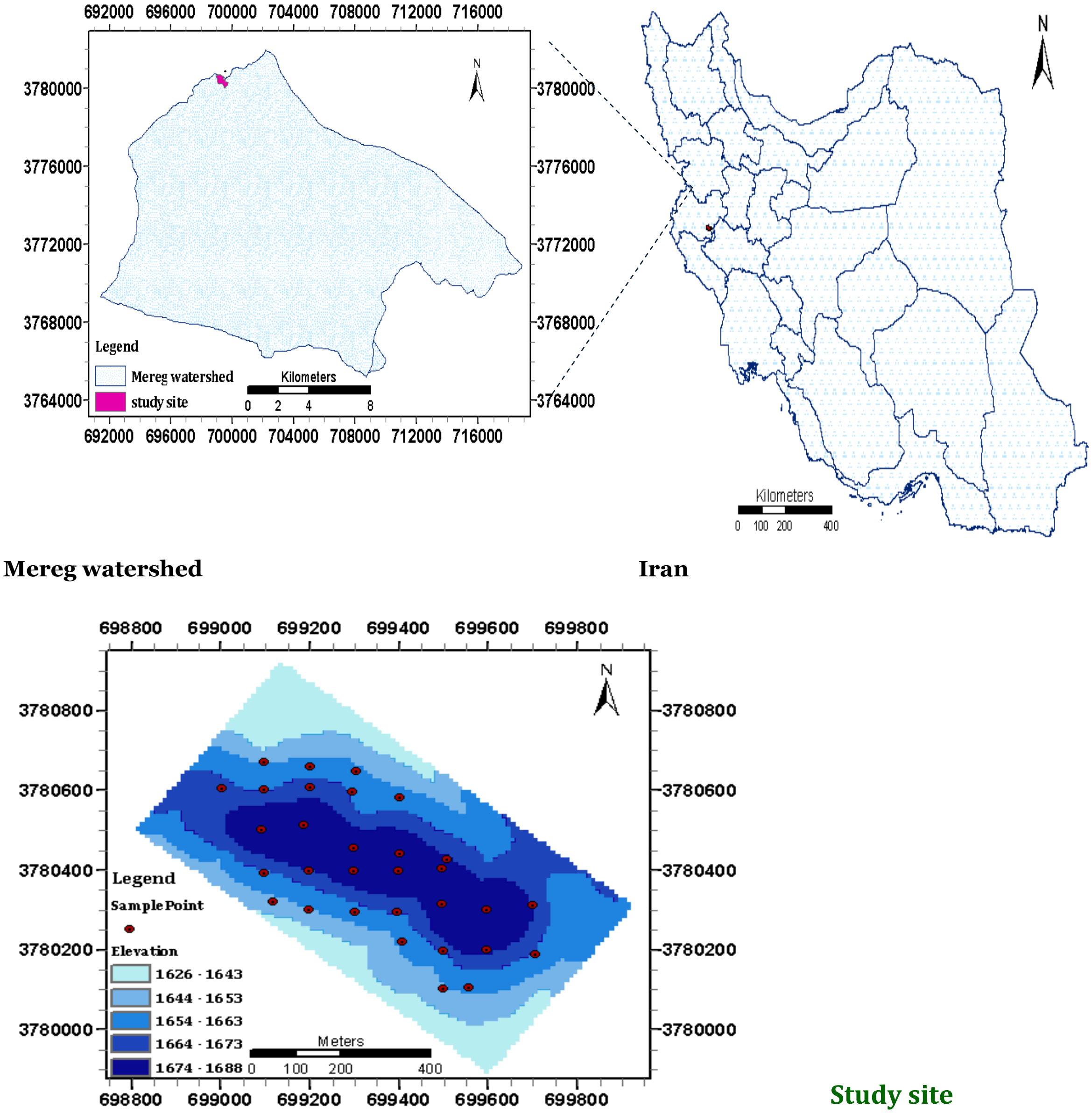

Fig.1. Location of the study area and soil sampling points.

After air-drying , soil samples were passed 2 mm sieve and then SOC was determined by the Walkley–Black method (Nelson *et al.*, 1996).

Terrain attributes have divided into primary and secondary (compound) attributes. Primary attributes (such as Aspect, slope, curvature, etc) are calculated directly from the elevation data. Compound attributes(such as Wetness index, Stream power index, etc), involve combinations of primary attributes and are indices that describe the spatial variability of specific process occurring in the landscape (Wilson and Gallant, 2000).

In this study, primary attributes were elevation, slope percent, transformed aspect, plane curvature and profile curvature. Secondary attributes consist of wetness index (WI), stream power index and slope-aspect combinative index. The selected terrain attributes, were derived from a 10 m digital elevation model (DEM).

The topographic wetness index is an indicator of soil moisture distribution across the landscape, and is calculated as equation (1):

$$WI = \ln\left(\frac{A_s}{tan\beta}\right) \qquad (1)$$

Where A_s is the specific catchment area value and β is slope angel(Beven *et al.*, 1984).

Stream power index (SI) is the potential of overland flow to erosion and related landscape processes, and is calculated as equation (2):

$$SI = \ln\left(A_s . tan\beta\right) \qquad (2)$$

Where A_s is the specific catchment area expressed as m² per unit width orthogonal to the flow direction, and β is the slope angle expressed in radians (Gessler *et al.*, 1995).

The transformed aspect (TA) was calculated as equation (3) according to (Beers *et al.*, 1966; Somaratne *et al.*, 2005):

$$TA = \cos\ (45 - Aspect) \qquad (3)$$

Slope-aspect combinative index (TAS) incorporates the effect of slope on direct-beam radiation. According to equation (4), TAS was obtained by Multiplying TA and sinus value of slope degree(Somaratne *et al.*, 2005). :

$$TAS = Sin\ (slope\ degree).TA \qquad (4)$$

Data analyses

Descriptive statistics of the variables and correlation coefficients between SOC and selected terrain attributes were done using the SPSS software. Multiple linear regression and the RBF artificial neural network were employed to predict SOC variation under influence of topographic attributes.

Multiple linear regression (MLR)

To predict the relationship between independent variables (terrain attributes) and a dependent variable (SOC), multiple linear regression was carried out. The multiple linear regression equation is as equation (5):

$$Y = b_o + b_1x_1 + b_2x_2 + \cdots + b_nx_n + \varepsilon \qquad (5)$$

Where Y is the predicted value of the dependent variable, b_1 through b_n are the estimated regression coefficients, x_1 through x_n are independent variables, b_o is the value of Y when all of the independent variables are equal to zero and ε is measured errors.

In this study, the SPSS 19 PASW (IBM Com., Chicago, USA) statistical software was used for developing multiple linear regression model.

Radial Basis Function Artificial neural network

Artificial neural networks (ANNs) were originally devised as a computational model of the human brain. Neural networks are advanced pattern recognition algorithms capable of extracting complex, nonlinear relationships among variables(Somers and Casal, 2008).

There are a few different types of ANNs and each differs from others in network structure and parameters. In this study, Radial Basis Function (RBF) artificial neural network were developed in Matlab. 7.11.0 (R.2010.b).

The RBF neural networks are special classes of the feed-forward neural network models. Networks consist of a hidden layer of units with radial basis activation function and an output layer of linear summation unit(s). As the RBF, often Gaussian activation functions are used, therefore the corresponding units are called Gaussian (kernel) units (Fig.2).

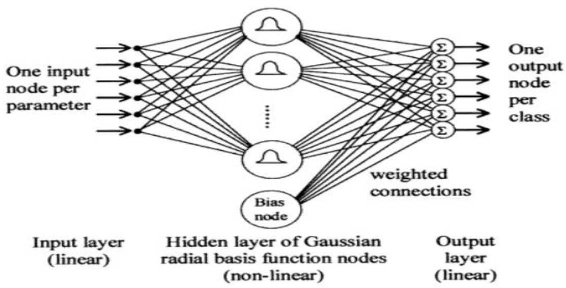

Fig.2. Architecture of RBF neural network.

The radial basis function has a center and a radius (also called a spread). The RBF is a special class of neural network in which the activation of a hidden neuron is determined by the distance between the input vector and a prototype vector. Prototype vectors refer to centers of clusters formed by the patterns or vectors in the input space (Burša and Lhotská, 2008; Amiri and Derakhshandeh, 2011; Dash *et al.*, 2013). Two network parameters of the RBF neural network including the spread value and the number of neuron in hidden layer were improved during the RBF training to get minimum error and maximum correlation coefficient. The RBF dataset was subdivided into two sets: 70% of the data were used for training and 30% of the data for testing.

Data preprocessing

All input data were normalized to a range of 0–1 using the following equation:

$$\frac{(x_i - x_{max})}{(x_{min} - x_{max})} \quad (6)$$

Performance criteria

The performance of the models was evaluated by the root mean squared error (RMSE), the mean bias error (MBE) and the correlation coefficient (R). These criteria were calculated to control the performance of the prediction capacity of models developed in this study (see equations 7-9).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \quad (7)$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i) \quad (8)$$

$$R = \frac{\sum_{i=1}^{n}(O_i - \overline{O_i})(-\overline{P_i})}{\sqrt{\left(\sum(O_i - \overline{O_i})^2\right)\left(\sum(P_i - \overline{P_i})^2\right)}} \quad (9)$$

Where $n, P_i, O_i, \overline{P_i}$ and $\overline{O_i}$ are number of observations, predicted value, measured value, mean of predicted value and mean of measured values, respectively.

Sensitivity analysis

Sensitivity analysis was performed on optimum the RBF model in order to investigate the effects of topographic attributes on SOC. It was done by removing one input in the model and obtaining the RMSE changes at each step.

Results

Descriptive statistics for soil organic carbon and terrain attributes are given in Table 1. The soil organic carbon varied from 1.11 to 2.49%. To explain the SOC variability, coefficient of variation was calculated and moderate variability (CV=25.66) was obtained for SOC.

Table 1. Descriptive statistics for SOC and terrain attributes.

Staistics	SOC (%)	Elevation (m)	Slope (%)	Profile Curvature (rad/m)	Plan Curvature (rad/m)	TA	TAS	Wetness Index	Stream Power Index
Minimum	1.11	1651.00	0.70	-1.25	-1.65	-1.00	-0.99	6.23	0.10
Maximum	2.49	1684.00	31.15	1.03	1.06	1.00	1.00	12.79	757.70
Variance	0.18	115.87	71.14	0.35	0.48	0.54	0.35	2.43	448.76
Coefficient of variation	25.66	0.65	51.62	-118.65	-115.65	148	421.46	18.13	13.10
Skewness	0.62	0.11	-0.18	-0.25	-0.28	-0.22	-0.16	0.71	1.62
Kurtosis	-0.61	-1.49	-0.47	0.04	-0.25	-1.63	-1.27	0.43	2.66

The result of the correlation analysis between SOC and the topographic factors are shown in table 2. Correlation analysis between SOC and terrain attributes showed that there was a positive linear correlation between SOC and plane curvature(r=0.39, p<0.05) and negative linear correlation between SOC and profile curvature (r=-0.53, p<0.01).

Table 2. Correlation coefficients between SOC and selected terrain attributes.

Pearson correlation	Elevation (m)	Slope (%)	Profile Curvature (rad/m)	Plan Curvature (rad/m)	TA	TAS	Wetness Index	Stream Power Index
r	0.10	-0.24	-0.53	0.39	0.20	0.07	0.05-	-0.28
Sig.(2-tailed)	0.60	0.20	0.00	0.05	0.27	0.72	0.80	0.13

Multiple linear regressions

The multiple linear regressions were used to evaluate the relationships between SOC as dependent variable and terrain attributes as the independent variables. *Kolmogorov*-Smirnov test results for SOC (k-s= 0.6, sig=0.86) and residual (k-s= 0.55, sig=0.92) indicated that SOC and model residuals were normally disturbed ($p>0.05$).

The results of ANOVA applied to the MLR for SOC are presented in Table 3. F test ($p<0.01$) indicated that the MLR model was highly significant. The MLR equation was developed (Equation10). According to the result, profile curvature was identified as the predictor to MLR model and could explained about 28% of the variation of soil organic carbon by profile curvature in the studied area.

Table 3. Results of ANOVA applied to the MLR for soil organic carbon.

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.463	1	1.463	11.201	0.002[a]
Residual	3.789	29	0.131		
Total	5.252	30			

a. Predictors: (Constant), profile curvature

$$SOC = 1.616 - 0.37\ Profile\ Curvature \quad (10)$$

The results of evaluation criteria for the MLR model are presented in Table 4. The obtained correlation coefficient value between the measured and the predicted SOC values was also 0.528 (Fig.3). The MLR model could explain about 28 % of the variation of soil organic carbon by terrain attributes in the study area. The MBE value indicated that the MLR model was predicted the SOC without bias error.

Table 4. Performance evaluation criteria for the MLR model.

Model	R	RMSE	MBE
MLR	0.528	0.349	0.000

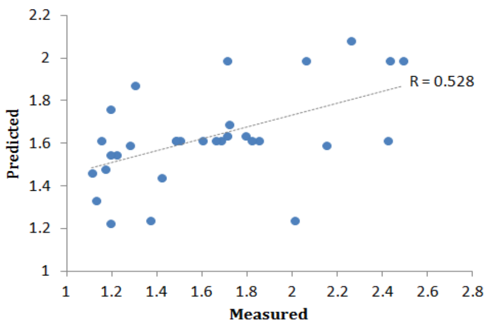

Fig.3. Scatter diagram of measured values versus predicted values for MLR.

Radial Basis Function Network

The number of neurons and spread value were determined by trial and error. According to the results, optimum RBF network has 15 neurons in hidden layer and 2 spread values. The best RBF model performance criteria for train and test dataset were given in table 5. As seen from Table 5 and Fig.4, the RBF model was highly acceptable for prediction of SOC.

Table 5. Performance evaluation criteria for the RBF model train and test dataset.

Dataset	R	RMSE	MBE
Train	0.954	0.087	0.000
Test	0.832	0.418	0.177

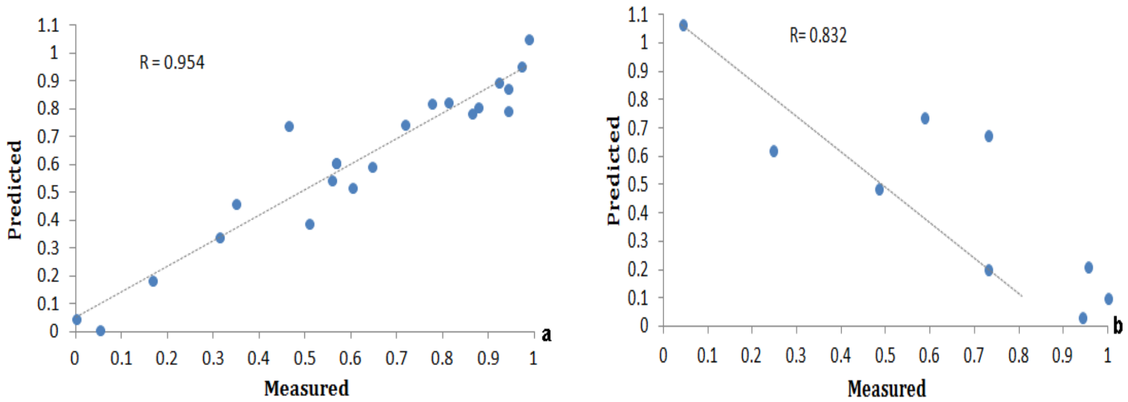

Fig.4. Scatter diagram of measured values versus predicted values for the RBF train dataset (a) and test dataset (b).

Positive value of MBE was indicated that the test dataset underestimated the SOC and the MBE value for train dataset was shown the RBF model was predicted the SOC without bias error. Relationship between measured and predicted SOC for train and test datasets are shown in Fig.4.

According to the results, the RBF model could explain about 91% of the variation of soil organic under influence of topographic attributes. As seen from Table 5 and Fig. 4, RBF model is highly acceptable for prediction of SOC. Comparison of the Fig.3 and Fig.4 shows the higher accuracy of RBF model than the MLR model.

Results of sensitivity analysis for the RBF model in the study site, suggested that SOC content were mostly sensitive to the profile curvature, plan curvature, TA and slope percent (Fig.5).

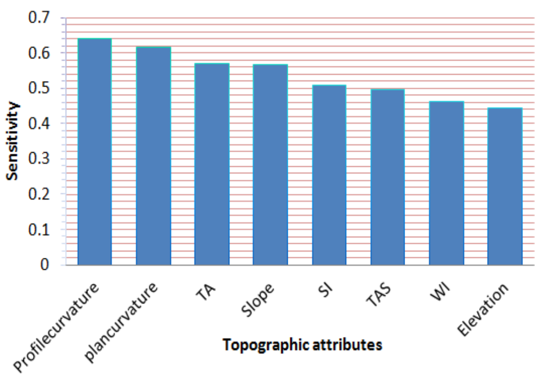

Fig.5. Sensitivity analysis for RBF model in study area.

Discussions

According to the R and RMSE values, it appears that the MLR model was to a large extent poor in predicting SOC. The RBF model (R=0.954, RMSE=0.087%) was more suitable than the MLR (R=0.528, RMSE=0.349%) model to predicting SOC. The Comparison the relative improvement of models showed that the RBF model was improved model accuracy 75% than the MLR model.

As the results of some studies (Yilmaz and Kaynar, 2011; Kalkhajeh *et al.*, 2012; Besalatpour *et al.*, 2013), Results of this study revealed that the RBF artificial neural network was superior to the MLR for prediction of soil characteristics. This might be due to: (1) ANNs models formed from local data produce more accurate predictions than those built from data spread from a wider area (Nemes *et al.*, 2003; Baker and Ellison, 2008). (2) the large amount of data required for developing a sustainable regression model, while the ANN models could recognize the relationships with less data for distributed and parallel computing natures (Besalatpour *et al.*, 2012). (3) In cases where linear models are inefficient to predict the relationships between soil properties and environmental variables, ANN models might be capable of determining the hidden non-linear relationships (Zhao *et al.*, 2010; Yilmaz and Kaynar, 2011).

According to the sensitivity analysis, among the selected terrain attributes, profile curvature, plan curvature, TA and slope percent were recognized as the best input to develop RBF model to predict SOC variation in study pastureland.

Yoo *et al*. (2006) also observed SOC storage varies systematically with slope curvature. On convex slope, the SOC storage decrease with increasing concavity. The SOC storage increases with increasing concavity on convergent slope. (Yoo *et al*., 2006)

In semi-arid areas, higher moisture availability in concave situations due to the accumulation of surface runoff and lower depth of the groundwater table particularly during the more humid seasons, promotes plant growth and litter fall (Schwanghart and Jarmer, 2011).

The microenvironment of different aspects of hill slopes is influenced by the intensity and duration of available sunlight (Yadav and Gupta, 2006). Slope aspect is related to the amount of solar radiation receive at a location particularly when combined with slope gradient (Wilson and Gallant, 2000), which can influence soil temperature and moisture content, plant productivity, soil microbial activity, soil organic matter decomposition and soil organic carbon content, subsequently (Lin, 2012). Thompson and Kolka (2005), reported high correlation between SOC and slope and aspect. (Thompson and Kolka, 2005)

A steeper slope gradient is associated with greater potential of erosion and less soil organic carbon content. Slope gradient is also a factor in several regional terrain attribute, particularly those with hydrologic interpretations such as WI and SI (Lin, 2012). Terra *et al*. (2004), investigated soil carbon relationships with terrain attributes and reported that WI and slope had the highest correlation with SOC.

In this study, the performance comparison showed that the ANN is a new and suitable method for minimizing the uncertainties in SOC predicting. RBF artificial neural network have an acceptable prediction capability, especially when compared with the MLR model and is capable in determining the non-linear relationships between soil organic carbon and terrain attributes.

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