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Estimation of Soil Organic Carbon in a Small-Scale Loessial Hillslope Using Terrain Derivatives of Northern Iran

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Authors
Maleki S.[1] *MSc*,
Khormali F.* *PhD*,
Karimi A.[2] *PhD*

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*Department of Soil Science, Faculty of Water and Soil Engineering, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran

[1]Department of Soil Science, Faculty of Water & Soil Engineering, Gorgan University of Agricultural Sciences & Natural Resources, Gorgan, Iran

[2]Department of Soil Science, Ferdowsi University of Mashhad, Mashhad, Iran

Correspondence
Address: Department of Soil Science, Faculty of Water and Soil Engineering, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran
Phone: +98 (17) 32269320
Fax: +98 (17) 32269320
khormali@yahoo.com

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ABSTRACT

Aims Soil organic carbon (SOC) is contemplated as a crucial proxy to manage soil quality, conserve natural resources, monitoring CO_2 and preventing soil erosion within the landscape, regional, and global scale. Therefore, the main aims of this study were to (1) determine the impact of terrain derivatives on the SOC distribution and (2) compare the different algorithms of topographic wetness index (TWI) calculation for SOC estimation in a small-scale loess hillslope of Toshan area, Golestan province, Iran. (3) Comparison between multiple linear regression (MLR) and artificial neural networks (ANN) methods for SOC prediction.

Materials & Methods total of 135 soil samples were taken in different slope positions, i.e., shoulder (SH), backslope (BS), footslope (FS), and toeslope (TS). Primary and secondary terrain derivatives were calculated using digital elevation model (DEM) with a spatial resolution of 10 m × 10 m. To SOC estimation (dependent variable) was applied two models, i.e., MLR and ANN with terrain derivatives as the independent variables.

Findings The results showed significant differences using Duncan's test in where TS position had the higher mean value of SOC (25.90 g kg^{-1}) compared to SH (5.00 g kg^{-1}) and BS (12.70 g kg^{-1}) positions. The present study also revealed which SOC was more correlated with TWI_{MFD} (Multiple-Flow-Direction) and TWI_{BFD} (Biflow-Direction) than TWI_{SFD} (Single Flow Direction). The MLR and ANN models were validated by additional samples (25 points) that can be explain 65% and 76% of the total variability of SOC, respectively, in the study area.

Conclusion These results indicated that the use of terrain derivatives is a beneficial method for SOC estimation. In general, an accurate understanding of TWI_{MFD} is needed to better estimate SOC to evaluate soil and ecosystem related effects on global warming of as this hilly region at a larger scale in a future study.

Keywords Artificial Neural Networks; Different Flow Direction; Loess; Multiple Linear Regression

CITATION LINKS

[1] Soil Fertility, erosion, runoff and ... [2] Geological controlling soil organic ... [3] Role of deforestation and hillslope ... [4] The influence of Catchment morphology, lithology and ... [5] Environmental factors controlling soil ... [6] Soil carbon sequestration impacts ... [7] Soil Organic Carbon Pools in Particle-Size Fractions ... [8] Linking spatial patterns of soil organic ... [9] Spatial variability of soil organic carbon ... [10] Predictive mapping of soil organic carbon ... [11] Digital soil mapping using artificial neural ... [12] Role of soil and topographic features ... [13] An evaluation of the role of hillslope ... [14] Soil carbon maps: Enhancing spatial estimates ... [15] A physically based variable contributing ... [16] Mapping soil organic matter using the topographic ... [17] Comparison of artificial neural network and ... [18] Topographic metric predictions of soil redistribution ... [19] Intelligent approaches to analysing the importance ... [20] Predicting soil organic matter by artificial neural ... [21] Digital soil mapping using remote sensing ... [22] Mapping soil organic matter using topographic ... [23] Can carbon (SOC) offset the climate ... [24] Soil survey laboratory method ... [25] On the calculation of the topographic ... [26] Soil moisture modeling using TWI and ... [27] The extraction of drainage networks from ... [28] Drainage networks from grid digital elevation ... [29] Soil attributes prediction using terrain ... [30] Neural networks: A Comprehensive ... [31] Prediction of soil organic matter variability associated ... [32] Spatial prediction of soil organic matter using terrain attributes in a hilly area. International Conference on Environmental Science and Information ... [33] Assessing uncertainty in soil organic carbon ... [34] Prediction of soil organic carbon across different ... [35] Spatial variability of soil organic matter using ... [36] Prediction modeling and mapping of soil ... [37] Effect of altitude and aspect on soil organic carbon ...

Introduction

Knowledge of variability of soil properties is necessary for precision planning and management of agricultural lands. Environmental factors, i.e., land use,[1] climate, parent material,[2] topography, and anthropogenic management effected on soil organic carbon (SOC).[3-5] SOC is a crucial proxy as one of the main parameters to evaluate soil quality[6] and management practices to conserve eco environment, monitoring CO_2,[2] climate change, and global warming. Karchegani *et al.*[7] pointed out that correct management of agricultural operation and maintenance of SOC are important factors in sustainable agriculture. Lal[6] also revealed that reducing of SOC is one of the major reasons of greenhouse gases and soil can store around 1500 Pg organic carbon (OC) in the 0–100 cm of soil.

The effect of topography on SOC variability is well documented.[5-9] As Bou Kheir *et al.*[10] expressed terrain derivatives may help estimation of SOC that due to a great influence on soil formation.

Digital elevation model (DEM) is an useful tool to derive terrain attributes for SOC mapping which have been used widely in soil studies[11] and SOC mapping where they can be incorporated in statistical methods and used as secondary variables and also enhance SOC map quality and reduce the cost of sampling.[12,13]

Mueller and Pierce[14] introduced soils with high moisture content have usually high SOC, consequently, it can be modeled quantitatively by useful terrain derivatives as topographic wetness index (TWI)[15] through the landscape positions.[16] Furthermore, there is a significant positive correlation between TWI and SOC[16] in steep slope lands.[8]

Several techniques have been used to understand the relationships between terrain derivatives and soil properties, especially SOC in different scales, i.e., multiple linear regression (MLR),[17] principal component analysis,[18] classification and regression tree,[19] and artificial neural networks (ANN).[17,20] In addition, Karchegani *et al.*[20] expressed that the integration of the intelligent models such as ANN with the use of auxiliary data including the remotely sensed data and terrain derivatives could be used for SOC estimation in the landscape scale. The results of Parvizi *et al.*[19] and Mahmoudabadi *et al.*[21] confirmed the ability of ANN in prediction of SOC, using terrain derivatives as independent parameters.

Loess material has a high amount silt particle that results in soil erosion and SOC loss, acquire an insight view of SOC can improve soil fertility, water holding capacity, and crop production, etc. Results of researches Maleki *et al.*[22] and Bameri *et al.*[9] showed that an important factor is topography with regard to SOC variations in surface loessial soils of cultivated lands. Regional scale estimations of SOC were calculated for Toshan watershed, including hills and plains with the high slope fluctuation and loess deposit material.[5] To the best of our knowledge, while no attempts have been done to estimate SOC using topography derivatives and low sampling intervals (As will be discussed in section 3.1). There is a strong correlation between moisture and SOC as done by Pei *et al.*[16] and Maleki *et al.*[22] There is, however, almost no data of soil surface and subsurface moisture available for different areas. There is, therefore, a need analysis and algorithms of moisture to bridge wetness to SOC to acquire detailed information and accurate understanding on flow distributions. Hence, we used the TWI relationships on the identification of SOC as proposed by Pei *et al.*[16] would provide a better vision of changes SOC and moisture first time which have a main role in future studies, i.e., land management, assessment of erosion potential, and digital soil mapping in this steep hillslope area.

In addition, findings of our study can be used for comparing and monitoring SOC data relation to global warming projects in other regions of Asian in future researches that are limited data on SOC in Asia.[23] Therefore, this study carried out to (1) assess the effect of slope position on SOC and soil properties, (2) compare the relationships of SOC and

TWI which calculated by different algorithms, (3) evaluate capability of MLR and ANN to predict SOC using terrain derivatives and comparing the efficiency of two models.

Materials & Methods

Description of study area and data collection

The study area is located in Toshan region (270259.77 to 270585.53 E and 4077096.87 to 4077101.19 N) with an elevation range of 171–246 m a.s.l. in a small catchment of Golestan Province, Northern Iran [Figure 1]. It should be noted that the elevation range of total area of Toshan watershed is 40–1500 m a.s.l. Soil moisture and temperature regimes are Xeric and Thermic, respectively, with mean annual precipitation, 620 mm and temperature, 16°C.

The locations of 135 soil samples were determined by fishnet strategy which the grid interval of soil samples was 24 m × 20 m. The locations of the soil samples were recorded by portable Global Positioning System. Soil samples were taken from 0 to 30 cm at four slope positions, i.e., shoulder (SH) (44 soil samples), backslope (BS) (39 soil samples), footslope (FS) (29 soil samples), and toeslope (TS) (23 soil samples) in a cultivated (agriculture land use) hillslope that is often grown wheat with a total area of 12 ha. Figure 2 shows the wireframe map with soil sampling locations in U shape landscape of the study area.

Laboratory analysis

After air-drying, all of the soil samples were homogenized and sieved <2 mm. The soil physical and chemical properties were analyzed including particle size distribution (the Bouyoucos hydrometer method),[24] bulk density (BD) (paraffin method),[24] SOC (Walkley-Black method),[24] equivalent calcium carbonate (CCE) (titration with acid),[24] mean weight diameter (MWD) (Kemper and Rosenau method),[24] soil pH (saturated paste), and electrical conductivity (EC) (saturated extract at 25°C).[24]

To determine the effect of slope positions on soil physical and chemical properties, one-way analysis of variance was applied with *post hoc* test (Duncan's test with $P < 0.05$). Levene's test was also used for determining equality of variances. For identification of all the terrain parameters and SOC components used the Kolmogorov–Smirnov test normal distribution. The SPSS software (version 22.0) was utilized for all of the analysis. Furthermore, the correlation

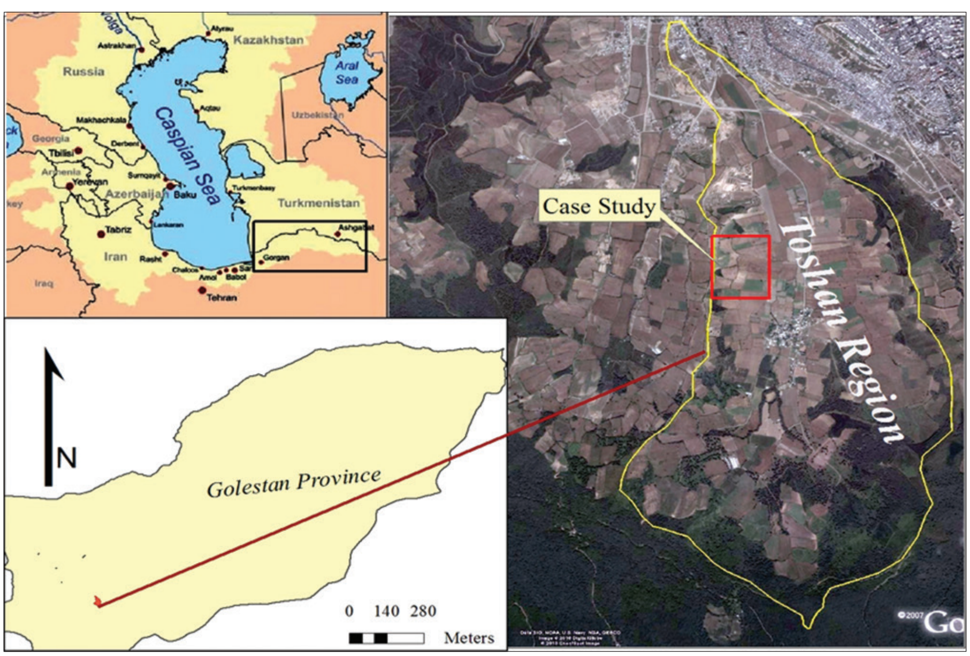

Figure 1: Location of the study area in Golestan province and Iran

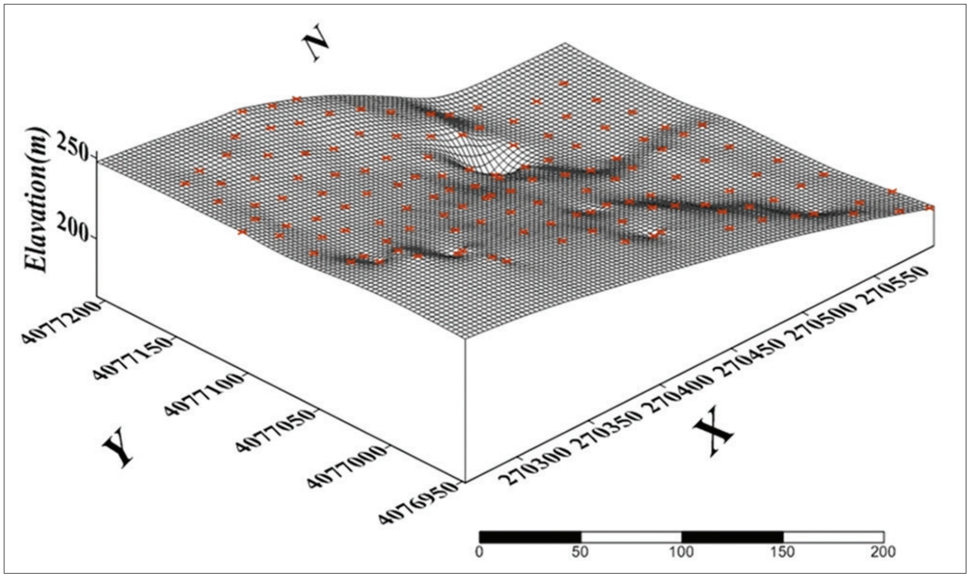

Figure 2: Wireframe map of the study area (unit of x- and y: UTM) showing locations of soil samples (redpoint)

between soil properties and terrain derivatives was assessed with using Pearson correlation coefficients.

Analysis of DEM

Primary terrain derivatives including profile curvature, plan curvature, tangential curvature, slope, aspect, and elevation were directly extracted from the DEM with a spatial resolution of 10 m × 10 m using ArcGIS Desktop 10.2 and SAGA GIS (version 2.2) software. Primary terrain derivatives were used for calculation of secondary terrain attributes including TWI, stream power index, and sediment transport index (LS). Definitions of the terrain derivatives are presented in Table 1.

TWI indirectly shows the runoff distribution and moisture through landscape as shown in Equation 1 which affects the SOC.[26]

$$\mathrm{TWI} = \ln\left(\frac{\alpha}{\tan\beta}\right) \quad (1)$$

Where the parameters of Equation 1 are α, the specific catchment area (SCA) and $\tan\beta$, the local slope gradient.[16] SCA indicates the potential flow accumulation to a unique location, and $\tan\beta$ shows the ability of local drainage.

According to Hass,[27] the three groups of algorithms have been proposed for TWI calculation are single flow direction (SFD), biflow direction (BFD), and multiple flow direction (MFD). SFD algorithms limit the surface and subsurface runoff from a single grid cell to only one other cell without considering any other neighbor cells.[27] The D8 (deterministic eight-node) is the simplest SFD algorithm that only flows in steep slope gradient.[28] Hass[27] expressed D8 method works well in valleys but produces many parallel flow lines and problems near catchment boundaries. RHO8 is another SFD algorithm introduced by Fairfield and Leymarie[29] that can prevent production of parallel flow lines. In BFD algorithms, flow in cells is broken into two parts. 2D-Lea, 2D-Jensen, and D-Infinity are species of BFD algorithms which were used D-Infinity in this study.

SFD and BFD algorithms have a main problem that cannot find the correct flow sides in flat areas. However, MFD algorithm allows diffuse flow from one grid cell proportionately to all of surrounding cells. FRho8 and FD8-Quinn algorithms are species of MFD algorithms and calculated in this study.

MLR and ANN

MLR and ANN with multilayer perceptron (MLP) with back propagation learning method were used for simulating the relationships of selected terrain derivatives with SOC in this study. It should be noted

Table 1: The terrain derivatives, abbreviations, units, definitions, and their equations

Parameter	Abbreviation	unit	Definition
Elevation	Elv	m	Height over sea level[25]
Slope	Slp	%	Gradient of line is changing of elevation in the direction and steepness[11]
Aspect	Asp	rad	Direction of the line of the steepest descent[25]
Profile curvature	Profc	m^{-1}	Rate of change of slope down a slope line[11]
Plan curvature	Planc	m^{-1}	Rate of change of aspect along a contour[11]
Tangential curvature	Tangc	m^{-1}	Multiplication of the sine of the slope angle in Planc[11]
Topographic wetness index	TWI	-	A measure of the topographic control on soil wetness or the ratio[25]
Sediment transport capacity index	LS	-	A measure of the topographic control on the sediment transport which is equivalent to the LS factor in the universal soil loss equation (USLE's LS factor)[25]
Stream power index	SPI	-	The topographic index for stream forming power of flow[25]

TWI: Topographic wetness index, LS: Length slope

that the common models of ANN is MLP as many researchers in soil science have been used it, e.g., Bodaghabadi *et al.*[11] Parvizi *et al.*,[19] and Karchegani *et al.*,[20] Equation (2) was used for calculation of input value in every neuron.[30]

$$\mathrm{net}_i^n = \sum_{i=1}^{m} \mathrm{w}_{ji}^n . \mathrm{O}_j^{n-1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left[Z(Xi) - Z^*(Xi)\right]^2}{\sum_{i=1}^{n}\left[Z(Xi) - \overline{Z}(Xi)\right]^2} \tag{2}$$

Where net_i^n is the input value of *i*th neuron in *n*th layer., w_{ji}^n is the connection weight between *i*th neuron in *n*th layer and *j*th neuron in the (*n*−1)th layer., O_j^{n-1} is the output of jth neuron in the (*n−1*)th layer, m is the number of neurons in the (*n−1*) the layer. Furthermore, Equation (3) showed the sigmoid function for activation of each neuron. Marquardt Levenberg learning rule[30] was used for iterations that achieve calibration test and an acceptable error.

$$\mathrm{Sig}(\mathrm{net}_i^n) = \frac{1}{(1+\mathrm{EXP}(-\mathrm{net}_i^n))} \tag{3}$$

Models of MLR and ANN were done using SPSS (version 22.0) and MATLAB (2011) software, respectively. Four parameters were used in both of data mining methods that are including of terrain derivatives of elevation, plan curvature, slope, and TWI_{MFD} based on FD8-Quinn method as independent variable and SOC as the dependent variable.

Finally, terrain derivatives were used to designing the ANN in the case of 60% of data sets and were used for the learning process and 20% for testing that the remaining of data sets (20%) were applied for verification. The data sets for learning, testing, and verification processes were selected randomly of different soil samples of the study area to avoid bias in estimation.

To identify the most important terrain derivatives affecting SOC, sensitivity analysis was done using SPSS software for ANN model. Bodaghabadi[11] said suitable model is a model with the highest performance and the least number of input data. To remove unimportant auxiliary data, sensitivity analysis was applied. A greater percent implied which the variable made an important contribution to the SOC estimation.

Evaluating of Models

To evaluate the accuracy, mean error (ME), root mean square error (RMSE), and coefficient of determination (R^2) were used as shown by Equation (4), (5), and (6):

$$ME=\frac{\sum_{i=1}^{n}\left[Z^*(Xi)-Z(Xi)\right]}{n} \quad (4)$$

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}\left(Z^*(Xi)-Z(Xi)\right)^2}{n}} \quad (5)$$

$$R^2=1-\frac{\sum_{i=1}^{n}\left[Z(Xi)-Z^*(Xi)\right]^2}{\sum_{i=1}^{n}\left[Z(Xi)-\overline{Z}(Xi)\right]^2} \quad (6)$$

Where Z (x_i) is the measured value of SOC, Z*(x_i) is the predicted value of SOC, is the mean value of SOC, and n is the number of samples.

Findings and Discussion

Soil properties in different slope positions

TS and SH positions have the highest and the lowest SOC, respectively [Table 2]. Because SH is affected by high slope gradient that is responsible for SOC and water loss of surface horizon. Consequently, SOC often accumulates in the lower position of landscapes on the steep slope that resulted in significant increase of SOC and vegetation cover. The lower SOC of the SH position is consistent with the findings of Khormali *et al.*[3] and Nadeu *et al.*[4] Furthermore, Bameri *et al.*[9] found that soils on FS and TS positions had larger SOC compared to soils in high slope positions. Therefore, careful evaluating of land use management is necessary for the enhancement of agriculture and natural ecosystem and soil fertility in this hillslope area. Remaining of straw of wheat, optimum fertilization especially manures and nitrogen fertilizer and fallow against direction of slope can help to increasing SOC and decreasing global warming.[2]

The highest clay content was also found in TS position [Table 2] with a silty clay texture. The lower amount of clay was in SH and BS positions which explained effect of steep slope gradient cause to soil erosion and the loss of clay of surface horizons as similar findings of Ajami *et al.*[5] Furthermore, Khormali *et al.*[3] reported the highest clay content in TS position. The mean value of sand, silt, and BD had no significant effects of slope positions in all of study area [Table 2]. The soil parent material of study area is loess,[9] subsequently, the most particle size is silt, and there were no statistically significant differences in different slope position. Table 2 shows the lowest MWD (0.19 mm) and the highest MWD (0.36 mm) were found in the BS and TS positions, respectively. The higher slope gradient, loss of SOC, increased amount of silt and fallow operations in the direction of slope (2) and (3) were the important reasons for the decreased MWD in higher positions (SH and BS).

The highest CCE is present in SH position and is significantly different from TS position. The higher surface erosion and the subsequent outcropping of the underneath calcium carbonate-rich layer are mainly responsible for the higher concentration of CCE in the SH position.

Table 2: Comparison of the mean values of studied soil properties in different slope positions

Slope position	Soil texture	(g kg^{-1})					(mm)	(g cm^{-3})
		Clay	Silt	Sand	SOC	CCE	MWD	BD
SH	SiCL	389.00^{ab}	459.00^{abc}	150.00^{a}	5.00^{a}	173.30^{a}	0.25^{a}	1.59^{a}
BS	SiCL	384.00^{b}	478.00^{a}	138.00^{a}	12.70^{b}	138.40^{a}	0.19^{a}	1.55^{a}
FS	SiCL	392.00^{ab}	467.00^{ab}	140.00^{a}	15.10^{b}	167.00^{a}	0.30^{b}	1.54^{a}
TS	SiC	410.00^{a}	419.00^{c}	170.00^{a}	25.90^{c}	81.40^{b}	0.36^{b}	1.58^{a}

Numbers with the similar letters are not statistically significantly ($P < 0.05$) different. SiCL: Silty clay loam, SiC: Silty clay. SH: Shoulder, BS: Backslope, FS: Footslope, TS: Toeslope, SOC: Soil organic carbon, CCE: Equivalent calcium carbonate, MWD: Mean weight diameter, BD: Bulk density

Relationships between terrain derivatives and soil properties

The negative correlation of SOC with slope and elevation and TWI_{MFD} with slope and elevation [Table 3] show the movement of water and SOC in surface is affected by slope which higher elevation and steep slope result in loss SOC and water retention. Furthermore, the observations of Liu *et al.*[31] indicated negative correlation between SOC and elevation (r = −0.26) and SOC and slope (r = −0.36). The significant correlation between CCE and TWI (r = −0.41) which indicate higher water cause to lower CCE content. This means that water caused the movement of CCE. A positive correlation was observed between LS and slope [Table 3], which also confirm higher water flows downward and resulting in higher erosion.

Plan curvature showed a negative correlation with SOC and TWI_{MFD} and positive correlation with slope and CCE [Table 3]. Furthermore, profile curvature showed negative correlation with TWI. Plan curvature is negative for diverging flow (on ridges) and positive for converging flow (in valleys), whereas profile curvature can differentiate upper slopes from lower slopes.[32] These results are explanatory for higher intensity of TWI and SOC in concave parts of slope with low slope which is in agreement with the findings of Pei *et al.*,[16] Liu *et al.*,[31] and Xiong *et al.*[33]

TWI has a significant positive association with SOC and MWD that areas with high water storage have high SOC and MWD. Guo *et al.*[32] used terrain derivatives to SOC prediction which showed negative and positive correlations between SOC and slope gradient (r = −0.57) and TWI and SOC (r = 0.30), respectively. These correlations indicate higher SOC present in gentle slopes areas with higher humidity. With regard, the small-scale hillslope, different algorithms of TWIs were calculated which select the best methods of TWI for SOC estimation, as will be discussed later [Table 4]. The researches of Nadeu *et al.*,[4] Li *et al.*,[18] and Mahmoudabadi *et al.*[21] introduced that SOC storage is dependent to topography and soil moisture status.

It should be noted that the lack of significant correlation between SOC and some terrain derivatives may often be a result of the low resolution of DEM which may be too coarse to model surface topographic situation at the small scale hillslope of study area. Because, DEM resolution is an important factor in soil-landscape modeling, but the results of it's depending on scale and resolution which has a significant effect in predictive soil distribution models. Loess soils are very sensitive erosion which may this factor to cause unusual effects on the correlations in the study area.

Different methods and modifications of TWIs had different results in terms of correlation with SOC [Table 4] which showed D-Infinity (BFD) and MFD algorithms (FRHO8 and FD8-Quinn) had stronger correlation with SOC than SFD (D8 and RHO8) algorithms in the study area. As TWI_{MFD} (FD8-Quinn algorithm) has larger coefficient compared to another algorithm. This result introduces FD8-Quinn algorithm could be better represent soil moisture distribution and

Table 3: Correlation coefficients between terrain derivatives and soil properties

Parameters	TWIMFD	Slp	LS	SPI	Tangc	Profc	Planc	Elv
Clay	0.04	0.13	0.09	0.08	0.16	0.07	−0.04	0.06
Silt	−0.16	0.18*	−0.1	−0.12	−0.18*	0.22**	0.14	0.17*
Sand	0.19*	−0.31**	0.6	0.09	0.1	−0.33**	−0.14	−0.25**
CCE	−0.41**	0.15	−0.12	−0.18*	−0.39**	−0.06	0.33**	0.16
pH	−0.07	−0.07	0.01	−0.01	−0.16	−0.08	0.11	0.51
EC	−0.05	0.01	−0.09	−0.05	−0.12	0.05	0.12	0.08
MWD	0.34**	−0.24**	0.02	0.04	−0.28**	0.04	−0.32**	−0.12
SOC	0.44**	−0.31**	−0.04	0.04	−0.19*	0.11	−0.25**	−0.26**

*Significant at the 0.05 level and ** Significant at the 0.01 level. SOC: Soil organic carbon, CCE: Equivalent calcium carbonate, MWD: Mean weight diameter, BD: Bulk density, EC: Electrical conductivity, LS: Length slope

Table 4: Correlation coefficients between different TWIs and SOC and R^2 of linear regression

Algorithm	Correlation coefficients with SOC	Equation	R^2
D8	0.35**	y = 0.189x + 0.397	0.12
RHO8	0.25**	y = 0.131x + 0.819	0.05
D-infinity	0.44**	y = 0.250x + 0.005	0.18
FRHO8	0.41**	y = 0.219x + 0.235	0.16
FD8-Quinn	0.44**	y = 0.249x − 0.096	0.19

**Significant at the 0.01 level

consequently estimation of SOC variation than another algorithm in the study area. Our results are similar with findings of Pei *et al.*[16] who reported the R^2 coefficient for D8 and FD8-Quinn algorithms 0.07 and 0.23, respectively. According to results of Hass,[26] determination of flow paths in flat areas with little height difference is critical issue of TWI. Hence, the results of MFD algorithm give a more realistic state of flow, especially in flat areas for spatial distributions of TWI. It should be noted that the lower correlation coefficients and R^2 may often be a result of the low resolution of DEM, slope aspect, soil vegetation, and SOC quality are also another factors which effect on SOC.

MLR Modeling

Finally, MLR analysis with stepwise regression method was developed for SOC estimation in the study area (Equation (7)). AS illustrated in Figure 3, MLR can explain 65% of the total variability of SOC using terrain derivatives (Equation 7) in this subhumid area. The results also indicated TWI as a main attribute of terrain derivatives in controlling SOC variability [Figure 4].

$$SOC\% = 0.92 + 0.33\ (TWI) - 0.009(ELV) - 0.2(planc) - (Slp) \quad (7)$$

The findings of Parvizi *et al.*[19] introduced which MLR explained 64% of SOC variations in the semiarid conditions.

ANN Modeling

Theoretically, ANN model uses many hidden layers for SOC estimation using terrain derivatives that acquire suitable parameters. The selection of optimum number of hidden neurons is an important process in developing MLP networks. Among the different tests, the hidden-layer nodes and the optimum iteration learning rates were determined 8 and 10,000 for SOC estimation [Table 5], respectively, with tangent sigmoid transfer function in hidden layer. As shown in Figure 5, the performance of network MSE in different epochs which is the best validation performance 0.011 at epoch 6. The findings of Somaratne *et al.*[34] also confirmed that tangent sigmoid transfer function was a more suitable selection to SOC estimation in different land use.

Finally, the results introduced that ANN can be recognize 76% of the SOC variability in the study area using terrain derivatives [Figure 5]. Karchegani *et al.*[20] also explained 64, 78, and 89 % of the total variability in SOC, for the model 1, 2, and 3, respectively, using auxiliary data including the land use types, terrain derivatives, and remotely sensed data in the hilly regions of western Iran. The results of Mirzaee *et al.*[35] showed that the ANN model with $R^2 = 0.63$ that used principal components as input variables, performed better than the (MLR) model. The findings of Tiwari *et al.*[36] also stated that ANN methods had a great potential for estimating and mapping spatial SOC content using field data and remotely sensed data with $R^2 = 0.90$ and RMSE = 0.07.

Comparison of MLR and ANN models to estimate SOC

The developed models of MLR and ANN were validated by additional soil samples (25 points) in the study region. Prediction of the studied models resulted in ME and RMSE values of −0.02, 0.23 in MLR [Table 6], and −0.01, 0.06 in ANN [Table 6], respectively. The result of comparing two models showed that ANN modeling was successful more than better of MLR in identifying SOC. Therefore, MLR cannot show the total SOC variability. This may be the result of nonlinear relationships between SOC and topography

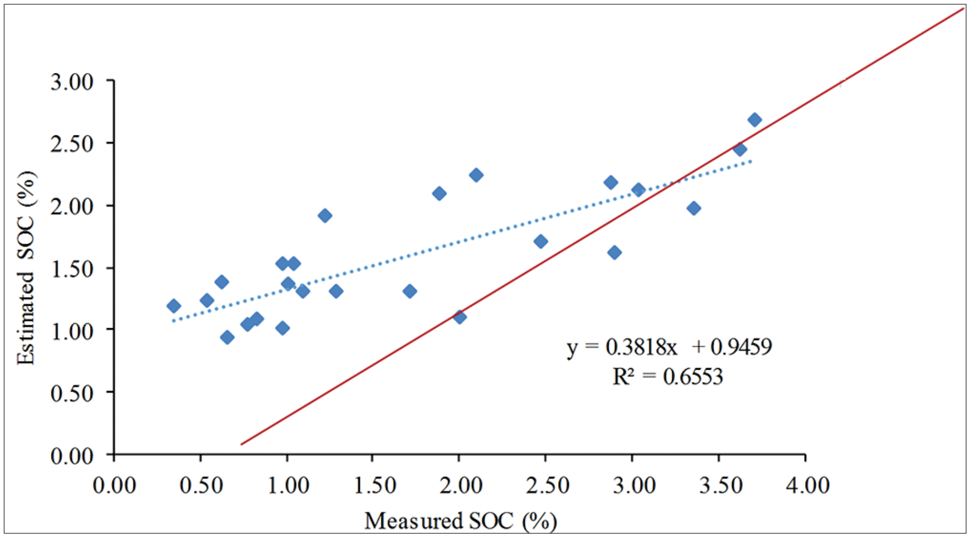

Figure 3: Relationships between measured and predicted soil organic carbon (%) by multiple linear regression

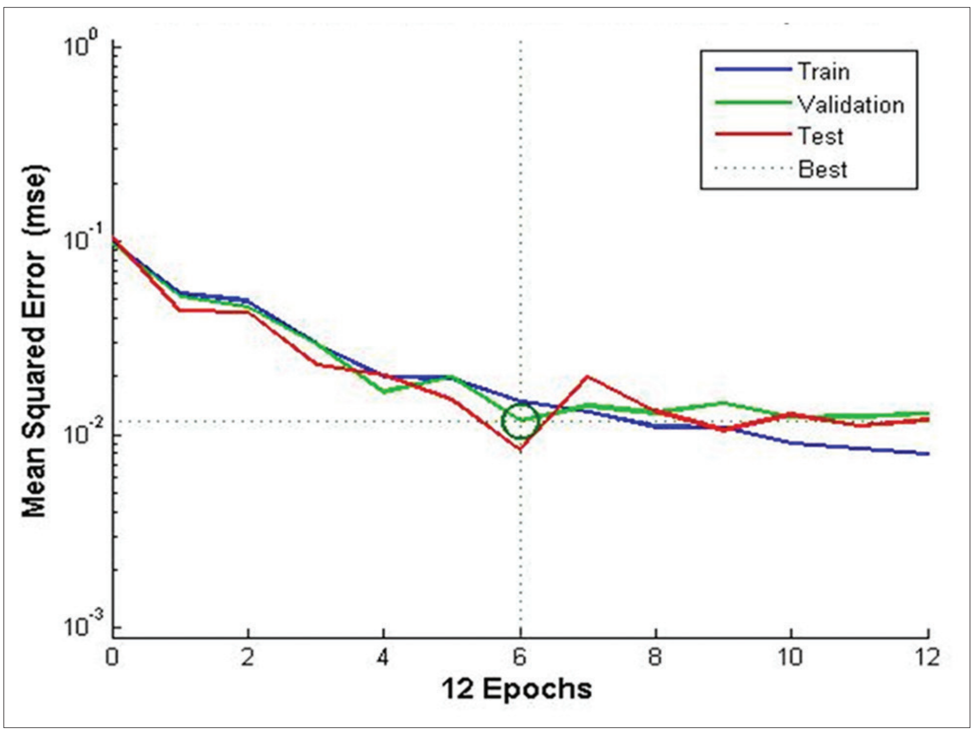

Figure 4: Performance of mean square error variation in network

derivatives. This is in agreement with findings of 19, 20, and 21 that introduced ANN model can be detect successfully SOC variability more efficiently than the linear models. Moreover, Mahmoudabadi *et al.*[21] pointed out that MLR needs a large dataset to have a high accurate prediction, whereas ANN model requires smaller dataset.

Important parameters influencing SOC

The parameter with high percent made an important contribution to the variability in SOC. Slope and TWI were identified as the most important parameter for SOC [Figure 6]. Other important parameters for estimation SOC included elevation, sediment transport

Table 5: Summary of the best results structure and optimum parameters of the ANN for estimating SOC

ANN structure	Transfer function	Iteration	Number of hidden layer	Number of hidden neurons
4-8-1	Tangent sigmoid	10000	1	8

ANN: Artificial neural networks, SOC: Soil organic carbon

Table 6: Trained model structures and performance

Data type	Method of models	R^2	ME	RMSE
Terrain derivatives	Stepwise regression	0.65	−0.02	0.23
Terrain derivatives	MLP networks with tangent- sigmoid transfer function	0.76	−0.01	0.06

MLP: Multilayer perceptron, ME: Mean error, RMSE: Root mean square error

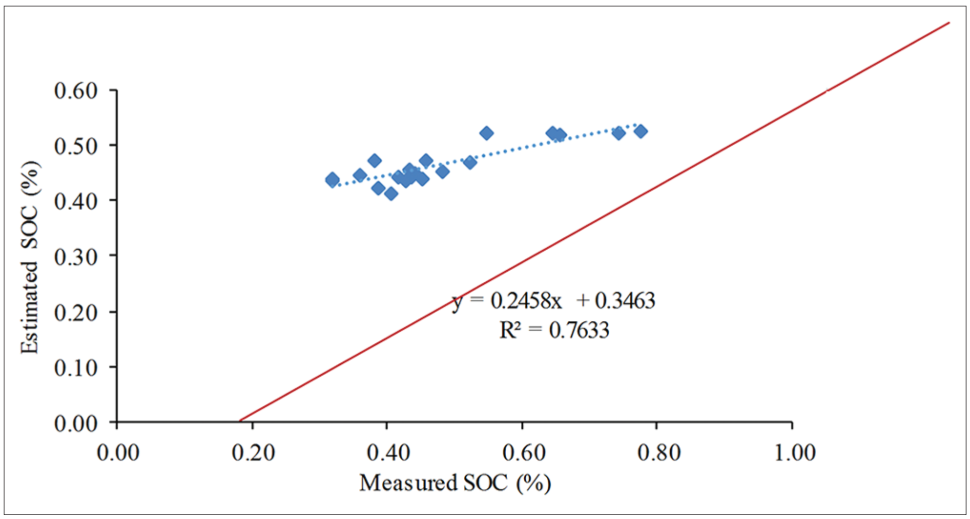

Figure 5: Relationships between measured and predicted soil organic carbon (%) by artificial neural networks

capacity index, and plan curvature. It should be noted the mentioned parameters had the strong correlation with SOC [Table 3] as previously described in section 4.2.

The results also showed that the slope and TWI have a large effect on SOC in this area. It is reported that in this region, slope gradient and moisture distribution have been identified as major processes of SOC variability. In general, steep slope positions have severe erosion, which is resulted in lower infiltration and SOC and greater runoff. The study was done by Ajami *et al.*[5] showed as for the significance of slope in SOC storage of loess hillslope. Therefore, erosional processes might have led to SOC decreasing. The LS is one of another most important topographic derivative in the ANN model that has a large effect on the quantity and quality of SOC.

Elevation had an important effect on SOC model as previously introduced in Table 3, it has a negative effect on SOC stabilization in this area. In line with our results, the similar relationships between SOC and elevation observed by Bangroo *et al.,*[37] and it included in SOC estimation equations. The result of sensitive analysis confirmed the importance of TWI in SOC distribution. It means that represents the processes of water accumulation at the soil surface as an indicator of the spatial distribution of soil moisture along the landscape. Hence, it can be effect on SOC variation.

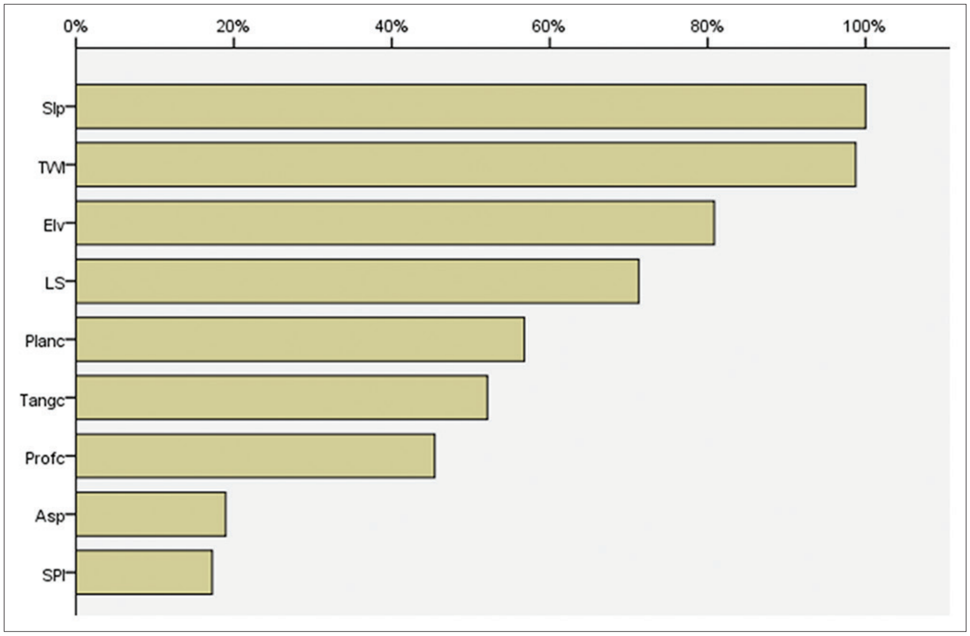

Figure 6: Contribution of each auxiliary data to estimation of SOC by ANN model

Conclusion

The results of present study showed accumulation of topsoil SOC is dependent to topographic position and derivatives at the small-scale hillslope. The overall results of the research show that in the natural areas with problems of soil sampling, analysis and costs of samples, there is a method; it can be use topographic derivatives for estimation SOC. On the other side, the correlation coefficient between SOC and TWI_{MFD} confirmed that SOC distribution is influenced by the type of algorithm and flow path, since TWI_{MFD} may be better reflect the flow stream. These results denoted using of TWI_{MFD} is important for estimation of SOC and achievement decision-making about global warming projects in areas such as this hilly region with steep hillslope in larger scale in future studies. Furthermore, it suggests measurement of soil moisture in the field and assessing the relationships between soil moisture and TWI and SOC.

The result of ANN model for estimation SOC in the present study explained 76% of SOC variability somewhat better than MLR with 65% of SOC variability that is having the same inputs and output, therefore, ANN produces promising results and its advantages can be utilized by developing or using new algorithms in future studies. To obtain a better estimation of SOC, in addition to terrain derivatives, data of remotely sensed, vegetation type, tillage practice, and agricultural management should be used as ANN input data in future studies. Furthermore, we suggest to apply other models, e.g., fuzzy logic, classification tree, and random forest. Besides, topography derivatives of UAV's DEM may be very good in steep hillslope and small scale; we suggest the using of it to assess impact of DEM resolution in similar study.

In steep hillslope, especially SH and BS positions, SOC was lower. Considering that hillslopes of this area are under cultivation for local population of Toshan village, further studies should be concluded changes of SOC with a density of vegetation type and assessing of optimal management of agriculture ecosystems to help mutation of ecosystem and increasing SOC for reducing global warming.

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تخمین کربن آلی خاک در مقیاس کوچکی از تپه‌های لسی
با استفاده از خصوصیات توپوگرافی در شمال ایران

صدیقه ملکی MSc
دانشکده مهندسی آب و خاک، دانشگاه علوم کشاورزی و منابع طبیعی گرگان، گرگان، ایران

فرهاد خرمالی* PhD
گروه علوم خاک، دانشکده مهندسی آب و خاک، دانشگاه علوم کشاورزی و منابع طبیعی گرگان، گرگان، ایران

علیرضا کریمی PhD
گروه علوم خاک، دانشکده کشاورزی، دانشگاه فردوسی مشهد، مشهد، ایران

چکیده

اهداف: پیش‌بینی مکانی کربن آلی خاک با توجه به نقش آن در مدیریت و پایداری خاک، جلوگیری از فرسایش خاک، پایش میزان دی‌اکسیدکربن هوا و گرمای جهانی از اهمیت خاصی برخوردار است. اهدف اصلی این تحقیق تعیین اثر خصوصیات توپوگرافی در پراکنش مکانی کربن آلی خاک و مقایسه الگوریتم‌های مختلف شاخص خیسی توپوگرافی برای تخمین کربن آلی خاک در یک مقیاس کوچک از تپه‌های لسی منطقه توشن، استان گلستان، ایران بود.
مواد و روش‌ها: تعداد ۱۳۵ نمونه خاک در چهار موقعیت مختلف شیب شامل شانه شیب، شیب پشتی، پای شیب و پنجه شیب جمع‌آوری گردید. خصوصیات توپوگرافی اولیه و ثانویه با استفاده از یک مدل رقومی ارتفاع با اندازه پیکسل ۱۰×۱۰ متر استخراج گردیدند. در نهایت به منظور تخمین کربن آلی خاک، رگرسیون خطی چندمتغیره و شبکه عصبی مصنوعی بین کربن آلی به عنوان متغیر وابسته و خصوصیات توپوگرافی به عنوان متغیرهای مستقل برقرار گردید.
یافته‌ها: بیشترین میزان کربن آلی با اختلاف معنی‌داری با استفاده از آزمون دانکن در پنجه شیب (۲۹/۹۰ گرم بر کیلوگرم) و کمترین میزان آن شانه شیب (۵/۰۰ گرم بر کیلوگرم) و شیب پشتی (۱۲/۷۰ گرم بر کیلوگرم) دیده شد. همچنین، کربن آلی خاک همبستگی بیشتری با الگوریتم‌های چندمسیره و دومسیره شاخص خیسی توپوگرافی نسبت به تک‌مسیره داشت. مدل رگرسیونی و شبکه عصبی مصنوعی نیز توانستند به ترتیب ۶۵ و ۷۶% از تغییرات مکانی کربن آلی را با استفاده از خصوصیات توپوگرافی در منطقه مورد مطالعه تبیین نمایند.
نتیجه‌گیری: این نتایج نشان می‌دهد که استفاده از خصوصیات توپوگرافی یک ابزار سودمند در تخمین کربن آلی خاک است. همچنین در مطالعات آینده برای تخمین دقیق کربن آلی خاک و تصمیم‌گیری در پروژه‌های گرمایش جهانی در قرن حاضر محاسبه الگوریتم‌های چندمسیره شاخص خیسی توپوگرافی در مناطق تپه‌ای شبیه به منطقه مطالعاتی در مقیاس بزرگتر ضروری است.

کلیدواژه‌ها
الگوریتم‌های مختلف جریان؛
خصوصیات توپوگرافی؛
شبکه عصبی مصنوعی؛
کربن آلی خاک؛
لس

*نویسنده مسئول
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آدرس پستی: گروه علوم خاک، دانشکده مهندسی آب و خاک، دانشگاه علوم کشاورزی و منابع طبیعی گرگان، گرگان، ایران
fkhormali@gmail.com و khormali@yahoo.com