THE EFFECT OF LAND TYPES AND CONSEQUENTLY LAND USE ON SOIL ORGANIC CARBON CONTENT – CASE STUDY: DAMAVAND REGION OF IRAN

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Abstract. Organic carbon is an important component of soil that influences soil fertility, biological activity, food security, and climate change. One of the important issues in soil science is the establishment of empirical relationships between different soil properties. The objectives of this research were to investigate the influence of different factors on soil organic carbon, such as total nitrogen, clay content, calcium carbonate equivalent and pH, for soils from various geomorphologic settings in the Damavand Region in Northwest Tehran, Iran. Regression models were developed for prediction of the organic carbon content of soils characteristics in this region. Lower SOC concentrations were measured for plateau soils (~4.92 g kg^{-1}), associated with lower plant biomass and reduced temperatures at higher elevations. In contrast, soils from River Alluvial Plain regions, which are currently utilized for gardening, had the highest organic carbon content (~22.05 g kg^{-1}). For all landform types (i.e., alluvial fan (irrigated farming lands), plateau (Rangeland), and River Alluvial Plain soils (garden)), SOC had positive and significant relationship with total nitrogen ($r = 0.962$, $p < 0.01$). Simple linear regression, multiple linear regression, and nonlinear regression models were also developed for describing the relationship between SOC and landforms physical and chemical characteristics.
Keywords: *physiographic characteristics, regression models, soil properties*

Introduction

Current investigation attempted to enhance the amount of organic carbon captured in soils. Organic matter is one of the most important indicators of soil quality. Recent efforts have been made to increase the carbon storage capacity of soils, having a positive effect on biological activity, fertility and productivity (Baldock et al., 2010). The sequestration of carbon in soil has the potential to offset greenhouse gas emissions (i.e., CO_2, CH_4, and N_2O) associated with climate change (Xun et al., 2010). Practical methods to increase carbon sequestration of particular research were developed. This requires an understanding of the influence of different land-management practices (e.g., tillage) on soil organic carbon (SOC) (Gaiser et al., 2008), which is complicated by the fact that SOC is affected by climate, soil type, vegetation type, topography and land drainage, as well as land management practice (Gami et al., 2009).

Zhao et al. (2017) researched the impact of shifts in land use on SOC in an agro-pastoral ecotone of Inner Mongolia. Li et al. (2016) estimated the impact of land use change on SOC sequestration in China from 1985 to 2005. However, the effect of shifts in land use on carbon budget in China's arid and semi-arid regions, such as the Shiyang River Basin, has received little attention, which limits our understanding of the mechanisms by which land use change affects the carbon cycle. Poeplau and Don (2015) showed that planting cover crops during winter and tilling them into the soil as additional carbon input can significantly enhance soil C on croplands.

It is important to identify the relationships between SOC and landscape features and to assess the amount and spatial variability of carbon storage in soils. Physiographic

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characteristics such as altitude, slope and aspect have an influence on the efficiency of carbon sequestration in different regions. Wang et al. (2010) showed that landscape characteristics influenced SOC. They measured lowest organic carbon accumulation in elevated areas and identified a significant negative relationship between SOC and elevation (r = –0.429**). The same relationship also found a significant negative correlation between SOC and slope (r = –0.195**).

Heidari et al. (2010) suggested that the highest levels of carbon are found in areas that have moderate rainfall and low elevation. These factors are unaffected by human activities (i.e., tillage), and have suitable climatic conditions (i.e., temperature and precipitation) so that the growth period is not limited. While the ability to estimate carbon sequestration in a wide range of environments is essential, this has been limited by the complexities of soil characteristics and environmental conditions (Padilla et al., 2010).

Topography is one of the most important factors affecting the amount of organic carbon in soils, but this is not a simple relationship. For example, Senthilkumar et al. (2009) found that the influence of topography on organic carbon storage varied between different agricultural systems. This was attributed to the accumulation of plant residues that affect SOC content in the uppermost 0–30 cm depth of the soil. Soil organic carbon also varies with slope, due the influence of leaching, soil erosion, vegetation, and other physical properties such as soil texture (Boulal and Macpherson, 2010).

Geostatistical methods provide a way of studying and predicting the spatial variability of SOC based on relationships with other soil properties and landscape characteristics (Zhang and McGrath, 2004). These relationships can be expressed as regression models (Vasques et al., 2010), developed using parameters that measured in the field, or for which data already exist (Sarmadian et al., 2010). Motallebi et al. (2011) also estimated soil hydraulic properties (e.g., bulk density, calcium carbonate content, and sand–silt–clay fractions) for a semi-arid region using similar models. However, few studies have examined the spatial patterns of SOC and its relationship with the physiographic properties in semi-arid regions (Heidari et al., 2010; Parvizi et al., 2010).

The objectives of this research were to: (i) investigate the influence of physical and chemical characteristics (e.g., total nitrogen, equivalent calcium carbonates, clay content and pH) on SOC and (ii) develop regression models between SOC and different landform types in the Damavand Region of Tehran, Iran.

Materials and methods

Study area

The Damavand Region is located in northeast of Tehran in Iran (*Fig. 1*), covers about 6272 ha at 35°35’55”–35°40’37”N and 51°59’11”–52°11’33”E. The climate is predominantly dry and cold, with a mean annual precipitation of 322 mm and a mean annual temperature of 11.6 °C (1999–2010 data) (Climatic Data Center, 2010). Height above sea level varies between 1800 and 2200 m. The main landforms of the region are “alluvial fans, River Alluvial Plains, and plateaus” and soils classified as Entisols and Inceptisols using the USDA soil classification system (Keys to Soil Taxonomy, 2010).

A digital elevation model (DEM) of the region was developed in Arc-GIS from a topographic map (1:25,000 scale). Physiographic characteristics (slope, altitude, and aspect) were classified using the DEM, and landform units were subsequently

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determined. Landform units were determined by overlaying the slope, hypsometric and aspect maps.

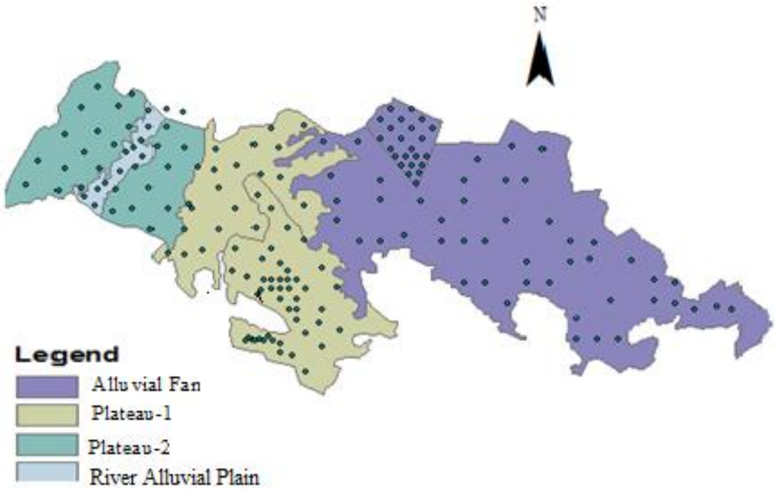

Figure 1. *Landform types and sampling sites in the Damavand Region of Tehran, Iran*

Dividing the slope according to the irrigation management division and determining the height adjustment according to the type of cover and management changes. Nine elevation classes (1820-1900 m, 1900-1950 m, 1950-1985 m, 1985-2020 m, 2020-2045 m, 2045-2075 m, 2075-2110 m, 2110-2150 m, 2150- 2200 m), four slope classes (0-5%, 5-12%, 12-25%, > 25%), and four aspects (north, south, west, east) were defined. ETM+ satellite images (from 2002), Indian Remote Sensing (IRS) satellite images (from 2007), and Moderate Resolution Imaging Spectroradiometer (MODIS) satellite images (from 2010) of the region were analyzed to delineate land type boundary from Rs and using GIS software. The use of remotely sensed data from satellite imagery or aerial photography has become commonplace in soil management studies (Karl and Maurer, 2010).

Soil sampling

Soil samples were collected from 0-25 cm soil depth, for each land unit. Sampling was done with a shovel of about 2 kg. Average slopes of alluvial fan 0-5% and clay loam texture, Plateau 1: average slopes 5-8% and silty clay loam texture, Plateau 2: average slopes 8-12% and sandy loam texture, River Alluvial Plains: average slopes 0-5% and loam texture. They were classified based on the relative area under each soil type, land use, slope, aspect, and elevation class. The plateau was divided into two groups due to the type of cover and management. The total number of 1607 sites was initially classified. According to the Minimum Decision Area (MDA) (*Eq. 1*), areas less than 10 ha were merged with neighbor polygons, reducing the number of sites by 160, as follows:

$$MDA(hac) = 1.6cm^2 \times 10^{-8}(hac.cm^2)(Scalefactor.mm^{-1}) \quad \text{(Eq.1)}$$

Sampling sites were located in the field using GPS in October 2010. At each sampling location, three separate points (approximately 10 m apart) was sampled at 0–

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30 cm soil depth. These three individual samples were combined to form a single bulk sample for each site. Samples were sealed in plastic bags and transported to the laboratory. At each location, recorded the latitude longitude, landscape position, slope class, aspect, elevation, land cover, and land management practice.

Laboratory analysis

Soil samples were air-dried and sieved in the laboratory to retain the <2 mm fraction. Soil pH was measured in a 1:1 suspension of soil and distilled water (McLean, 1982). Soil texture was measured using hydrometer method (Bouyoucos, 1962). Soil organic carbon was determined using the Walkey–Black method (Walkley and Black, 1934). Bulk density (BD) was measured using standard paraffin wax procedures. (USDA, 1995). Total Nitrogen (TN) was determined using the Kjeldahl method (USDA, 1995). Calcium carbonate equivalent (T.N.V), was measured using the Acidimetric method, which involved neutralization of the sample by a titrated acid. Back-titration using a base that used to determine CaCO3 content (USDA, 1995). Particle size distribution was determined using the hydrometer method (Gee and Bauder, 1979).

Statistical analysis

Descriptive statistical parameters for SOC were determined, including the mean, median, skewness, kurtosis, standard deviation, variance, coefficients of variation, maximum and minimum. Pearson correlation coefficients (r) were estimated for all possible paired combinations of the response variables to generate a correlation coefficient matrix. Kolmogorov–Smirnov tests showed that the data were not normally distributed; consequently, non-parametric tests were used. The Kruskal–Wallis test was used to assess differences in SOC between land units (Mills and Cowling, 2010). Simple linear regression, multiple regression, and simple nonlinear regression methods of predicting SOC were assessed. The limiting stepwise regression was applied on the input variables to prevent internal regression.

The performance of the regression models were evaluated by cross validation, where estimated and observed values are compared at each of the observed value location. Reliability of the models evaluated with an independent dataset. Estimated and observed values were compared using two criteria: mean absolute error (MAE) and mean bias error (MBE) (*Eqs. 2* and *3*):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|z^*(x_i) - z(x_i)\right| \qquad \text{(Eq.2)}$$

$$\mathrm{MBE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\left(\mathrm{z}^*(\mathrm{x_i}) - \mathrm{z}(\mathrm{x_i})\right) \qquad \text{(Eq.3)}$$

where z*(xi) is the value to be estimated at the location of xi, z (xi) the known value at the sampling site xi and n is the number of sites.

Geostatistical analysis was also used to infer the spatial variation of SOC at each site. The spatial distribution of SOC was predicted by the IDW method. In this study, the geostatistical analyses were produced with GIS software ArcGIS (version 9.3).

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Results

The results showed that there are significant differences of the Kruskal-Wallis ($p < 0.01$) test between soil organic carbon contents of the four land types (*Table 1*).

Table 1. *Comparing SOC among land forms ranks*

Landform-code	N	Mean rank
Alluvial fan (irrigated farming lands)	54	89.62
Plateau1 (dry farming)	56	66.29
Plateau2 (rangeland)	30	44.12
River alluvial plain (garden)	12	146.08
Total	152	

The highest SOC was measured in River Alluvial Plain soils (mean SOC = 22.04 g kg^{-1}), followed by alluvial fan soils (mean SOC = 7.75 g kg^{-1}), plateau 1 soils (mean SOC = 6.17 g kg^{-1}), and plateau 2 soils (SOC = 4.92 g kg^{-1}). The mean SOC value for the study area was 7.73 g kg^{-1} (*Table 2*).

Table 2. *Descriptive analysis of soil variables*

Parameter	Land type				
	Total area	Alluvial fan	Plateau 1	Plateau 2	River alluvial plain
Mean	7.74	7.750	6.170	4.920	22.05
Median	6.93	6.840	5.830	4.620	22.10
Variance	2.55	6.539	2.710	5.800	20.60
Std. deviation	5.05	2.980	1.650	2.410	4.54
Skewness	2.42	2.282	0.422	0.447	1.22
Kurtosis	6.57	6.539	-0.022	-0.684	2.56
Min	0.91	3.695	2.920	0.914	16.25
Max	33.16	20.222	10.210	9.250	33.16

To explain the spatial variability of SOC, the Inverse Distance Weighting (IDW) method was used. The organic carbon content was low for soils sampled from several sites in the study area, which was the main factor in their low fertility status. The distribution of organic carbon in the upper profile (0–30 cm) of soils is shown in *Figure 2*.

The results showed that soil organic carbon ranged from 0.1% to 3.2% (1–32 g kg^{-1}) in the study area. Organic carbon was very low in the some part of plateau with SOC < 4 g kg^{-1} and higher SOC > 16 g kg^{-1} in the all part of River Alluvial Plain.

The area under each land form had normal distribution (Kolmogorov-Smirnov test). Except total area and alluvial fan, the data distributed abnormal. Based on the result of this table, soil organic carbon was significantly positively correlated with %N ($r = 0.962^{**}$, $P < 0.01$) in total area. In general, the value of N significantly affected SOC for all landform classifications (*Table 3*).

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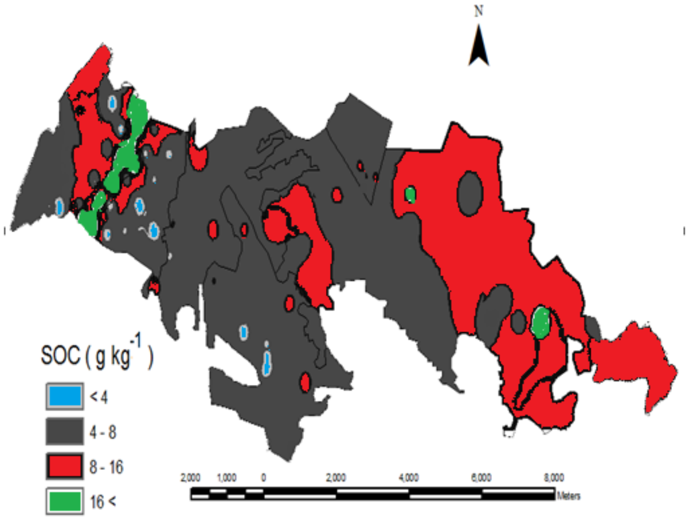

Figure 2. *Distribution of organic carbon in the study area*

Table 3. *Pearson correlations among soil physical, chemical variables and organic carbon in land form classification*

Land type	Total area	Alluvial fan	Plateau 1	Plateau 2	River alluvial plain
Variable	%N %T.N.V pH	%N	%N	%N Clay	%N
r	0.962** 0.407* -0.447*	0.893**	0.609*	0.730** 0.838**	0.960**
n	152	54	56	30	12

**Correlation is significant at the 0.01 level (2-tailed)
*Correlation is significant at the 0.05 level (2-tailed)

Linear and nonlinear regression equations to predict SOC from physiographic variables are shown in *Table 3*. For all landform types, TN had the highest correlation with SOC. There were significant differences between the types of landform ($r = 0.99^{**}$, $p < 0.01$). For each landform, two linear regression model and one nonlinear regression model were developed to predict SOC. In all equations, all or one of the independent variables such as TN, Clay, pH, Bd was used (*Table 4*).

Comparing nonlinear models in all land types, indicate that cubic models has highest coefficient of multiple determination (*Table 4*), and it is fitted for predicting SOC. Estimating regression models in each land type indicated, the models had not any over estimation or under estimation because MBE index was nearly zero (*Table 5*).

MAE value was greater in River Alluvial Plain than any other land types; which means high error in that location. Measured and predicted values were compared using the t-student test. Results showed no significant difference between them in each land type. This means that predicted models is approved and the relationship is reliable.

The significance level of coefficients in each land type for regression models was determined: for River Alluvial Plain, alluvial fan and total area; Correlation coefficient is significant at the 0.01 level. For Plateau 1 and Plateau 2; Correlation is significant at the 0.05 level. Standard Error was calculated 1.01, 0.33, 0.5 and 0.61 for River Alluvial Plain, alluvial fan, Plateau 1 and Plateau 2, respectively.

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Table 4. *Regression models used to estimate SOC*

Land types	Regression	Regression equation	r
Alluvial fan	Linear	OC(g kg^{-1}) = -2.475 + 10.882 N (g kg^{-1})	0.797
		OC(g kg^{-1}) = 17.725+7.488 N+0.004 T.N.V-3.082 pH-0.003 gravel + 2.615 Bd + 0.001 Clay + 0.003 Sand	0.830
	Nonlinear	OC(g kg^{-1}) = 15.172-26.57 N+19.458 N^2	0.837
Plateau 1	Linear	OC (g kg^{-1}) = 4.42+3.21 N	0.371
		OC(g kg^{-1}) = 51.941+1.99 N+ 0.003 T.N.V-5.656 pH+0.003 gravel-0.17 Bd-0.006 Silt-0.009 Sand	0.537
	Nonlinear	OC(g kg^{-1}) = -4.258+27.216 N-14.27 N^2	0.681
Plateau 2	Linear	OC (g kg^{-1}) = 1.041+9.34 N	0.533
		OC(g kg^{-1}) = -0.467+0.012 Clay+6.085 N	0.742
	Nonlinear	OC (g kg^{-1}) = $e^{2.475-0.365/N}$	0.681
River alluvial plain	Linear	OC(g kg^{-1}) = -1.699+11.725N	0.921
		OC(g kg^{-1}) = -2.837+11.539 N + 0.005 Clay	0.922
	Nonlinear	OC(g kg^{-1}) = 26.582-15.696 N+6.431 N^2	0.948
Total area	Linear	OC(g kg^{-1}) = -0.216+10.061 N	0.925
		OC(g kg^{-1}) = 15.5+10.161 N+0.004 T.N.V-2.21 pH	0.930
	Nonlinear	OC(g kg^{-1}) = 2.912+2.924 N+2.935 N^2	0.947

Table 5. *Index assessment and significant regression models*

Land types	Model	The correlation coefficient	MBE	MAE
Alluvial fan	Nonlinear	0.84	0.0	0.73
Plateau 1	Nonlinear	0.68	0.0	0.81
Plateau 2	Multiple linear	0.74	0.0	0.8
River alluvial plain	Nonlinear	0.95	0.0	0.9

Discussion

The Pearson's linear correlation analysis revealed a significant positive relationship between SOC and total nitrogen. The highest organic carbon contents measured in soils from the highest storage of N accumulation. It can be assumed that that TN affected SOC status significantly. It assumed that TN has a positive benefit in maintaining and restoring the SOC quality and quantity for cropland in the study area. In similar research, Parvizi (2010) showed that physical variables and land use type can identify carbon sources. In that research, regression models were developed in forestry with a higher coefficient.

In some land types, there was significant correlation between clay and SOC; it is assumed clay protects organic matter from decomposition and runoff. For instance, Kasel et al. (2011) investigated that across north-central Victoria in south-eastern of Australia, mean rates of SOC accumulation in whole soils were greater increase under

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the N-fixing trees. There was poor correlation between SOC and clay content across sites due to the clay mineralogy.

Differences in accumulation of SOC may also be related to physiographic condition such as slope, aspect, elevation, land use, the structure of root systems that could contribute to SOC distribution.

Soil organic carbon originates primarily from plants, thus vegetation and land use history is one of the most important driving factors of SOC (Jafarian and Kavian, 2013; González et al., 2010; Strickland et al., 2010). Accurate and reliable estimates of SOC storage in landscapes and land use are critical to the development of effective policies and strategies to mitigate atmospheric and climate change (Sylvia et al., 2016; Lufafa et al., 2008; Zhao et al., 2010). This research was provided where these findings were used to create a reference of regression models. This information was found to be valuable in supporting the evaluation of SOC field surveys, which are increasingly becoming available. I would also recommend to search on available topographic and management variables to develop models to estimate soil organic carbon.

Conclusion

Soil organic carbon in the land forms of the study area was abnormal, and had an arithmetic mean of 7.7 g kg^{-1}. The highest organic carbon content (22.04 g kg^{-1}) was in River Alluvial Plain region that has lowest elevation, and include river surrounded by river sediment. This fertility area was used for garden utilization. These results explained relationships between organic carbon and land types and land use attributes. In some parts of alluvial fan, including cropland utilization, the level of soil organic carbon (7.75 g kg^{-1}) could be explained by the input of litter, organic manure, decomposition and loss by the soil erosion. Addition of chemical fertilizer and manure could increase SOC in topsoil. Chemical fertilizer can increase root production of crops and products' yield, subsequently increasing organic residue input into the soil.

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