

Spatial Distribution of Soil Organic Matter and Soil Organic Carbon Stocks in Semi-Arid Area of Northeastern Syria

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Abstract

Although soil organic matter (SOM) forms a small portion of the soil body. Nevertheless, it is the most important component of the soil ecosystem, as well as of the carbon global cycle. In the semi-arid environment, there has been little research on the spatial distribution of SOM and soil organic carbon (SOC) stock. In this study, stratified random samples of total 30 soils were collected from two different soil depth (topsoil, subsoil) of Al Balikh plain and used for mapping the spatial variability of SOC and to estimating the SOC stock. The result showed that the values were relatively homogenate, with the normal decreasing trend with increasing the depth. The standard deviation (Std. D) for both SOC and SOC stock indicates homogeneous and absence of outliers values, whereas the coefficient of variation (C.V) indicates non-dispersion and clustering of values around the average. SOC was 0.38%, 0.17% in topsoil and subsoil respectively; the corresponding averages of SOC stock were 1.23 kg·m⁻² and 1.14 kg·m⁻² respectively, these values reflecting typical characteristics of poor SOC semi-arid soil. The correlation between SOC and SOC stock was ($R^2 = 0.996$, $p < 0.001$) in topsoil and it was ($R^2 = 0.941$, $p < 0.001$) for subsoil. The semivariograms were indicated that both SOC and SOC stock were best fitted to the exponential model. Nugget, range, and sill were equal to 0.002, 0.036, and 0.044, respectively for SOC in topsoil, and 0.014, 0.071, and 0.081, for SOC in the subsoil. For SOC stock, it was 0.0, 0.036, and 0.0508, respectively in topsoil. In the subsoil, the values were 0.1899, 0.086, and 4.159, respectively. SOC and SCO stock in both two layers are shown a strong spatial dependence, for which were 4.3, 17.2 for SOC in topsoil and subsoil respectively, and 0.0, 4.5 for SOC stock in topsoil and subsoil respectively, thus, which can be attributed to intrinsic factors.

Keywords

Soil Organic Carbon Stock, Semi-Arid, Semivariogram, Exponential Model, Flood Plain

1. Introduction

There is great interest in recognizing the soil system as the most important long-term organic carbon (OC) reservoir in terrestrial ecosystems contributing to global climate change [1]-[6]. SOM which is a major source of OC is composed of a variety of plant and animal residues in different stages of decomposition [7]. SOC content is indispensable for the assessment of SOCS, and its importance also has been emphasized by [8] [9] [10] and others, as an important role in the agricultural productivity and soil sustainability and quality [11] [12] [13]. The sources and the decomposing factors of SOM vary in space and time [14]. Also, it is sensitive to environmental changes [15] [16]. Whereas, several factors such as soil type, climate, terrain, hydrology, land use, geology, etc. affect their distribution [17]. Organic matter often binds to fine particles, particularly clay [2], and the high amount of SOM tends to be limited to the soil surface, probably at a depth of 5 to 10 cm [18]. For this reason, most soil studies focus on topsoil, not on the whole soil profile. In fact, a considerable fraction of the total soil organic carbon (SOC) stock is known to be stored in the subsoil [19] [20], whereas a substantial amounts (27% - 77%) of SOC could occur at depths greater than 20 cm [21]. Therefore, it should not be neglected in an ecosystem service context [22].

However, the reliable assessment and monitoring of SOCS is a key importance for soil conservation as well as in mitigation strategies for increased atmospheric carbon [23]; as such, small changes in the soil carbon storage may significantly affect the (CO₂) concentration of the atmosphere [24]. This situation increases the importance of SOM in a semi-arid region due to its extensive extension and its constant exposure to extreme climatic conditions, for all that there is little research examining SOC in these areas. The semi-arid lands are areas with an aridity index range from 0.2 to 0.5 [25] [26], vulnerable soil, and either desertified or prone to desertification. It is still questionable how much SOC is stored in the arid soils, as the SOC pool tends to decrease exponentially with temperature [27], and consequently, it has soils of low OC content (less than 1%) [28] [29], which can lead to progressive degradation of their quality and productivity [30]. Nevertheless, these areas might play a key role in the mitigation of climate change effects by reducing the rate of enrichment of atmospheric (CO₂) [29]. Spatial representation of the SOC is considered very essential for regional planning, soil management, soil evaluation, and agriculture practices [31]. Remote sensing and GIS play vital roles in the preparation of spatial illustration [32]. During the last decade, various digital soil map techniques were used to ex-

amined the accuracy of SOC prediction by comparing different methods such as linear regression, ordinary kriging, co-kriging, regression kriging, inverse distance weighted, splines etc. [23] [33] [34] [35] [36]. Nevertheless, there is no particular method, which predicts the SOC with the best accuracy; all the deterministic interpolation methods where results tend to oversimplify the reality [37].

Many geostatistics methods have used the location samples for soil mapping [38] [39] [40] [41] [42]. However, Geostatistics has an ability to distinguish the continuous nature of SOC and is able to detect random variations during modeling [43], and the spatial autocorrelation is considered to interpolate into a continuous surface from sample points [44]. In the east of Syria, arid and semi-arid lands are widely dominated, with annual precipitation ranging from 200 mm in mid-east to less than 50 mm in the south-east, represents Al Badia ecosystem, which is a transition zone between desert in the east and south and Mediterranean ecosystem in the west. The soils in this rainfed area are characterized by their low content of organic matter makes topsoil fragile and may experience degradation, desertification, and wind erosion. However, the SOC, which is a key for crop production here, has not been widely studied; it is believed that the improvement of crop production in these areas should be associated with the sustainability of soil productivity if it cannot be improved and increased [45].

The objectives of this study were to evaluate the stature of the soil organic carbon content in the study area, to study the spatial variability of SOM content in this intensively cropped land, and to estimate the OC stock within such kind of semi-arid land.

2. Material and Methods

2.1. Study Area

The study area is located about 50 km northeast of the city of Ar-Raqqa, The total area is 15274.97 ha, between of 39°02'10.0" - 38°47'10.0"N, and 36°08'10.0" - 36°00'10.0"E, in a deposited fan of Al-Balikh river with elevation about 290 (a. m. s. l) (Figure 1).

The site represents a flat region of a reclaimed agricultural field in the east of Syria [46]; hence, there is no considerable topographic relief within the area under consideration [47]. The area submitted to steppe climate [48], which is semi-arid climate with an average annual rainfall of less than 200 mm and hot dray summer session with annual mean temperature 17°C where evaporation reaches up to 14 mm/d. For the most part, somewhat poorly drained soils originated from alluvial and proluvial Quaternary depositions, in which Aridisols of Gypsid and Calcids suborders are predominate [47]. Many investigations addressed this area before constructing a complete irrigation and drainage system, e.g. [49], Nedeco from Netherlands in 1963; Sir Alexander Gibb and Partners from England in 1966; and Sogeria from France in 1976 [46]. Shallow water tables exist all year between 1 and 10 m. From a geological point of view, the

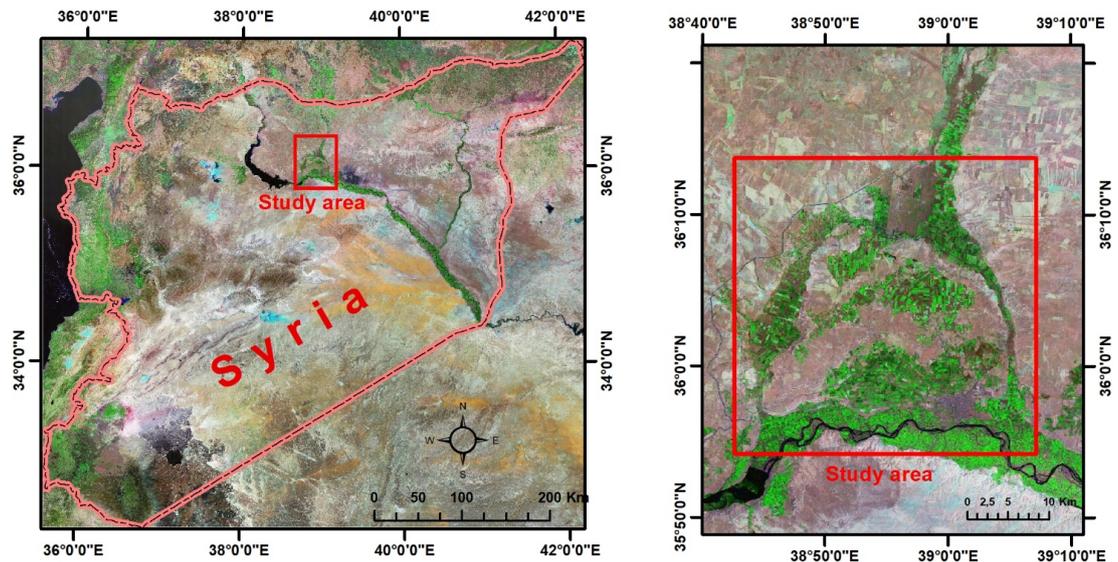


Figure 1. Location of Al Balikh plain north east Syria. Sources: Landsat ETM+ (April 2012 path 172, raw 35).

area is composed of Quaternary alluvium (loam, sandy loams, gravel, mud, pebbles, and sands) [50]. Land reclamation project area started in 1970; where irrigation system, drainage networks as well as leveling have been conducting and the area has entered into investing since 1973, mainly cotton, in rotation with wheat are often planted [46].

2.2. Soil Sampling and Chemical Analysis

Spatial distribution of SOM requires determination of soil OC concentrations, and for determination of soil OC concentrations, additional parameters of bulk densities (BD), stone contents, and soil depth are required [51].

Soil sampling was executed using a Global Position System (GPS) in order to restrict sampling points in the field and to record longitude, latitude, and elevation of each point. BD was measured for topsoil (0 - 30 cm) and subsoil (30 - 60) by using the method of [52].

Soil samples were taken from well-distributed 30 soil profiles; then the samples were air-dried and ground to pass through 2 mm sieve prior to analysis. Samples were analyzed for carbonates (subtraction method, after removing OC at 550°C). OC content in fine earth was determined in duplicated samples using the potassium dichromate oxidation [53], and soil organic carbon was calculated using the Equation (1) [54]:

$$\text{SOM} = 1.72 \times \text{SOM} \quad (1)$$

Percentage of coarse fragments was assessed by visual estimates (by comparing with area charts). The SOC stocks in topsoil and subsoil were calculated from SOC concentrations and BD. To avoid overestimation of SOC stocks, the fraction of coarse fragments (mineral particles < 2 mm) was considered, the SOCS was calculated after [55]:

$$\text{SOCS} = d \times \text{BD} \times (C_{\text{tot}} - C_{\text{min}}) \times CF_{st} \quad (2)$$

where: SOCS is SOCS [kg/m^2], C_{tot} and C_{min} are total and mineral carbon [$\text{g}\cdot\text{g}^{-1}$], d is depth of horizon/depth class [m], BD is bulk density [kg/m^3], CF_{st} is correction factor for coarse fragments content ($1 - (\% \text{gravel} + \% \text{stones})/100$).

2.3. Statistical and Geostatistical Analysis

The statistical analyses of extreme maximum and minimum values, mean, Standard deviation, Kurtosis, Skewness, Coefficient of Variation, were conducted to assess the pattern of distribution of data frequency and to find out the relationship between environmental and soil variable which is not always linear and it is usually complex. Kriging is a geostatistical method that is very popular nowadays [56] [57], commonly used to interpolate soil property datasets from discrete points to a spatially continuous surface [58] [59]. Kriging and its derivative methods are considered more accurate and stable for prediction of SOC [60] [61]. Ordinary Kriging (OK) often gives better interpolation for estimating values at unmeasured locations [34] [38] [62]-[67]. Moreover, it is the superior method for interpolation of SOC spatial distribution [68]; therefore, the OK was used to generate maps of SOM distribution. Kriging estimate $z^*(x_0)$ and error estimation variance $\sigma_k^2(x_0)$ at any point x_0 , were calculated as follows [69]:

$$z^*(x_0) = \sum_{k=0}^n \lambda_i Z(x_i) \quad (3)$$

$$\sigma_k^2(x_0) = \mu + \sum_{k=0}^n \lambda_i \gamma(x_0 - x_i) \quad (4)$$

where λ_i are the weights μ is the lag range constant; and $\gamma(x_0 - x_i)$ is the semivariogram value corresponding to the distance between x_0 and x_i [70] [71].

Semivariograms were used to quantify the spatial variation of each regionalized geostatistical variable and to determine the spatial continuity and distribution structure of OM. Because it simply enumerates the relationship between the degree of similarity between the two measurements of some variable $Z(x_i)$ separated by distance h , which is termed the lag [72] [73], as follows:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \quad (5)$$

where: $\gamma(h)$ are the samivariograms, $z(x_i)$ and $z(x_i + h)$ are experimental measures of any two points separated by the vector h , and $N(h)$ is the number of pairs separated by a lag distance h , $Z(x_i)$, and $Z(x_i + h)$ are values of Z at positions x_i and $x_i + h$ [74].

The semivariograms obtained from the data were fitted to produce geostatistical parameters, including nugget variance (C_0), structured variance (C_1), and sill variance ($C_0 + C_1$). The nugget/sill ratio (spatial dependencies) $C_0/(C_0 + C_1)$, was calculated to imitate the spatial autocorrelation of the values. The spatially dependent variables were classified as: strongly spatially dependent if the ratio was $\leq 25\%$, mid-spatial-dependent if the ratio was $25\% - 75\%$ and weakly spatially dependent if the ration was $\geq 75\%$ [75] [76] [77]. Parameters obtained from the semivariograms were used to produce thematic maps of the SOM in topsoil and subsoil, [69]:

$$Z^*(x_0) = \sum_{i=1}^n \lambda_i \cdot Z(x_i) \quad (6)$$

where: $Z^*(x_0)$ - interpolated value of variable Z at location x_0 , $Z(x_i)$ -values measured at location x_i , λ_i - weighed coefficients calculated on the basis of the semivariogram when:

$$\sum_{i=1}^n \lambda_i = 1 \quad (7)$$

The weights, calculated in this way, make it possible to obtain non-biased interpolated values, *i.e.*, the expected value:

$$E[Z^*(x_0) - Z(x_0)] = 0 \quad (8)$$

The estimated variance:

$$\text{Var}[Z^*(x_0) - Z(x_0)] = \text{minimu} \quad (9)$$

3. Results and Discussion

The field measurement and laboratory analyses across 30 sites within two descending soil layers are presented in **Table 1**. In general, the soil was similar to other Euphrates soil, in terms of topsoil partly eroded by aeolian erosion, although, the soil showed differing distinctly, in terms of organic matter content [78], in **Table 1**.

Soil Thickness is moderate to somewhat deep, ranging from 30 cm to more than 90 cm, this is relatively thicker than the typical soil of the area, it can be explained by long and continues irrigated agriculture and deep plowing application. Another important phenomenon is raising of soil water table even to 50 cm soon after profile excavating (**Figure 2**).

Table 1. Field measurement and laboratory analyses for the soil of Al Balikh plain.

Soil profile	Topsoil					Subsoil				
	Depth cm	B.D. kg/m ³	Clay %	SOC %	SOCS kg/m ²	Depth cm	B.D. kg/m ³	Clay %	SOC %	SOCS kg/m ²
P1	30	1.2	34	0.40	1.27	50	1.4	20	T*	N.D
P2	15	1.29	26	0.40	1.36	50	1.32	36	0.40	2.3
P3	15	1.21	36	0.29	0.91	50	1.31	36	0.79	7.02
P4	20	1.23	36	0.29	0.93	70	1.33	20	T	N.D
P5	25	1.3	10	0.29	0.98	40	1.3	10	T	N.D
P6	30	1.23	40	0.87	2.78	30	1.36	10	T	N.D
P7	50	1.3	28	0.63	2.15	50	1.4	10	T	N.D
P8	30	1.31	44	0.69	2.37	90	1.39	20	T	N.D
P9	15	1.2	10	0.06	0.18	50	1.27	20	T	N.D
P10	15	1.21	10	0.40	1.28	80	1.38	44	T	N.D
P11	30	1.26	30	0.12	0.38	105	1.3	10	T	N.D

Continued

P12	10	1.25	34	0.12	0.38	80	1.36	46	T	N.D
P13	20	1.2	20	0.52	1.63	53	1.33	36	0.70	4.4
P14	35	1.23	44	0.52	1.67	35	1.21	10	0.78	2.96
P15	25	1.3	43	0.56	1.92	55	1.4	12	T	N.D
P16	20	1.34	42	0.51	1.78	50	1.36	44	0.19	1.19
P17	30	1.32	42	0.06	0.19	70	1.47	46	T	N.D
P18	32	1.21	36	0.45	1.43	93	1.29	14	T	N.D
P19	23	1.18	44	0.23	0.70	70	1.53	34	T	N.D
P20	25	1.24	36	0.40	1.28	50	1.29	40	0.39	2.25
P21	30	1.21	34	0.17	0.54	30	1.31	20	T	N.D
P22	35	1.21	38	0.51	1.61	50	1.29	28	T	N.D
P23	3	1.17	44	0.62	1.90	40	1.54	20	T	N.D
P24	25	1.18	38	0.17	0.52	70	1.53	10	T	N.D
P25	18	1.27	36	0.12	0.38	50	1.34	14	0.10	0.59
P26	18	1.2	22	0.45	1.42	50	1.36	40	0.10	0.59
P27	30	1.22	34	0.34	1.08	90	1.32	42	0.29	3.11
P28	20	1.22	40	0.28	0.90	80	1.24	48	0.58	5.2
P29	15	1.24	24	0.40	1.31	55	1.33	38	0.50	3.26
P30	30	1.21	30	0.56	1.78	50	1.37	40	0.19	1.198

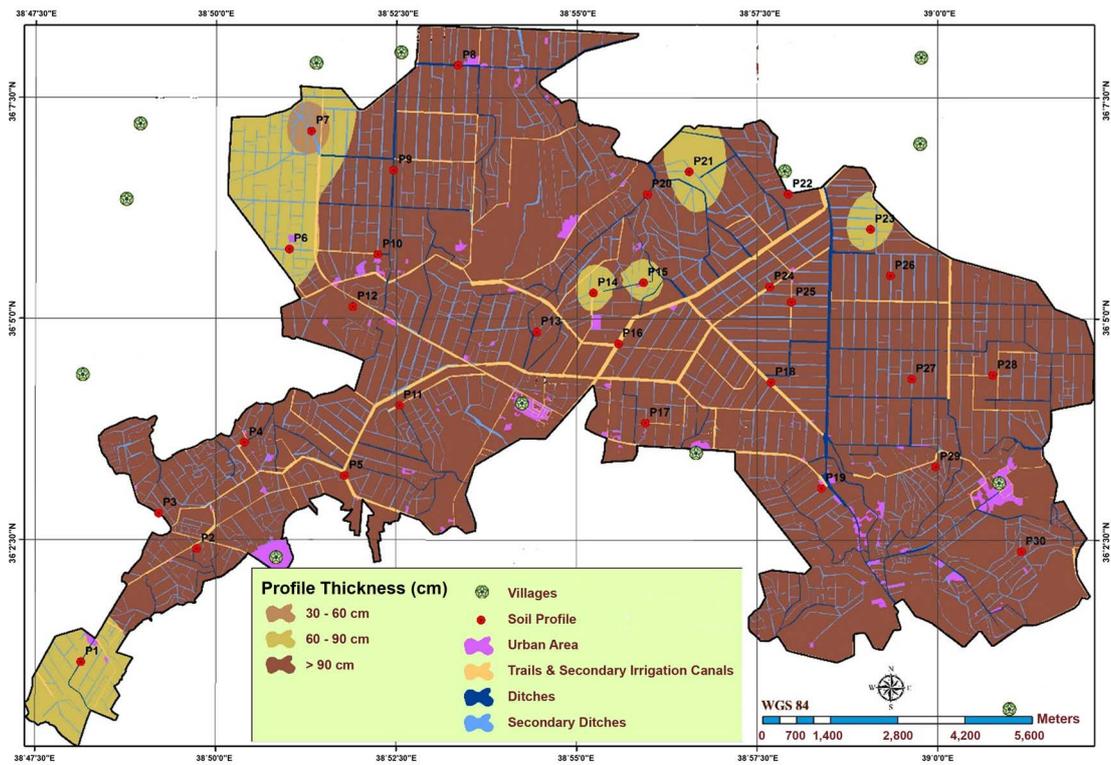


Figure 2. Soil thickness (cm) in the study area.

Soil clay content is moderate, and there is not much difference between the clay content in top and subsoil, the average for tops soil is 33% and for subsoil is 27%, (Figure 3).

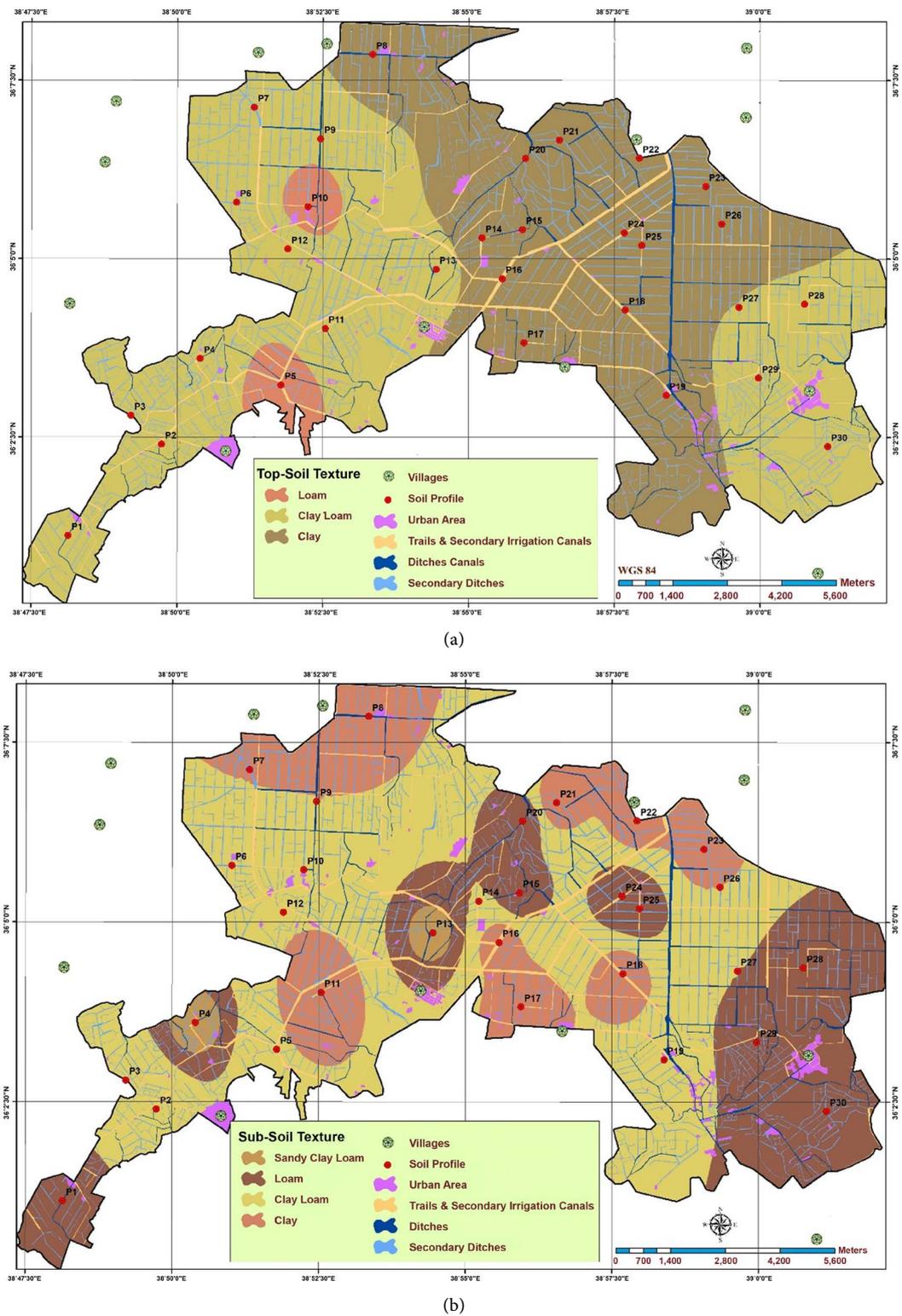


Figure 3. Spatial distribution of soil texture in topsoil (a) and subsoil (b).

The statistical analyses of SOM and SOCS are presented in **Table 2**, where SOC exhibited large variations between the two soil strata, ranging from 0.06% - 0.87% with an average of 0.38% in topsoil, and from 0.01% - 0.79% with an average of 0.17% in the subsoil. The corresponding average of SOCS was 1.23 kg·m⁻² and 1.14 kg·m⁻² respectively. Thus, the soil can be termed as a poor to very poor of SOM and SOCS within both top- and subsoil, this is typical for semi-arid soil, (**Figure 4**).

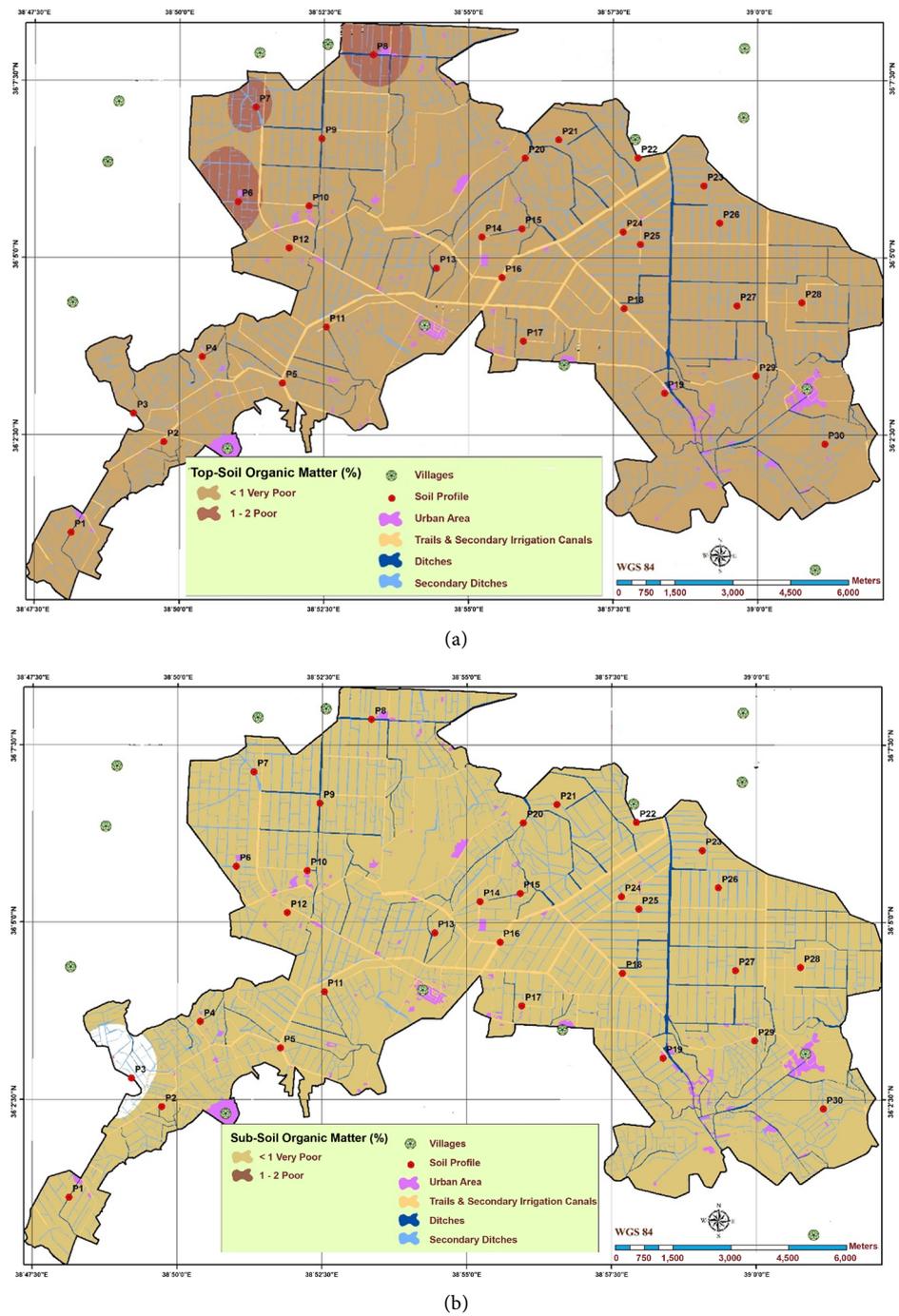


Figure 4. Spatial Distribution of Soil Organic Matter content in topsoil (a) and subsoil (b).

Table 2. Summary statistics of the SOC and SOC stock within the soil of Al Balikh plain (n = 30).

Variable	Min.	Max.	Mean $\bar{x} \pm t_{\alpha,0.05}$	Median	Std. D.	Skewness	Kurtosis	Quartile		CV	Pearson Correlation Coefficients (SOC, SOC)	
								1.St.	3.St.			
SOC (%)	Topsoil	0.06	0.87	0.38 ± 0.09	0.4	0.20	0.20	2.54	0.22	0.51	0.52	0.996
	Subsoil	0.01	0.79	0.17 ± 0.09	0.01	0.25	1.39	3.43	0.01	0.29	1.47	0.94
SOCs kg/m ²	Topsoil	0.18	2.78	1.23 ± 0.09	1.27	0.66	0.24	2.49	0.69	1.66	0.53	0.996
	Subsoil	0.01	7.02	1.14 ± 0.09	0.01	1.85	1.66	4.38	0.01	2.25	1.62	0.94

However, since arid and semi-arid land accounts for about 55% of the total Syrian land, which is one of the fragile ecosystems and most sensitive to climate change, it is therefore obvious that its SOCS, which is already too low to be strong affected by climate change.

SOC showed a normal decreasing trend with increasing the depth. The higher of SOC in topsoil has been associated with the growth of root systems [79] and active soil microbial [80] [81], and with the quantity of above Stubble of harvested crops and biomass addition on the soil surface [82] [83] [84].

These cause a greater impact on the surface soil layer than on the deeper layers and can homogenize the spatial distribution of SOC in topsoil. In contrary, the preferential transport of SOC via cracks after dry periods could further increase the heterogeneity of SOC in the subsoil, this is can explain the high SOC stock in the subsoil of some profiles, e. g. P3 and P28. The standard deviation (Std. D) for both SOC and SOC stock indicates homogeneous and absence of outliers values, this is enhanced by the low (C.V), which indicates non-dispersion, and clustering of values around the average.

The relationship between SOM and SOC stock were statistically investigated (Pearson Correlation Coefficients); SOC stock in both top and subsoils was highly correlated with SOM, the correlation within topsoil was ($R^2 = 0.996$, $p < 0.001$) and it was ($R^2 = 0.941$, $p < 0.001$) for subsoil.

As known, demonstration of variation requires a normal distribution of data; otherwise, the proportional effect will occur. Skewness and kurtosis coefficients were used to describe the shape and flatness of data distribution respectively. **Table 3**, showed high kurtosis (leptokurtic), due to data concentrated around the average, and positively skewed slight rightward.

Thus, data logarithmic transformation was applied to reduce the skewness and make the data almost to be closer to a normal distribution, (**Figure 5**).

Variograms of the data after transformation also showed a pure nugget effect and have a somewhat lower sill and range. The information derived from semi-variograms, which abridged in **Table 3**, is pointed out the reality of different spatial dependence for collected soil properties from the field and indicated that both SOC and SOC stock were best fitted to the exponential model. Nugget, range, and sill were equal to 0.002, 0.036, and 0.044, respectively for SOC in topsoil, and 0.014, 0.071, and 0.081, respectively for SOC in the subsoil. For SOC

Table 3. The coefficient of the variogram models.

Variable	Method	Variogram	Model	Nugget	Range	Partial sill	Sill	Nugget/sill (%)	
SOC %	Topsoil	Ordinary Kriging	Semivariogram	Exponential	0.002	0.036	0.044	0.046	4.3
		Ordinary Kriging	Semivariogram	Spherical	0.02	0.036	0.02	0.04	50
	Subsoil	Ordinary Kriging	Semivariogram	Exponential	0.014	0.071	0.067	0.081	17.2
		Ordinary Kriging	Semivariogram	Spherical	0.026	0.062	0.051	0.077	33.7
SOC kg/m ²	Topsoil	Ordinary Kriging	Semivariogram	Exponential	0.0	0.036	0.508	0.508	0.0
		Ordinary Kriging	Semivariogram	Spherical	0.205	0.036	0.282	0.487	42
	Subsoil	Ordinary Kriging	Semivariogram	Exponential	0.1899	0.086	3.97	4.1599	4.5
		Ordinary Kriging	Semivariogram	Spherical	0.655	0.062	3.099	3.754	17.0
OC-SOC	Topsoil	Ordinary Cokriging	Semivariogram; Semivariogram	Exponential	0.0	0.0365	0.0475; 0.0930; 0.0930; 0.5085	-	-
		Ordinary Cokriging	Semivariogram; Semivariogram	Spherical	0.001; 0.0031	0.0365	0.0468; 0.0849; 0.0849; 0.5098	-	-
	Subsoil	Ordinary Cokriging	Semivariogram; Semivariogram	Exponential	0.0	0.07	0.0916; 0.2350; 0.2350; 3.9105	-	-
		Ordinary Cokriging	Semivariogram; Semivariogram	Spherical	0.0208; 0.5841	0.0573	0.0625; 0.2859; 0.2859; 3.0605	-	-

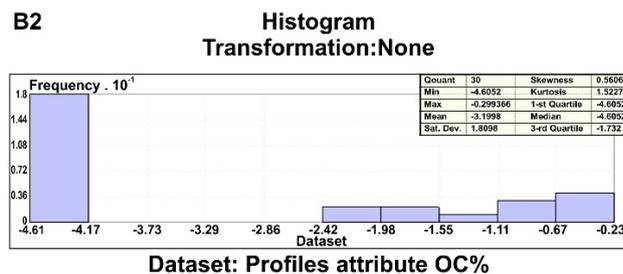
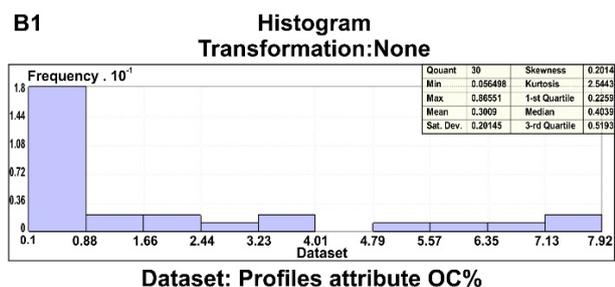
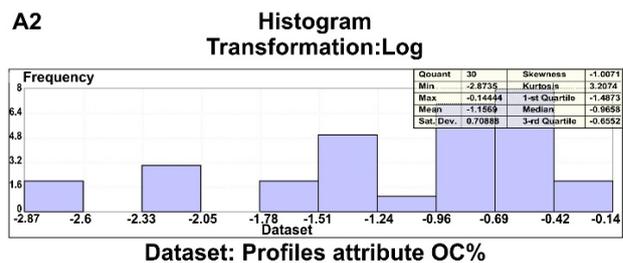
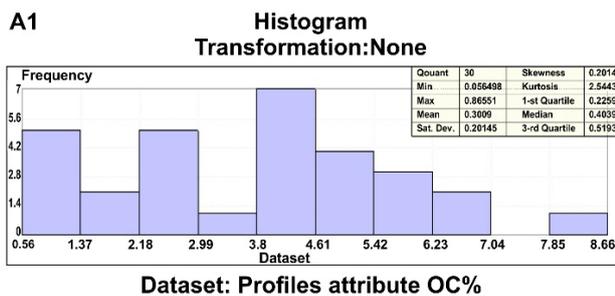


Figure 5. Histograms of SOC Frequency distribution before transformation and after log transformation in topsoil (a) and subsoil (b), (n = 30).

stock, it was 0.0, 0.036, and 0.0508, respectively in topsoil, and 0.1899, 0.086, and 4.159, respectively for in subsoil.

The semivariogram of the SOC indicated a slightly higher nugget effect in the subsoil than in the topsoil, implying a random and inherent variability, the similar suggestion for SOC stock. The sill values, representing total variation, showed a normal increasing trend from topsoil to subsoil for SOC, while the sit-

uation was the opposite for SOC stock because the subsoil, in general, is thicker than topsoil.

The spatial dependencies that reflect the degree of autocorrelation between the sampling points; were 4.3 and 17.2 for SOC in topsoil and subsoil respectively, and 0.0 and 4.5 for SOCS in topsoil and subsoil respectively. The higher the spatial dependence between the samples points, the highest the spatial correlation, thus the data are shown a strong spatial dependence for SOC and SCO stock for both two layers, which can usually be attributed to intrinsic factors and for that the variables did not differ over short distances.

4. Conclusion

This study highlights the important contribution of semi-arid land in the eastern Mediterranean region in the global carbon cycle. In this study, considering SOM and SOC stock varying in both lateral and spatial directions, such variation can fallow systematic changes as a function of the microrelief, and/or soil management practices. The environmental conditions at Al Balikh plain as a semi-arid area are not favorable for organic matter developing and accumulation; this is because of external factors (Climate, low precipitation, and hot dry summer) and internal factor (Geology, surface gypsic crest). These factors create abiotic stress that leads to low biomass forming. Moreover, organic carbon is more readily oxidize under hot, dry conditions, thus low carbon stock. Both SOC and SOC stocks were generally in the same level as those in other regions. The exception is that SOC was a little higher than these in the similar soils of the Euphrates region; this attributes to the area that is under intensive agriculture rotation for more than four-decades. It is clear to conclude that SOC stock mainly stores in the topsoil. The geostatistical analysis of the data indicates high systematic variability and low random variability. The spatial correlation was described using an exponential model, which was best fitted for data. A strong spatial dependence is shown for SOC and SCO stock within both two layers (topsoil, subsoil). Finally, the soils in arid and semi-arid areas have low organic matter content, a fragile structure, and coarse texture. Therefore, they are more sensitive than other soils to climate change, which can lead to accelerate loss of SOC stock, and a gradual deterioration in their quality and productivity.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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