EEET ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology 2023, 24(8), 261–271
https://doi.org/10.12912/27197050/172004
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Received: 2023.07.20
Accepted: 2023.09.07
Published: 2023.10.13

Contribution to the Modeling of the Organic Matter of Moroccan Forest Soils within the Context of Global Change – Case Study of the Central Plateau

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ABSTRACT

Organic matter is a major component of soil. It is of considerable ecological importance given its role in determining soil health, influencing ecosystem productivity and climate. For this reason, it is essential to carry out studies to evaluate its dynamics in natural ecosystems. In this study, the authors aimed to explore the dynamics of soil organic matter (SOM) in forest ecosystems of the Central Plateau in Morocco, as well as to investigate the potential of spectral vegetation indices in modeling SOM. To this end, the soil samples for analysis were collected from 30 sites across three vegetation types, including cork oak, Barbary thuja and scrub (matorral). In addition, the normalized difference vegetation index (NDVI) was extracted from Landsat 8 images to be used to model SOM using linear regression. The obtained results showed a weak, although statistically significant ($\alpha < 0.05$), correlation between NDVI and SOM at 0.45. In addition, only the scrub type showed a statistically significant ($\alpha < 0.05$) relationship between its corresponding SOM and NDVI, and was therefore retained for modeling. Vegetation type had a statistically strong influence ($\alpha < 0.01$) on SOM, with cork oak and garrigue ecosystems having the highest and lowest SOM contents with 5.61% and 2.36%, respectively. In addition, the highest SOM contents were observed under slightly acidic pH soils on mild, warm slopes at high altitude sites, while the lowest were found in lowland areas with predominantly weakly evolved soil.

Keywords: organic matter, natural ecosystems, forest soils, NDVI, Morocco

INTRODUCTION

Organic matter plays an essential role in soil functioning. It contributes strongly to soil structure, physical and chemical fertility, water holding capacity, and is the main source of matter and energy for living soil organisms (Dai et al. 2014; Nocita et al. 2013; Guo et al. 2017). In addition, soil organic matter (SOM) plays an important role in climate regulation, as soils are the largest terrestrial carbon reservoir, capable of storing up to 4800 Pg (Ciais et al. 2013; Houghton 2014). Indeed, SOM, which is composed of more than 50% carbon, participates in the evolution of carbon dioxide (CO_2) concentration in the atmosphere. Since the intensity of climate change depends mainly on the evolution of atmospheric CO_2 concentration, an increase in soil organic carbon (SOC) in the form of SOM could help mitigate the effects of climate change (Couteaux et al. 2003; Lal et al. 2004; Lützow et al. 2006; Benjamin et al. 2008; Mabit and Bernard 2010; Lal 2016; Martin et al. 2021). Therefore, any change in vegetation composition can alter SOM dynamics and related ecosystem services. Although the importance of plants in SOM formation and carbon cycling is now well established, predicting SOM from vegetation composition in a variety of ecosystems remains challenging due to poor understanding of the mechanisms and potential interactions with biophysical attributes modulating vegetation-SOM relationships (Schelfhout et al. 2020; Laganière et al. 2022).

The type of vegetation that dominates an ecosystem plays an important role in influencing SOM. Indeed, studies have shown that SOM content and quality are mainly dependent on surface vegetation and land use types, having a significant correlation with residual plant leaves penetrating the soil and interaction with microbial species in the soil (Jia et al. 2006; Castellano et al. 2015; Fu et al. 2020; Wu et al. 2022). Thus, understanding the distribution of SOC on the soil surface and its influencing factors further improves the understanding of the subsurface carbon cycle mechanism and enhances the understanding of the soil carbon sink function. In Moroccan ecosystems, despite great floristic and pedological diversity, forest resources are often severely degraded, resulting in organic and mineral impoverishment of soils (Roose, 2002; Badraoui, 2016; Dallahi et al., 2023). Thus, the acquisition of data on the dynamics of SOM will make it possible to understand the functioning of ecosystems according to their management mode and thus to avoid the progression of forest degradation, and even promote their restoration. This includes forest management activities, such as reforestation with well-adapted species that promote the OM uptake into the soil.

The distribution of SOM depends on several factors, including vegetation type, soil type, climate, land use, among others (Fang et al. 2012; Liu et al. 2015). This leads to a wide variety of approaches adopted for its assessment. Reflectance spectroscopy in the visible and near- and mid-infrared bands has yielded satisfactory results (Miltz and Don, 2012, Conforti et al. 2013; Nawar et al. 2016; Lefèvre et al. 2017; Chakraborty et al. 2017) while approaches such as Walkley and Black (Walkely and Black, 1934), Mebius (Mebius, 1960), colorimetric (Nelson and Sommers, 1996), and dry burning have performed reasonably well in past studies, in spite of some limitations. SOM predictions are important to meet the requirements of land use, climate change, and simulations of future situations (Amundson et al., 2015; Jin et al., 2017). However, conventional soil analyses are both painstaking with high labor intensity and costly, making it essential to develop a corresponding non-destructive, rapid, and cost-effective analysis method.

Therefore, this study was undertaken with the following main objectives: (1) to assess the utility of modeling SOM content from NDVI derived from Landsat 8 images; (2) to assess the influence of three ecosystem types, including cork oak, Barbary thuja, and scrub (matorral), on SOM and NDVI; and (3) to characterize the aforementioned ecosystems in terms of their ability to derive SOM content.

MATERIALS AND METHODS

Study area

General description

The study area (Figure 1) extends over the forest massifs of Timekssaouine and Houderrane, covering an area of about 16550 ha. It is located 5 km from the city of Khémisset, in the northern region of Morocco, 110 km from the capital, Rabat. These forests are characterized by a varied geological range with a strong dominance of the Paleozoic bedrock, which is mainly composed of pelites, sandstones and quartzites, severely folded and tectonized during the Hercynian orogeny. Pedologically, similar to the forests of the Moroccan central plateau, the study area is marked by the dominance of weakly developed soils and underdeveloped mineral soils (Figure 2). The most dominant elevation clusters are located between 400 and 800 m, representing about 89% of the study area where slopes below 50% exceed 80% of the area. The climate of the study area is characterized by a mean annual precipitation that varies from 432 to 509 mm. It is subject to important interannual variation and spatiotemporal variability. On the other hand, mean temperatures vary between 4°C in the coldest months and 34.4°C in summer.

Vegetation

The tree vegetations (Figure 3) that dominate the forests of the study area are the cork oak (*Quercus suber*) and the Barbary thuja (*Tetraclinis*

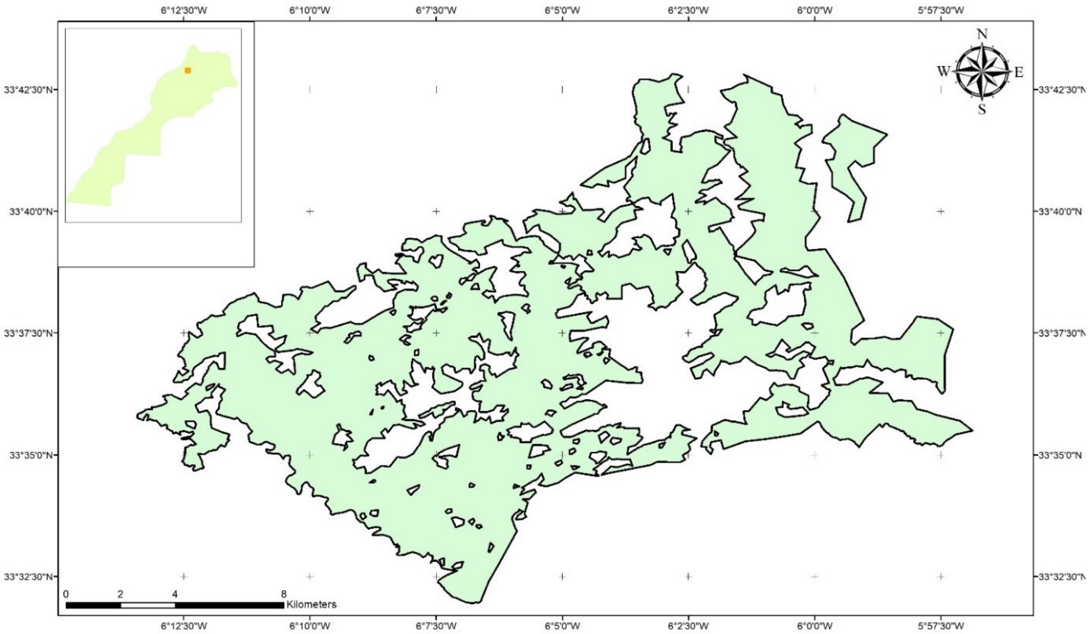

Figure 1. Geographic location of the study area

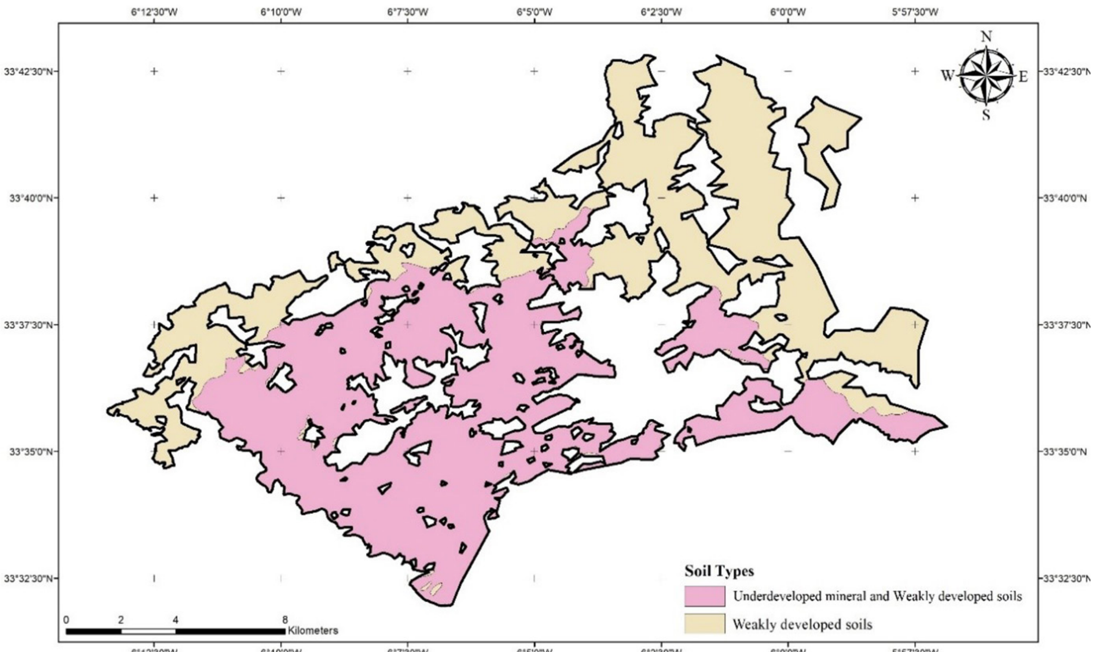

Figure 2. Dominant soil types of the study area

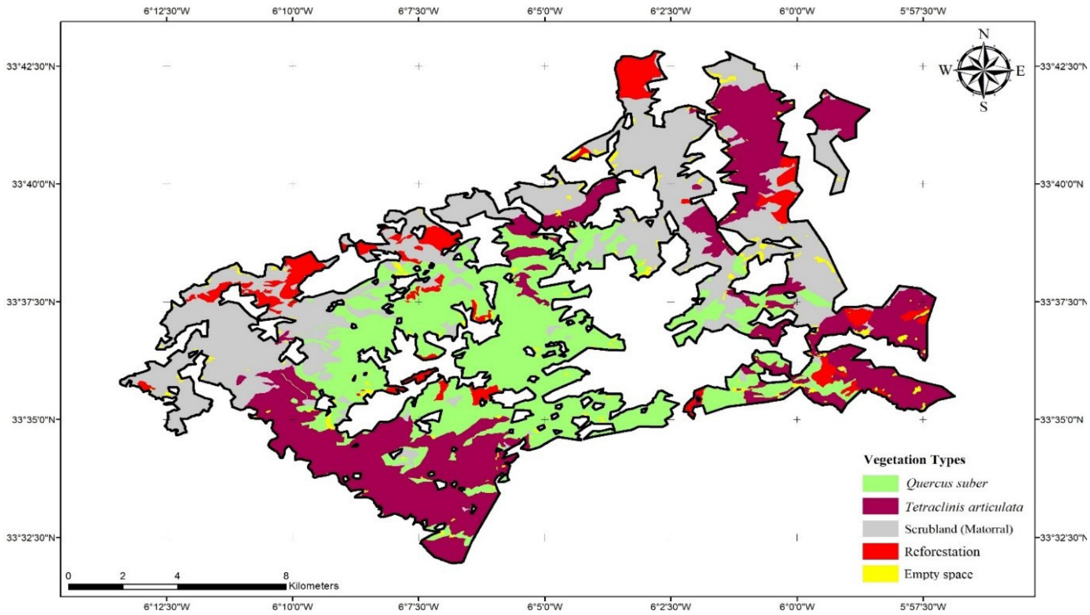

Figure 3. Dominant vegetation types of the study area

articulata). The cork oak stands extend over an area of about 4939 ha, dominating the low altitudes where the substrates are siliceous and offer a floristic procession dominated by *Cistus sp*. shrubs. On the other hand, the Barbary thuja is spread over an area of 4457 ha. Owing to its rustic character and its indifference to the nature of the substrate, this conifer grows mainly on weakly developed soils along medium to steep slopes. In addition, secondary species constitute an important part of the study area, exceeding 5500 ha. They mainly dominate the scrubland areas and are composed of *Pistacia lentiscus, Olea europea var Oleastre, Cistus salviaefolius, Arbutus unedo, Rhus penthaphylla, Chamaerops humilis*, among others.

Methods

Satellite data

The corresponding satellite image data used in the study were obtained from the USGS website (http://earthexplorer.usgs.gov/). Thus, Landsat 8 images for the 2018 period were downloaded from which the Normalized Difference Vegetation Index (NDVI) was extracted based on the formula in Equation 1.

$$\mathrm{NDVI} = \frac{(\mathrm{Band\ 5} - \mathrm{Band\ 4})}{(\mathrm{Band\ 5} + \mathrm{Band\ 4})} \quad (1)$$

where: Band 4 and Band 5 correspond to the near infrared and red reflectance bands, respectively.

Soil sampling and analyses

A total of 30 samples were collected across the three vegetation types characterizing the study area. Specifically, for each vegetation type, soil samples were collected from a depth of 0 to 30 cm using an auger and stored in sealed bags for laboratory analysis. The "feel method" was the technique used in the field, while particle size analysis was performed in the laboratory to determine soil texture. Using the latter technique, texture can be expressed using the triangular diagram, based on the percentages of fine soil elements. The determination of organic carbon in soil samples was based on the Walkley-Black (1934) chromic acid wet oxidation method. The organic matter in soil is oxidized by a solution of potassium dichromate. The reaction is assisted by the heat generated when two volumes of sulfuric acid are mixed with one volume of dichromate. The residual dichromate is assayed with ferrous sulfate and in this case the titer is inversely proportional to the amount of carbon present in the soil sample. The soil organic content was multiplied by the Van Bemmelen (1980) factor of 1.724 to obtain the SOM content. Determination of pH was done by weighing 20 g of air-dried soil into a beaker and adding 50 ml of deionized water, resulting in a soil:water ratio of 1:2.5. The suspension was stirred intermittently for 30 minutes and then allowed to stand for 12 h. Then, the electrode was dipped into the clear supernatant, followed by recording the pH once the reading stabilized.

Table 1. Selected variables for hierarchical classification

Variable		Description
Soil type	Soil 1	Weakly evolved soils
	Soil 2	Raw mineral
Soil texture	Text 1	Clayey
	Text 2	Silty
	Text 3	Silty clayey
	Text 4	Silty clayey sandy
	Text 5	Silty sandy
pH	pH 1	5–6
	pH 2	6–7
	pH 3	7–8
SOM	SOM 1	< 4%
	SOM 2	4% < SOM < 6%
	SOM 3	> 6%
Elevation	Alt 1	< 500 m
	Alt 2	500 m < Alt < 700 m
	Alt 3	> 700 m
Slope	Slop 1	< 15%
	Slop 2	15% < Slop < 25%
	Slop 3	> 25%
Aspect	Expo 1	ENE
	Expo 2	NNW
	Expo 3	WSW
	Expo 4	SSE
Ecosystem type	Eco 1	Cork oak
	Eco 2	Scrubland
	Eco 3	Barbary thuja

Data analyses

The Pearson correlation matrix was used to investigate the relationship between different soil properties and site characteristics, while multiple linear regression was adopted to find the relationship between SOM, elevation and NDVI. To assess the influence of vegetation type on both NDVI and SOM, one-way ANOVA was leveraged, followed by the Newman-Keuls post-hoc test to identify the difference between vegetation types. The significance level for both statistical tests was set at (α < 0.05). In addition, the hierarchical cluster analysis approach was used to assess the relationships between different soil properties and site characteristics (Table 1), and thus establish a characterization of SOM based on these parameters.

RESULTS

Soil and NDVI analysis of the ecosystem types

The results of the soil properties and NDVI (Figure 4) analyses across the three vegetation types dominating the study area are presented in Table 2. Soil pH was very slightly acidic to near neutral under the three vegetation types, ranging from 6.49 to 6.83. As expected, Barbary thuja, the needle-like leaves of which acidify the soil, had the lowest pH values on average. Soil

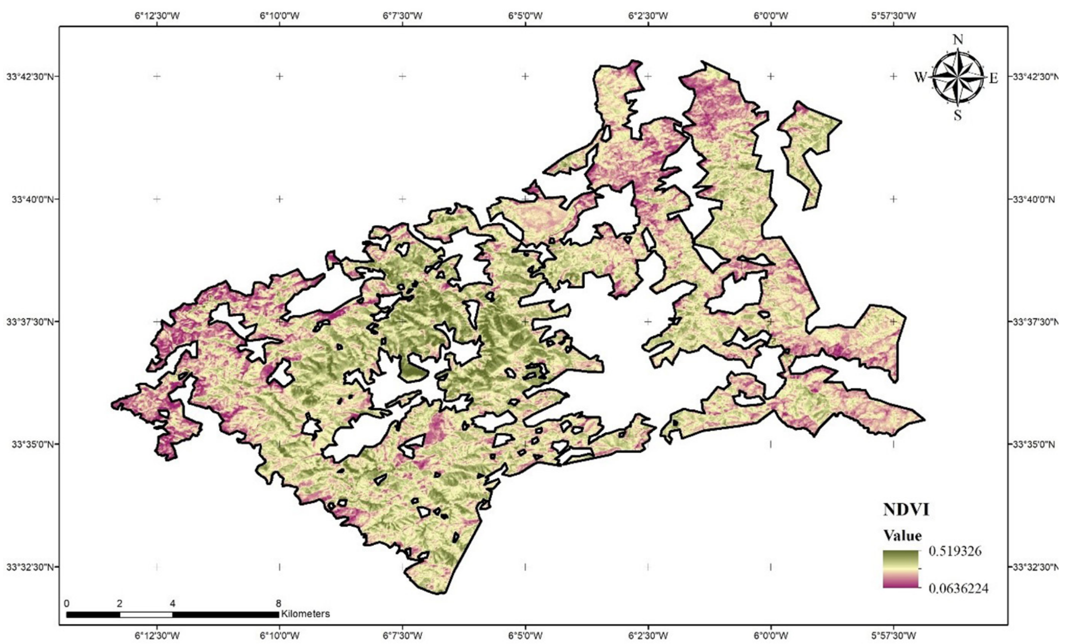

Figure 4. NDVI distribution of the study area

Table 2. Soil physico-chemical properties and NDVI of the three ecosystem types

Parameters			Cork oak	Barbary thuja	Scrubland
Soil properties	pH		6.76 ± 0.29	6.49 ± 0.69	6.83 ± 0.61
	C (%)		3.25 ± 1.28	2.24 ± 1.16	1.37 ± 0.45
	MO (%)		5.61 ± 2.20	3.89 ± 1.94	2.36 ± 0.79
	Texture (%)	Clay	24.36 ± 7.42	27.23 ± 9.86	35.30 ± 7.51
		Silt	30.39 ± 7.43	33.52 ± 7.96	33.21 ± 6.39
		Sand	45.25 ± 11.48	39.25 ± 12.03	31.49 ± 10.83
NDVI			0.34 ± 0.05	1.29 0.05	0.21 ± 0.06

carbon and therefore SOM were highest under cork oak, while they were lowest under the scrub vegetation type. Indeed, SOM was observed to be between 2.36% and 5.61%, corresponding to scrubland and cork oak respectively. Regarding soil texture, the clay fraction, which plays an important role in regulating SOM content, was highest under the scrubland at 33.21%, while the lowest under the cork oak stands at 24.36%. NDVI was generally low in all three vegetation types, not exceeding 0.34, observed for the cork oak vegetation type.

Relationship between NDVI, site and soil properties

The results of the correlation test to assess the relationship between site and soil properties and NDVI are presented in Table 3. Soil carbon and consequently SOM showed low, although statistically significant ($\alpha < 0.05$), correlation coefficients with NDVI at 0.44 and 0.45, respectively. An even weaker relationship between organic matter content and soil pH was observed, with a coefficient less than 0.2. Consistent with the former observations, a weak, although highly statistically significant ($\alpha < 0.01$), relationship between SOM and elevation was observed at 0.48. On the other hand, elevation was observed to be very strongly ($\alpha < 0.001$) correlated with NDVI, presenting a coefficient of 0.73.

Relationship between NDVI and SOM content by ecosystem type

The results of the one-way ANOVA test to study the effect of vegetation type on SOM and subsequently NDVI are presented in Table 4. Both cork oak and Barbary thuja forests, corresponding to the reasonably well-established stands, presented no statistical significance in their corresponding SOM. In contrast, a statistically significant ($\alpha < 0.05$) relationship between SOM corresponding to the degraded scrubland and NDVI was observed. On the basis of the observed influence of scrubland vegetation type on SOM, as well as NDVI, a linear regression test was performed to establish the relationship between SOM and NDVI (Table 5). As a result, the corresponding equation (Equation 2) was selected for the modeling of SOM throughout the study area.

$$SOM = 0.35 + 9.63 * NDVI \tag{2}$$

Table 3. Pearson correlation matrix illustrating the relationship between the variables studied

Vegetation type		df	SS	MS	F	p-value
Cork oak	Regression	1	0.429	0.429	0.080	0.785
	Residual	8	43.093	5.387		
	Total	9	43.522			
Barbary thuja	Regression	1	5.880	5.880	2	0.229
	Residual	8	27.768	3.471		
	Total	9	33.648			
Scrubland	Regression	1	3.161	3.161	10.526	0.012*
	Residual	8	2.403	0.300		
	Total	9	5.564			

Note: *, ** and *** indicate significant correlations at $\alpha < 0.05$, $\alpha < 0.01$ and $\alpha < 0.001$, respectively.

Table 4. One-way ANOVA investigating the relationship between NDVI and SOM by vegetation type

Vegetation type		df	SS	MS	F	p-value
Cork oak	Regression	1	0.429	0.429	0.080	0.785
	Residual	8	43.093	5.387		
	Total	9	43.522			
Barbary thuja	Regression	1	5.880	5.880	2	0.229
	Residual	8	27.768	3.471		
	Total	9	33.648			
Scrubland	Regression	1	3.161	3.161	10.526	0.012*
	Residual	8	2.403	0.300		
	Total	9	5.564			

Note: * indicates significance at $\alpha < 0.05$.

Table 5. Linear regression results investigating the relationship between NDVI and SOM in the scrubland ecosystem

Regression	Coefficients	Standard error	t-stat	p-value
Intercept	0.3463	0.6441	0.5376	0.6054
NDVI	9.6301	2.9683	3.2444	0.0118

Effect of ecosystem type on SOM and NDVI

The results of the ANOVA test investigating the effect of ecosystem type on SOM and NDVI are presented in Table 6. It was observed that the nature and type of vegetation had a statistically high ($\alpha < 0.01$) and very high ($\alpha < 0.001$) influence on SOM and NDVI, respectively.

On the basis of the strong observed influence of vegetation type on SOM and NDVI, the Newman-Keuls test performed for multiple comparison of means identified homogeneous groups for both parameters. The results are presented in Table 7 and show two distinct groups for SOM and NDVI. For SOM, the first group is represented by cork oak whose corresponding SOM had the highest observed content at 5.6%. On the other hand, Barbary thuja and scrubland represent the soils with the lowest SOM content (2.4%). Regarding NDVI, the cork oak and Barbary thuja group was characterized by the highest observed values (up to 0.34), while the scrubland type had the lowest values.

Characterization of SOM in the study area

The results of the hierarchical cluster analysis reveal two distinct groups (Figure 5) based on the content of SOM. The first group is characterized by a generally high SOM content (> 4%) and concerns cork oak ecosystems. The corresponding stands are characterized by a slightly acidic pH and are found on gentle and warmer slopes and high-altitude sites (> 500 m). In addition, the soil is often characterized by clay, silt, sandy-silt and sandy-clay textures. On the other hand, the second group is characterized by a low level of soil organic matter (often below 4%). It is found in the ecosystems corresponding to the Barbary thuja and scrubland vegetation types, where the pH is often basic, the aspect leads to often wet conditions and is characterized by low altitude stands

Table 6. One-way ANOVA to evaluate the effect of vegetation type on SOM and NDVI

Ecosystem	Source	df	SS	MS	F	p-value
SOM	Model	2	52.81	26.405	8.617	0.001**
	Error	27	82.735	3.064		
	Total	29	135.545			
NDVI	Model	2	0.094	0.047	14.946	0.0001***
	Error	27	0.085	0.003		
	Total	29	0.179			

Note: ** and *** indicate significance at $\alpha < 0.01$ and $\alpha < 0.001$ level, respectively

Table 7. Newman-Keuls post-hoc results identifying distinct groups based on SOM and NDVI

Ecosystem	Vegetation type	Group	
SOM	Cork oak	A	
	Barbary thuja		B
	Scrubland		B
NDVI	Cork oak	A	
	Barbary thuja	A	
	Scrubland		B

(< 500 m). In addition, the corresponding soil is weakly evolved, the texture of which is generally of a silty-clay nature.

DISCUSSION

The obtained results revealed the highest SOM rates under deciduous stands dominated by cork oak, while the lowest were observed under conifers (Barbary thuja) and especially under matorrals. This difference in SOM content between different vegetation types is well documented in the literature given that vegetation is the main source of organic matter in soil, primarily in the form of organic carbon (Mueller et al., 2015; Schelfhout et al., 2017). The high content observed under the cork oak in the presented study can be explained by the return to the soil of a quality litter from the cork oak, as opposed to the litter of the Barbary thuja which is of acidifying nature (Boca et al. 2020). Indeed, the greater litter input of oaks results in maximum soil carbon storage, as observed by Sheikh et al. (2009) in their study comparing soil carbon storage under oak and pine stands in the Indian Himalayas. Moreover, Augusto et al. (2015) noted that deciduous trees tend to induce faster litter decomposition than conifers due to their tissue chemistry, resulting in generally higher SOM contents. In turn, the SOM content observed under cork oak was generally high (> 4%), it remains considerably lower than that observed under other Moroccan oaks. Indeed, El Mderssa et al. (2019) recorded higher SOM contents under holm oak (*Quercus rotundifolia*) and zean oak (*Quercus canariensis*) in the central Middle Atlas region of the country. The markedly higher SOM content under forest stands compared to scrubland (matorral) may be related to the return of a significant amount of biomass and litter to the soil under the former ecosystem. Nevertheless, the SOM content (2.36%) under the matorral ecosystem in this study was notably lower than that observed by Kannouch (2016) in the central Middle Atlas, where SOM was recorded up to 6.74%.

Soil properties, such as pH and texture, are important as they influence other physical and chemical properties of the soil, and thus play a key role in the dynamics of organic matter in the soil (Zhou et al. 2020). In this study, soils were generally slightly acidic, which could be explained by the acidic chemical nature of the dominant sandstone and shale lithologic material in the study area (Duchaufour 1977), as well as the acidifying nature of the litter, particularly

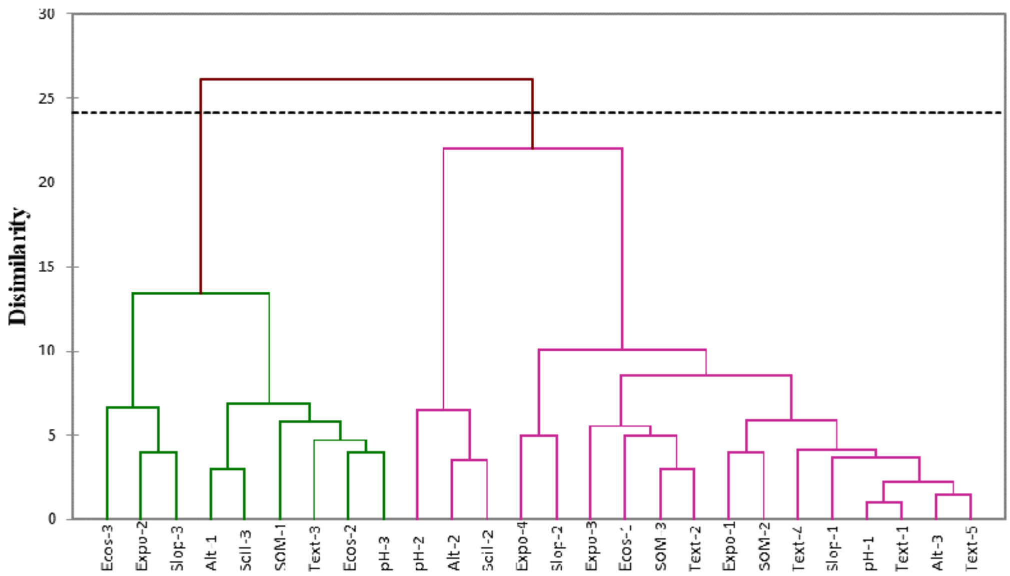

Figure 5. Hierarchical cluster analysis dendrogram of the ecosystem types

from the lignin-rich needles produced by Barbary thuja. In contrast, acidic soils are often characterized by lower organic matter content due to accelerated SOM depletion (Tripathi et al. 2018; Zhou et al. 2020), this was not the case in the presented study. Indeed, the highest organic matter contents were recorded in these soils compared to the slightly basic soils. This could be explained by a relatively basic pH favoring microbial mineralization and humification activities of the microflora where bacteria dominate. Nevertheless, it should be noted that soil pH is not always a determining influence in SOM dynamics. Indeed, Tonon et al. (2010) observed only a small effect of soil pH on the chemical composition of organic matter in their study in Rothamsted (UK), suggesting that physical mechanisms are often more important, especially in the presence of the finest soil fractions.

Soil texture has a distinct influence on organic carbon accumulation because of the physical protection of SOM induced by the aggregation of fine particles, such as clay and fine silt (Jobbágy & Jackson, 2001). The plant communities presenting the highest SOM contents in this study were established on relatively coarse texture soils. Indeed, under these soils, SOM and clay form the clay-humus complex which, owing to its negative surface charges, adsorbs a part of the cations of the soil solution. Moreover, this complex confers a certain stability and resistance to the SOM preventing its degradation and favoring its accumulation as has been highlighted by Martí-Roura et al. (2019).

Terrain characteristics, such as slope and elevation, play an important role in controlling organic matter variations (Moghiseh et al. 2013), especially in arid and semi-arid climates (Shedayi et al., 2016; Merabtene, 2021). In the conducted study, the highest SOM levels were recorded at sites above 500 m. Similar observations of increasing SOM with elevation were noted by Massaccesi et al. (2020) up to mid-elevation areas, followed by a decrease in high elevation areas. This could be explained by vegetation characteristics taking precedence over terrain factors as driving factors, thus strongly influencing subsurface processes (Bardgett et al. 2014; Bargali & Bargali 2020). Indeed, Sheikh et al. (2009) observed organic matter under both oak and pine stands to decrease at high altitudes in their study in India. High elevation areas are often characterized by increased precipitation and low temperatures that can lead to inhibition of SOM decomposition rates (Gutiérrez-Girón et al. 2015; Wan et al. 2019). Indeed, slow mineralization rates of organic matter in the form of carbon lead to increased organic matter reserves.

CONCLUSIONS

This study was undertaken to evaluate the dynamics of SOM in different ecosystems with varying dominant vegetation types in Morocco. Although edaphic and location-specific conditions such as soil pH and texture, among others, were observed to play a role, the obtained results indicate that the conditions related to elevation and vegetation have a distinct effect on SOM. Specifically, the nature of the vegetation litter more strongly controls the content and distribution of SOM. Indeed, the highest SOM rates are recorded under deciduous stands primarily dominated by cork oak, while the lowest are observed under conifers as well as degraded scrubland. This is associated with the return to the soil of high-quality litter from deciduous trees, as opposed to conifers the litter of which has an acidifying effect on chemical composition in the soil. Although NDVI was used to model SOM, its use was limited to the scrubland ecosystem. Hence, its applicability in the region remains in question. A study based on other vegetation indices could complement the obtained results and further highlight the potential of using spectral data in soil modeling.

REFERENCES

1. Amundson R., Berhe A.A., Hopmans J.W., Olson C., Sztein A.E., Sparks D.L. 2015. Soil and human security in the 21st century. Science 348, 1261071. https://doi.org/ 10.1126/science.1261071.
2. Augusto L., De Schrijver A., Vesterdal L., Smolander A., Prescott C., Ranger J. 2015. Influences of evergreen gymnosperm and deciduous angiosperm tree species on the functioning of temperate and boreal forests. Biol Rev, 90: 444-466. https://doi.org/10.1111/brv.12119
3. Badraoui M. 2016. Connaissance et utilisation des ressources en sol au Maroc. Rabat, Maroc, Institut national de la recherche agronomique, 27 p.
4. Bardgett R.D., Mommer L., De Vries F.T. 2014. Going underground: Root traits as drivers of ecosystem processes. Trends Ecol. Evol. 29, 692–699
5. Bargali K., Bargali S.S. 2020. Effect of size and altitude on soil organic carbon stock in homegarden agroforestry system in Central Himalaya, India, Acta Ecologica Sinica, Volume 40, Issue 6,

2020, Pages 483-491, ISSN 1872-2032, https://doi.org/10.1016/j.chnaes.2020.10.002.

6. Boča A., Jacobson A.R., Van Miegroet H. 2020. Aspen Soils Retain More Dissolved Organic Carbon Than Conifer Soils in a Sorption Experiment. Front. For. Glob. Change 3:594473. doi: 10.3389/ffgc.2020.594473
7. Castellano M.J., Mueller K.E., Olk D.C., Sawyer J.E. 2015. Six, J. Integrating Plant Litter Quality, Soil Organic Matter Stabilization, and the Carbon Saturation Concept. Glob. Chang. Biol. 21, 3200–3209.
8. Chakraborty S., Li B., Deb S., Paul S., Weindorf D.C., Das B.S. 2017. Predicting soil arsenic pools by visible near infrared diffuse reflectance spectroscopy. Geoderma 296:30–37. doi:10.1016/j.geoderma.2017.02.015
9. Ciais P., Sabine C., Bala G., Bopp L., Brovkin V., Canadell J., Chhabra A., DeFries R., Galloway J., Heimann M., Jones C., Thornton P. 2013. “Carbon and other biogeochemical cycles,” in Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, eds T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley (Cambridge, UK; New York, NY: Cambridge University Press), 465–570.
10. Conforti M., Castrignano A., Robustelli G., Scarciglia F., Stelluti M., Buttafuoco G. 2015. Laboratory-Based Vis–NIR Spectroscopy and Partial Least Square Regression with Spatially Correlated Errors for Predicting Spatial Variation of Soil Organic Matter Content. Catena, 124, 60–67.
11. Couteaux M.-M., Berg B., Rovira P. 2003. Near Infrared Reflectance Spectroscopy for Determination of Organic Matter Fractions Including Microbial Biomass in Coniferous Forest Soils. Soil Biology and Biochemistry, 35, 1587–1600.
12. Dai F., Zhou F.Q., Lv Z.Q., Wang X.M., Liu G.C. 2014. Spatial prediction of soil organic matter content integrating artificial neural network and ordinary kriging in Tibetan Plateau. Ecol. Indic. 45, 184–194.
13. Dallahi Y., Boujraf A., Meliho M., Orlando C.A. 2023. Assessment of forest dieback on the Moroccan Central Plateau using spectral vegetation indices. Journal of Forestry Research, 34(3), 793–808.
14. Duchaufour P. 1977. Pédologie. Tome I. Pédogenèse et classification. Ed. Masson, Paris, 477 p.
15. El Mderssa M., Belghazi B., Benjelloun H., Zennouhi O., Nassiri L., Ibijbijen J. 2019. Estimation of Carbon Sequestration; Using Allometric Equations; in Azrou Cedar Forests (Cedrus atlantica Manetti) in the Central Middle Atlas of Morocco under Climate Change. Open Journal of Forestry, 9, 214–225. Doi: 10.4236/ojf.2019.93011.
16. Fang H.S., Cheng G., Yu J, Zheng P., Zhang M., Xu Y., Li X., Yang P. 2012. Responses of CO2 efflux from an alpine meadow soil on the Qinghai Tibetan Plateau to multi-form and low-level N addition Plant Soil, 351, pp. 177–190
17. Fu D., Wu X., Duan C., Smith A.R., Jones D.L. 2020. Traits of Dominant Species and Soil Properties Co-Regulate Soil Microbial Communities across Land Restoration Types in a Subtropical Plateau Region of Southwest China. Ecol. Eng. 153, 105897.
18. Guo L., Zhao C., Zhang H., Chen Y., Linderman M., Zhang Q., Liu Y. 2017. Comparisons of spatial and non-spatial models for predicting soil carbon content based on visible and near-infrared spectral technology. Geoderma 285, 280–292.
19. Gutiérrez-Girón A., Díaz-Pinés E., Rubio A., Gavilán R.G. 2015. Both altitude and vegetation affect temperature sensitivity of soil organic matter decomposition in Mediterranean high mountain soils. Geoderma 237–238, 1–8. doi:10.1016/j.geoderma.2014.08.005
20. Houghton R.A. 2014. The contemporary carbon cycle. Treatise on Geochemistry 8, 473–513, https://doi.org/10.1016/B0-08-043751-6/08168-8
21. Jia X., Li X., Zhang Z. 2006. Spatial heterogeneity of soil organic carbon and nitrogen under Ammopiptanhus mongolicus community in arid desert zone. Ying yong sheng tai xue bao = The journal of applied ecology 17(12), 2266–2270. https://doi.org/10.1360/yc-006-1280
22. Jin X.L., Song K.S., Du J., Liu H.J., Wen Z.D. 2017. Comparison of different satellite bands and vegetation indices for estimation of soil organic matter based on simulated spectral configuration. Agric. For. Meteorol.
23. Laganière J., Augusto L., Hatten J.A., Spielvogel S. 2022. Editorial: Vegetation Effects on Soil Organic Matter in Forested Ecosystems. Front. For. Glob. Change 4:828701. doi: 10.3389/ffgc.2021.828701
24. Lefèvre C.R., Fatma A., Viridiana W. 2017. Liesl What is SOC? W. Liesl (Ed.), Soil organic carbon the hidden potential, FAO, Rome, Italy, pp. 1-9
25. Liu S., An N., Yang J., Dong S., Wang C., Yin Y. 2015. Prediction of soil organic matter variability associated with different land use types in mountainous landscape in southwestern Yunnan province, China. CATENA, 133, 137–144. doi:10.1016/j.catena.2015.05.010
26. Lützow M.V., Kögel-Knabner I., Ekschmitt K., Matzner E., Guggenberger G., Marschner B., Flessa H. 2006. Stabilization of organic matter in temperate soils: mechanisms and their relevance under different soil conditions – a review. European Journal of Soil Science 57(4): 426–445.
27. Mabit L., Bernard C. 2010. Spatial distribution and content of soil organic matter in an agricultural field in eastern Canada, as estimated from geostatistical tools. Earth Surface Processes and Landforms, 35(3), 278–283. Doi:10.1002/esp.1907

28. Martí-Roura M., Hagedorn F., Rovira P., Romanyà J. 2019. Effect of land use and carbonates on organic matter stabilization and microbial communities in Mediterranean soils. Geoderma 351, 103–115. doi:10.1016/j.geoderma.2019.05.021
29. Massaccesi L., De Feudis M., Leccese A., Agnelli A. 2020. Altitude and Vegetation Affect Soil Organic Carbon, Basal Respiration and Microbial Biomass in Apennine Forest Soils. Forests; 11(6):710. https://doi.org/10.3390/f11060710
30. Mayer M., Prescott C.E., Abaker W.E.A., Augusto L., Cécillon L., Ferreira G.W.D., James, J., Jandl R., Katzensteiner K., Laclau J.P., Laganière J. 2020. Tamm Review: Influence of forest management activities on soil organic carbon stocks: A knowledge synthesis. For. Ecol. Manag. 466, 118127. doi: 10.1016/j.foreco.2020.118127
31. Mebius L.J. 1960. A Rapid Method for the Determination of Organic Carbon in Soil. Analytica Chimica Acta, 22, 120–124.
32. Merabtene M.D., Faraoun F., Mlih R., Djellouli R., Latreche A., Bol R. 2021. Forest Soil Organic Carbon Stocks of Tessala Mount in North-West Algeria- Preliminary Estimates. Front. Environ. Sci. 8:520284. doi: 10.3389/fenvs.2020.520284
33. Miltz J., Don A. 2012. Optimising Sample Preparation and near Infrared Spectra Measurements of Soil Samples to Calibrate Organic Carbon and Total Nitrogen Content. Journal of Near Infrared Spectroscopy. 20(6): 695–706.
34. Moghiseh E., Heidari A., Ghannadi M. 2013. Impacts of deforestation and reforestation on soil organic carbon storage and CO2 emission. Soil Environ 32 (1), 1–13.
35. Mueller K.E., Hobbie S.E., Chorover J., Reich P.B., Eisenhauer N., Castellano M.J., Chadwick O.A., Dobies T., Hale C.M., Jagodziński A.M., Kałucka, I. 2015 Effects of litter traits, soil biota, and soil chemistry on soil carbon stocks at a common garden with 14 tree species. Biogeochemistry 123, 313–327. doi: 10.1007/s10533-015-0083-6
36. Nawar S., Buddenbaum H., Hill J., Kozak J., Mouazen A.M. 2016. Estimating the soil clay content and organic matter by means of different calibration methods of vis-NIR diffuse reflectance spectroscopy. Soil Tillage Res. 155:510–522. doi:10.1016/j.still.2015.07.021
37. Nelson D.W., Sommers L.E. 1996. Total carbon, organic carbon, and organic matter. In Sparks, D.L., et al., Eds., Methods of Soil Analysis. Part 3, SSSA Book Series, Madison, 961–1010.
38. Nocita M., Stevens A., Noon C., van Wesemael B. 2013. Prediction of soil organic carbon for different levels of soil moisture using Vis-NIR spectroscopy. Geoderma 199, 37–42.
39. Roose E. 2002. Influence de la gestion de la biomasse sur l’érosion et la séquestration du carbone. Résumé des conclusions du colloque « Érosion du carbone », Montpellier, 23-28 sept. 2002. Bulletin du réseau érosion, 22 (4):4–14.
40. Schelfhout S., Mertens J., Verheyen K., Vesterdal L., Baeten L., Muys B., De Schrijver A. 2017. Tree Species Identity Shapes Earthworm Communities. Forests 8, 85. doi: 10.3390/f80 30085
41. Shedayi A.A., Xu M., Naseer I., Khan B. 2016. Altitudinal gradients of soil and vegetation carbon and nitrogen in a high altitude nature reserve of Karakoram ranges. Springer Plus 5(1), 320. doi:10.1186/s40064-016-1935-9
42. Sheikh M.A., Kumar M., Bussmann R.W. 2009. Altitudinal variation in soil organic carbon stock in coniferous subtropical and broadleaf temperate forests in Garhwal Himalaya. Carbon Balance Manage 4, 6 (2009). https://doi.org/10.1186/1750-0680-4-6
43. Tonon G., Sohi S., Francioso O., Ferrari E., Montecchio D., Gioacchini P., Ciavatta C., Panzacchi P., Powlson D. 2010. Effect of soil pH on the chemical composition of organic matter in physically separated soil fractions in two broadleaf woodland sites at Rothamsted, UK. European Journal of Soil Science, 61: 970–979. https://doi.org/10.1111/j.1365-2389.2010.01310.x
44. Tripathi B.M., Stegen J.C., Kim M., Dong K., Adams J.M., Lee Y.K. 2018. Soil pH mediates the balance between stochastic and deterministic assembly of bacteria. ISME J, 12, 1072–1083
45. Van Bemmelen J.M. 1890. Über die Bestimmung des Wassers, des Humus, des Schwefels, der in den colloïdalen Silikaten gebundenen Kieselsäure, des Mangans u. s. w. im Ackerboden. Die Landwirthschaftlichen Versuchs-Stationen, 37, 279–290
46. Walkley A., Black I.A. 1934. An examination of Degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method. Soil Science, 37, 29-38. Doi : 10.1097/00010694-193401000-00003
47. Wan Q., Zhu G., Guo H., Zhang Y., Pan H., Yong L., Ma, H. 2019. Influence of Vegetation Coverage and Climate Environment on Soil Organic Carbon in the Qilian Mountains. Sci Rep 9, 17623. https://doi.org/10.1038/s41598-019-53837-4
48. Wu X., Fu D., Duan C., Huang G., Shang H. 2022. Distributions and Influencing Factors of Soil Organic Carbon Fractions under Different Vegetation Restoration Conditions in a Subtropical Mountainous Area, SW China. Forests, 13, 629. https:// doi.org/10.3390/f13040629
49. Zhou W., Han G., Liu M., Zeng J., Liang B., Liu J., Qu R. 2020. Determining the Distribution and Interaction of Soil Organic Carbon, Nitrogen, pH and Texture in Soil Profiles: A Case Study in the Lancangjiang River Basin, Southwest China. Forests. 2020; 11(5):532. https://doi.org/10.3390/f11050532