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Factors regarding the spatial variability of soil organic carbon in a Mexican small watershed

Factores relacionados con la variabilidad espacial del carbono orgánico del suelo en una microcuenca Mexicana

Fatores relativos à variabilidade espacial do carbono orgânico do solo em uma pequena bacia hidrográfica Mexicana

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Abstract

Understanding the stocks of Soil Organic Carbon (SOC) and elucidating the variables influencing its spatial distribution within a small watershed are imperative for advancing targeted climate change mitigation strategies, specifically directed toward soil and water conservation. The selection of this watershed is predicated upon its three-decade-long implementation of diverse soil and water conservation practices. Therefore, the objective of this study was to analyze land use, vegetation cover, slope and soil and water conservation practices (SCWP) as factors that influence the variability and spatial distribution of soil organic carbon in a small basin in the Mixteca Alta region of the state of Oaxaca. Mexico. Soil samples (77) were collected to determine SOC storage. These samples were interpolated using the QGIS Smart-Map plugin to obtain a spatial COS predictive model. Thematic maps were generated for each factor. Areal statistics, Pearson's correlation and principal component analysis (PCA) were performed to explain COS variability. The results in the variability of SOC with respect to vegetation cover and land use, showed adult pine plantations with the highest value of SOC with 36.8 $t.ha^{-1}$, followed by seasonal agriculture with 28.8 $t.ha^{-1}$. The most effective management practice for storing COS was the stone terrace with 35.0 $t.ha^{-1}$. Our results indicate that vegetation cover and land use complemented by soil and water conservation practices are the main drivers of SOC storage in small watersheds.

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Resumen

Comprender los niveles del Carbono Orgánico del Suelo (COS) y las variables que controlan su distribución en una pequeña cuenca permitirá promover estrategias de mitigación contra el cambio climático orientadas a la conservación de suelo y agua. La selección de esta cuenca se basa en la implementación durante tres décadas de diversas prácticas de conservación de suelo y agua. Por ello, el objetivo de este estudio fue analizar el uso de la tierra, la cubierta vegetal, la pendiente y las prácticas de conservación del suelo y agua como factores que influyen en la variabilidad y la distribución espacial del carbono orgánico del suelo en una pequeña cuenca en la región de la Mixteca Alta del estado de Oaxaca, México. Se tomaron 77 muestras de suelo para determinar el almacenamiento de COS. Se realizó la interpolación de las observaciones de COS utilizando el complemento QGIS Smart-Map para obtener un modelo predictivo COS espacial. Se generaron mapas temáticos para cada factor. Se realizaron análisis estadísticos por área, correlación de Pearson, y análisis de componentes principales (PCA) para explicar la variabilidad espacial de COS. Los resultados en la variabilidad del COS con respecto a la cobertura vegetal y el uso de la tierra, mostraron a las plantaciones de pino adulto con el mayor valor de COS con 36,8 $t.ha^{-1}$, seguido de la agricultura de temporal con 28,8 $t.ha^{-1}$. La práctica de gestión más eficaz para almacenar COS fue la terraza de piedra con 35,0 $t.ha^{-1}$. Los resultados indican que la cobertura vegetal y el uso de la tierra complementados con prácticas de conservación del suelo y agua son los principales impulsores del almacenamiento de COS en pequeñas cuencas hidrográficas.

Palabras clave: sistemas de información geográfica, manejo de cuencas, QGIS Smart-Map, prácticas de conservación de suelo y agua.

Resumo

Compreender os stocks de Carbono Orgânico do Solo (COS) e elucidar as variáveis que influenciam a sua distribuição espacial dentro de uma pequena bacia hidrográfica são imperativos para o avanço de estratégias específicas de mitigação das alterações climáticas, especificamente dirigidas à conservação do solo e da água. A seleção desta bacia hidrográfica baseia-se na implementação, ao longo de três décadas, de diversas práticas de conservação do solo e da água. Portanto, o objetivo deste estudo foi analisar o uso do solo, a cobertura vegetal, a declividade e as práticas de conservação do solo e da água (SCWP) como fatores que influenciam a variabilidade e a distribuição espacial do carbono orgânico do solo em uma pequena bacia na região de Mixteca Alta do estado de Oaxaca. México. Amostras de solo (77) foram coletadas para determinar o armazenamento de SOC. Essas amostras foram interpoladas usando o plugin QGIS Smart-Map para obter um modelo preditivo espacial de COS. Foram gerados mapas temáticos para cada fator. Estatísticas de área, correlação de Pearson e análise de componentes principais (ACP) foram realizadas para explicar a variabilidade do COS. Os resultados na variabilidade do SOC em relação à cobertura vegetal e uso do solo, mostraram as plantações de pinus adulto com o maior valor de SOC com 36,8 $t.ha^{-1}$, seguidas pela agricultura sazonal com 28,8 $t.ha^{-1}$. A prática de manejo mais eficaz para armazenamento de COS foi o terraço de pedra com 35,0 $t.ha^{-1}$. Nossos resultados indicam que a cobertura vegetal e o uso da terra complementados por práticas de conservação do solo e da água são os principais impulsionadores do armazenamento de SOC em pequenas bacias hidrográficas.

Palavras-chave: sistemas de Informação Geográfica, gestão de bacia hidrográfica, QGIS Smart-Map, práticas de conservação do solo e da agua.

Introduction

Since 2011, concentration of carbon dioxide (CO_2) in the atmosphere have increased, reaching an annual average of 410 ppm (IPCC,2021). Soil has the largest reserves of terrestrial organic carbon; current estimates of the global stock of soil organic carbonrange from 1,500 to 2,400 Pg C, according to Lal *et al*. (2021). Soil organic carbon (SOC) is the C that remains in the soil after partial decomposition of all added organic residues and is produced by living organisms (Lefèvre, 2017).SOCplays a critical role in climate change mitigation and food security (Wang *et al*., 2020), and its distribution is spatially and temporally variable (Wiesmeier *et al*., 2019). The variability and spatial distribution of SOC is partly controlled by environmental conditions such as vegetation cover and land use (Borůvka *et al*., 2022; Yescas *et al*., 2018).

Determining the variables that control soil organic carbon distribution at the small watershed scale is important for planning and implementing appropriate soil and water conservation practices (SWCP). These practices are used to reduce soil erosion, but also to retain large amounts of organic carbon in the same sediments to reduce greenhouse gas emissions to the atmosphere (Mekonnen and Getahun, 2020). Considering the intense land degradation that affects almost half of Mexico's territory, the Mexican government has implemented various public policies with subsidies, under which landowners have implemented land conservation practices. However, these impacts have not been evaluated in terms of carbon storage (Cotler *et al*., 2015). In this sense, this study aims to provide reliable quantitative data that will allow decision and policymakers to further promote SWCP in Mexico.

The objective of this study was to evaluate the effects of land use, vegetation cover, slope, and soil and water conservation practices on the variability and spatial distribution of soil organic carbon (SOC) in a small watershed in the Mixteca Alta region of Oaxaca State, Mexico.

Material and methods

Study area

The study area is a 44.6 ha small watershed, known as "El Arenal" located in the High Mixteca region in the municipality of San Miguel Tulancingo, state of Oaxaca, México, between coordinates 97°27' W, 17°45' N, at 2,200 m above sea level (figure 1). The climate of the study area is temperate (Cw_0). The precipitation is 544.7 mm per year and the average temperature is 15.9 ºC. The study area is characterized by steep slopes, low vegetation cover and erosion. In this small watershed, there are soil and water conservation practices such as land terraces, stone terraces, stone dams, gabion dams, ditches, reforestation with pines and contour furrows.This study area was chosen because it is representative, since it has a variety of soil and water conservation practicesimplemented in the watershed during the last 30 years, which allows comparisons of soil organic carbon estimates.

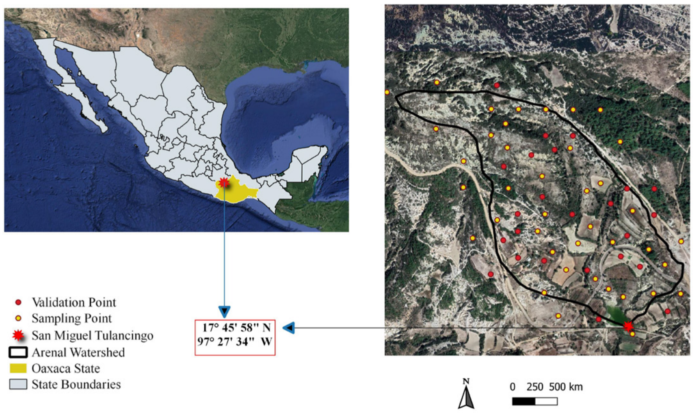

Figure 1. Location of study area.

The study area is a small watershed with 44.6 ha, called "El Arenal", located in the municipality of San Miguel Tulancingo, Oaxaca, México. The yellow and red dots correspond to the 77 COS samples collected in the field.

Preparation of the SOC map

The creation of the map SOC was divided into six steps: a) selection of sampling sites, b) soil sampling, c) determination of SOC, d) data statistics, e) interpolation map, and f) validation map, as indicated below:

a) *Selection of sampling sites:* a manual digitization of a Sentinel-2 satellite image from 26/09/2018 was performed to distinguish land uses at 10 m spatial resolution. The digitized land use polygons were used to design a stratified simple random sample (Gruijter *et al*., 2006), taking into account that SOC varies spatially due to vegetation cover and land use.

b) *Soil sampling:* a single soil sample of one kilogram from the superficial layer (0 to 30 cm) was collected from the selected site or its immediate vicinity (Borůvka*et al*., 2022; Yescas *et al*., 2018; Paz*et al*., 2016). Land use and management, hydrologic condition, and soil-water conservation practices were recorded at each site. The total number of sampling sites was 77 (figure 1).

c) *Determination of SOC*: The soil samples collected were analysed in the laboratory to obtain organic carbon in $g.kg^{-1}$according to the method of Walkley and Black (1934), the bulk density in $g.cm^{-3}$ was determined by the paraffin method and the percentage of rock fractionation that represents particles > 2 mm with respect to a known volume. Subsequently, the SOC expressed in $t.ha^{-1}$ was determined according to the formula used by Nabiollahi *et al*. (2021) proposed by Penman *et al*. (2003):

$$SOC = OC \bullet \text{Bulk Density} \bullet \text{Depth} \bullet \text{Coarse Fragments} \bullet 10 \quad (1)$$

Where: SOC = the soil organic carbon stock for soil of interest in $t.ha^{-1}$; OC = concentration of organic carbonin g / kg; Bulk Density = the mass of soil sample per volume in the fine soil fractionin $g.cm^{-3}$; Depth = sampling depth or thickness or soil layerin m; Coarse Fragments = 1 – (% volume of coarse fragments / 100); the final multiplier of 10 is introduced to convert units to $t.ha^{-1}$. These values measured in the laboratory will be called the observed SOC.

d) *Data statistics:* The statistical values that characterize the sample were analysed and extracted by means of its measures of centrality, position and dispersion, with the statistical panel tool in QGIS. Also, distribution pattern analysis was performed to determine if the points have aclusteringor dispersion pattern, with the QGIS Nearest NeighbourIndex (NNI) tool (Ose, 2018).

e) *Interpolation map*: the sample was divided into 70 % training data and 30 % validation data using the random selection module in QGIS. The method used for interpolation was developed and proposed by Pereira *et al*. (2022) in the Smart-Map Plugin Tool, installed from the QGIS Plugin Repository. This tool uses Machine Learning (ML) algorithms. The area-weighted average of the predicted SOC will be called the estimated SOC.

f) Validation map: The accuracy of the prediction was evaluated by comparing the estimated values $\hat{z}x_1$ with the actual observations at validation points Z (xi) according to Boubehziz *et al*. (2020).

Factors related to SOC

Land Use

For the classification of satellite imagery, a free and open-source plugin for QGIS was used, developed by Luca Congedo and known as Semi-Automatic Classification Plugin (SCP). Sentinel-2 satellite imagery data with a spatial resolution of 10 m, taken September 26, 2018 was used to create the land use map.

Vegetation cover

Soil Adjusted Vegetation Index (SAVI) was used for determiningthe percentage of vegetation cover using the method proposed by Bingfang and Qiangzi (2004) which assumes that each pixel receives two signals, one coming from soil and the other from vegetation. The formula for calculating vegetation cover is as follows:

$$\%CV = \frac{SAVI - SAVI_{bs}}{SAVI_{veg} - SAVI_{bs}} * 100 \quad (2)$$

Where: *% CV* is the percentage of vegetation cover; *SAVI* is the Soil Adjusted Vegetation Index observed in the pixel; $SAVI_{bs}$ is the Soil Adjusted Vegetation Index of a pixel withbare soil and $SAVI_{veg}$ corresponds of a pixel completely covered with vegetation.

Slope

The slope of the terrain in percentage, was calculated with the Slope tool using QGIS and a digital elevation model (DEM) with a spatial resolution of 15 m (INEGI, 2020); the output slope dataset was classified according to Jahn *et al*. (2006) into the following categories: flat (0-1 %), very gently sloping (1-2 %), gently sloping (2-5 %), sloping (5-10 %), strongly sloping (10-15 %), moderately steep (15-30 %), steep (30-60 %), and very steep (> 60 %). Next, we used the Profile tool, a QGIS add-on that allows us to draw lines on the elevation base map and create elevation profiles.

Soil and water conservation practices (SWCP)

SWCP wererecordedfor the 77 samplingsites in the field. Sixty-nine sampling points were within the small watershed; 33 of them had SWCP, while 36 had no practice (the remaining 8 points are outside the small micro watershed and their value was that they were used to correctly interpolate the SOC map outside the boundaries). Eachsite was characterized with its respective SWCP. Land management practices (recorded at the point level) were spatialized by Thiessen polygons. These polygons were used to assign 0 to locations without land conservation practices and 1 to locations with land conservation practices. Pearson's correlation coefficient was estimated to examine the relationship between soil conservation practices and SOC.

Principal Component Analysis (PCA)

A principal component analysis (PCA) was performed to decipher the grouping of environmental variables that explain variability in the small watershed. The ACP was conducted in ArcMap 10.8, with the variables in raster format: SOC land use, vegetation cover, soil conservation practices, and slope. According to Figueroa *et al*. (2018), the principal components with the highest eigenvalues explain the largest percentage of variability.

Results and discussion

Descriptive statistics of observed SOC

The results ofdescriptive statistics of the observed soil organic carbon (t.ha^{-1}) at 0–30 cm depth indicates aminimum value: 1.58, maximum value: 84.72, range: 83.14, mean value: 25.74, standard deviation: 18.70 and variation coefficient: 73, these results show the SOC magnitudesashighly variable and heterogeneous. On the other hand, the results of the analysis of the distribution pattern estimated with the QGIS nearest neighbour analysis tool exposes an average observed distance of 76.85, an average expected distance of 59.99 anda NNI of 1.28. These results exhibit two facts, 1) the average observed distance is greater than expected and 2) a clustered pattern (NNI >1). This variability is explained because samples were obtained at an average distance of 90 m, which can vary with respect to the position of the slope, land use, vegetation cover, and management. Yescas *et al*. (2018) observed that the behaviour of the variability in the SO Cis mainly due to land use.

Spatial estimation of SOC

The map of SOC in t.ha^{-1} resulted from interpolation with the machine learning algorithm implemented in the Smart Map plugin is depicted in figure 2.The cross-validation show a mean prediction error (ME) of 0.98 t.ha^{-1}, a root-mean-square prediction error (RMSE) of 3.770 t.ha^{-1} and a high value of R^2 (0.96). This R^2 indicated a strong correlation between predictors and observed SOC. The RMSE was lower than the one obtained by Yescaset *al*. (2018) of 4.69 t.ha^{-1} with ordinary kriging (KO) model. This implies a better fit of the model ML with respect to the KO.The total content of SOC predicted in the small watershed was obtained by (previously rescaling to the spatial resolution of the raster dataset) summing up all corresponding pixels of the study area totalling 101,826 t.ha^{-1} in 44.2 ha, while the average SOC was 23.77 t.ha^{-1}. Paz et al. (2016) associated this value to areas without apparent vegetation and xeric scrub. In this case, our study area has all forms of water erosion in addition to low vegetation cover.

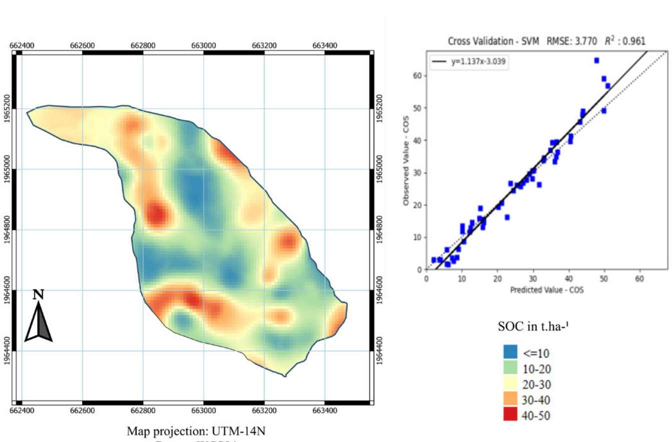

Figure 2. Map SOC Prediction (t.ha^{-1}) and cross-validation results.

On the map, the areas marked with blue are those with the lowest COS content and the red are the areas with the highest storage. The cross-validation resulted ina strong correlation between predictors and observed SOC whit a R^2 (0.96).

Factors that influence SOC storage in the small watershed

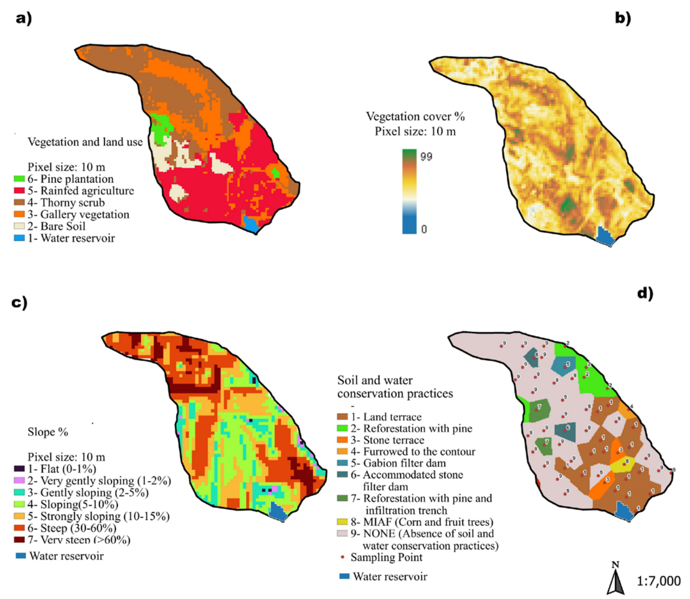

Figure 3. Environmental variables cross-correlated to soil organic carbon. a) Vegetation and land use, b) Vegetation cover (%), c) Slope (%), and d) Soil and water conservation practices.

Vegetation and land use

Variability of SOC at each site was partially controlled by land use and vegetation (Table 1). The largest carbon stocks were associated with areas of adult pine plantations; however, they represented only 1.32 ha of the study area. Despite, this value represents a small area within the small watershed, this result is still outstanding. This is because if we would want to increase the carbon storage in soil, an effective way to do this, is by planting trees. Second, rainfed agriculture showed the highest SOC value in the study area (estimated: 25.6 t.ha^{-1}, observed: 28.8 t.ha^{-1}), distributed over 15.6 ha, which emphasizes the importance of rainfed agriculture for soil carbon storage. Third, thorny scrub showed similar results to rainfed agriculture (estimated: 24.4 t.ha^{-1}, observed: 25.9 t.ha^{-1}). The spatial variability of vegetation and land use along the small watershed is shown in figure 3a.

Table 1. SOC variability by land use.

Land use	Area	SOC observed value	SOC estimated value	Total content of SOC in the watershed	Reference value Paz *et al.* (2016)
	(ha)	(t.ha^{-1})		(t)	(t.ha^{-1})
Adult pine Plantation	1.2	36.8	29.6	3,544.6	65.8
Rainfed agriculture	15.6	28.8	25.6	39,654.1	46
Thorn scrub	14.4	25.9	24.4	35,186.1	28
Gallery vegetation	10	17.6	20.1	20,100.6	32.9
Bare soil	3	6.4	10.8	3,340.5	19
Water	0.4	0	0	0	0

Vegetation cover

The 74 % of the study area is dominated by sites with vegetation cover less than 50 %, and areas with vegetation cover greater than 75 % account for only 3.7 %. According to our results, the greater the vegetation cover, the greater the storage of SOC. The areas with cover > 75 % have an estimated average of 30 t.ha^{-1} as adult pine plantation, those with values of vegetation cover less than 50 % have an estimated average of 21.1 t.ha^{-1}, which explains the average data for the small watershed. These results are consistent with those of Nabiollahi *et al*. (2021), which indicate that the loss of natural vegetation cover leads to a reduction of SOC. Therefore, to increase soil carbon reserves, it is necessary to increase vegetation cover. The spatial distribution of vegetation cover along the small watershed is shown in Figure 3b.

Slope and profile analyses on the small watershed

There are significant differences between SOC and the different slope percentages. The average results for each slope category are as follows: flat (13.4 t.ha^{-1}), very gently sloping (21.4 t.ha^{-1}), gently sloping (25.8 t.ha^{-1}), sloping (24.1t.ha^{-1}), strongly sloping (20.2 t.ha^{-1}), moderately steep (21.5 t.ha^{-1}), steep (28.5 t.ha^{-1}). Our results showed no significant relationship between slope and soil organic carbon content in accordance whit Gadisa and Hailu (2020) and Bai and Zhou (2019). This can be explained by the result obtained from cross-sectional profileconducted in the lower part of the small watershed (Figure 4). Here it can be seen that regardless of the slope category, the SOC value is varying according to land use. In this sense, the profile shows an agricultural use with values up to 49 t.SOC.ha^{-1} with a slope of 10-15 %, which contrasts in this profile with 9 t.SOC.ha^{-1} of the bare soil in the same slope category.

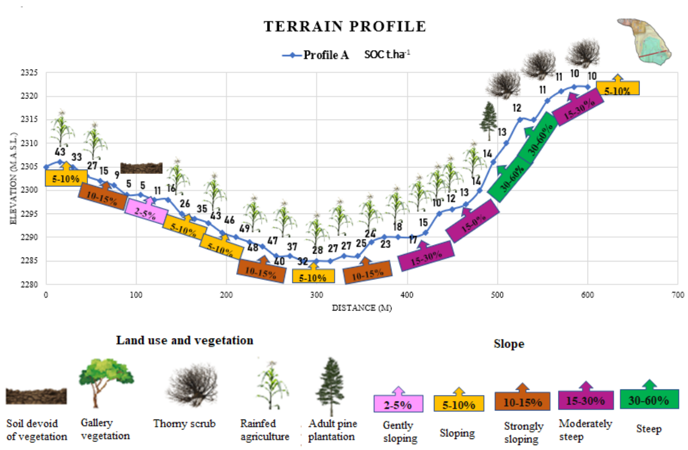

Figure 4. Profile analyses the lower part in small watershed, regarding elevation, slope, land use and SOC storage. The variation in soil organic carbon (SOC) is not determined by the slope but rather by vegetation and land use.

Soil and water conservation practices (SWCP)

Table 2 shows that stone terrace was the soil management practice that stored the most carbon in the surface layer (first 30 cm), with 35 t.ha^{-1}. Second, aforestation with adult pines combined with an infiltration trench with 32.1 t.ha^{-1}. The management practice equivalent to bare soil was the combination of fruit trees interspersed with corn, commonly known in Mexico as MIAF (corn and fruit trees grown simultaneously); these trees are still in their early stages of growth and are planted with a spacing of 8 meters between rows. The soil management method that stored the least SOC in the topsoil layer was the gabion filter dam with 5.1 t.ha^{-1}. This value was unexpected because Mekonnen & Getahun (2020) found that gabion dam trapped 106.29 t.ha^{-1} in 5104 m^3 sediment. However, this can be explained because water that flows into the gabion dam probably washes soil, leaches the SOC or transports it out the reservoir. Therefore, it is suggested to analyse the sediment trapped in these sediment storage dams at different depths.

Table 3 shows the observed SOC values at the sampled sites in relation to soil depth and SWCP. Severely degraded areas and with no soil are associated with lower SOC storage and lack of soil management practices. Sites deeper than 30 cm, on the other hand, were associated with the presence of SWCP.The difference between the observed and estimated values is due to the fact that the area calculated comes from the geometry of the Thiessen polygons, which in turn correspond to the spatial distribution of the sample points.

Table 2. SOC variability respect to soil and water conservation practices.

Thematic Class	Soil and water conservation practices	SOC Estimated Value (t.ha^{-1})	SOC Observed Value (t.ha^{-1})
1	Land terrace	25.3	27.3
2	Adult pine plantation	26.6	29.0
3	Stone terrace	29.6	35.0
4	Furrowed to the contour	26.7	21.4
5	Gabion filter dam	8.6	5.1
6	Accommodated stone filter dam	20.1	17.5
7	Reforestation with pine and infiltration trench	25.0	32.1
8	MIAF (Corn and young fruit trees)	14.8	8.4
9	None (Absence of soil and water conservation practices)	22.3	21.2

Table 3. SOC variability with respect to the depth of the sampled soil.

Soil Depth (cm)	SOC Observed Value (t.ha^{-1})	Soil and water conservation practices
3	1.6	None
5	2.3	None
15	10.3	None
20	15.9	None – Pine Plantation
25	32.6	None – Pine Plantation
30	27.0	Land terrace, Reforestation with pine, Stone terrace, Furrowed to the contour, Gabion filter dam, Accommodated stone filter dam, Reforestation with pine and infiltration trench, MIAF

Principal Component Analysis

The principal components (PCs) captured the variability of the original variables in the following proportions: PC_1 (49.34 %), PC_2 (40.65 %), PC_3 (9.88 %), PC_4 (0.09 %) and PC_5 (0.02 %). The accumulative value for the first three components was 99.8%. When analysed the weights of the principal components in the matrix of eigenvalues and eigenvectors, PC_1 revealed that the COS variable (0.50) and the vegetation cover variable (0.86) were directly and proportionally related to the component, as they had a positive sign in the loading. PC_2 disclosed that the COS variable (-0.86) and the vegetation cover variable (0.50) were representative but with inverted signs in this relationship. Meanwhile, in PC_3, it was shown that only the Slope variable (0.99) was representative in a directly and proportionally related manner to that component. Furthermore, the Pearson's correlation coefficient obtained to examine the relationship between the four explaining variables (*i.e.*, land use, vegetation cover, conservation practices and slope) and SOC was 0.16, 0.08, 0.06 and 0.04, respectively. These values align with the findings of Yescas et al. (2018), Bai and Zhou (2019), and Gadisa and Hailu (2020), supporting the notion that land use and vegetation cover primarily influence SOC variability, while slope carries a lower weight.

Conclusion

The analysis of observed and estimated SOC in a small watershed revealed significant variability and heterogeneity. The SOC distribution pattern was successfullymodeledwith spatial interpolation and subsequently related to four explaining variables includingland use, vegetation cover, conservation practices and slope. Soil and water conservation practices played a crucial role, enhancing SOC stock by preventing soil erosion. To safeguard SOC reserves, it is crucial to enhance vegetative cover and supplement land use with SWCP. Through these measures, not only can erosion be effectively managed, but they also play a pivotal role in curbing CO_2 emissions, thereby mitigating the impact of global warming.

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