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Soil Organic Carbon May Decline Under Climate Change: A Case Study in Mexican Forests

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Abstract: Soil organic carbon is essential for ecosystem health, influencing water retention, soil fertility and biodiversity. However, climate change and deforestation are reducing SOC globally. This study models and projects changes in the SOC of Mexican forest soils under different climate scenarios. Over 100 models were developed relating SOC to the Lang index (precipitation and temperature), altitude, slope, bulk density, texture and soil depth. The results indicate that SOC can be effectively modelled to assess scenarios for decision making. The highest SOC levels were found in tropical rainforests and mesophyll forests and the lowest in broadleaved forests of the Sonoran plain. Climate change is projected to reduce SOC in forest ecosystems by up to 11%, especially in temperate forests. Conversely, mesophyll forests are expected to experience a slight increase in SOC of 3% due to rising temperatures and changing precipitation patterns. This decline could lead to increased HGH and reduced carbon storage capacity. This study highlights the need for sustainable management practices and multidisciplinary research to mitigate these impacts and emphasises the importance of comprehensive strategies for long-term environmental sustainability.

Keywords: forestry; spatial modelling; SOC; carbon dynamics; forest landscape

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Citation: López-Teloxa, L.C.; Monterroso-Rivas, A.I. Soil Organic Carbon May Decline Under Climate Change: A Case Study in Mexican Forests. *Land* **2024**, *13*, 1711. https://doi.org/10.3390/land13101711

Academic Editors: Nejc Bezak, Carla Sofia Santos Ferreira and Vesna Zupanc

Received: 14 September 2024
Revised: 11 October 2024
Accepted: 17 October 2024
Published: 18 October 2024

1. Introduction

Soil organic carbon (SOC) plays an important role in terrestrial ecosystems. It improves soil structure, reduces erosion, increases water and nutrient retention and promotes biodiversity. All this supports plant growth and the provision of high-quality ecosystem services [1]. SOC accumulation in soils increases with soil depth and varies with climate and dominant land use [2]. Spatially, the distribution of SOC is not uniform: deeper soils tend to accumulate more carbon than thinner soils, while SOC stability can vary significantly between regions due to variations in local factors such as soil horizon, soil type and primary land use [3].

The interaction between soil properties (such as texture and structure) and the biophysical environment (such as local climate, slope) plays a key role in SOC dynamics. In other words, some of these variables determine the capacity of soils to sequester and store carbon [4]. The landscape in which an ecosystem develops also strongly influences the distribution and storage of SOC. Topography, slope and elevation are factors that influence the amount of carbon that accumulates in soils. In areas with steep slopes, soil erosion is more intense, reducing the capacity of soils to sequester carbon, whereas in flatter areas, organic matter accumulation is higher due to less erosion and higher water retention [5]. In addition, landscape fragmentation caused by human activities such as agriculture alters natural SOC cycles by creating habitat edges that are more vulnerable to carbon loss and soil degradation [6]. These landscape factors, in combination with climate and land use practices, determine the capacity of soils to act as carbon pools [7].

Some of the key factors affecting SOC in soils are soil texture, topography, land use, climate, soil moisture and temperature, soil depth and bulk density [8–10]. The latter two, soil depth and bulk density, play a crucial role in less compacted soils, which generally store more carbon [11,12]. Altitude and slope also influence the microclimate and promote soil erosion, which is higher at higher altitudes due to better moisture conditions [13,14]. To these characteristics, we can add two current ones: deforestation and climate change.

Conversion of primary forests to other uses, such as cropland, leads to significant reductions in SOC storage [15]. Globally, the conversion of forests and grasslands to agricultural land has led to significant reductions in SOC [6]. In addition, climate change induces changes in SOC composition and stability, highlighting the sensitivity of soil organic matter to climate variability and the implications for carbon sequestration and greenhouse gas emissions [16,17]. These SOC losses, exacerbated by inappropriate agricultural practices, land degradation and climate change, have serious consequences as they reduce the soil's capacity to retain and infiltrate moisture, thereby affecting regional hydrology and weather patterns [7].

Modelling facilitates understanding of the complex mechanisms that influence SOC dynamics, especially under conditions of climate change. Therefore, multidisciplinary research with increased modelling accuracy is needed [18]. Accurate quantification and prediction of SOC content is crucial for understanding global and regional carbon fluxes. This will provide insight into the important implications they may have for climate change mitigation and environmental sustainability. Several approaches have therefore been explored to improve SOC prediction, including machine learning techniques such as Random Forests, Support Vector Machines, Adaptive Boosting and K-nearest Neighbours, which have been shown to be effective in making predictions at high spatial resolutions [19].

In the context of major problems such as desertification and land degradation in Mexico [20], SOC modelling can identify areas at risk and trigger strategies to increase soil carbon. In the country, SEMARNAT-INECC reported that deforestation of forest areas released 5129 million tonnes of carbon into the atmosphere in 2015, highlighting the vulnerability of these SOC stocks [21]. SOC modelling is essential for forest managers to implement sustainable management practices that promote long-term soil health and productivity [22]. Sustainable management practices in Mexico's forests can improve carbon storage and soil fertility [23,24].

If current trends in SOC loss continue, significant ecosystem changes are predicted that could trigger major social and economic changes on the planet [25,26]. Therefore, the objective of this work is to model and project changes in forest soil carbon stocks in Mexico under different climate change scenarios. The hypothesis is that future changes in temperature and precipitation will trigger important environmental changes such as those observed in SOC. This study is an important contribution to the understanding of carbon storage patterns in Mexican soils and highlights the importance of including both physiographic and climatic variables in predictive SOC models.

2. Materials and Methods

The projection of SOC under different climate change scenarios was carried out in three stages: delineation of forest landscape units, modelling, and calculation of SOC in the baseline period and climate change scenarios. All stages involved mapping and area estimation, as presented below and in Supplementary Material Tables S1–S3. Each stage is described in more detail below:

2.1. Forest Landscape Delineation

Forest landscapes were delineated by integrating the physiography of the terrain with the dominant forest vegetation of the country. The physiography of Mexico [27], divided into fifteen provinces, was represented at a scale of 1:250,000 (Figure 1).

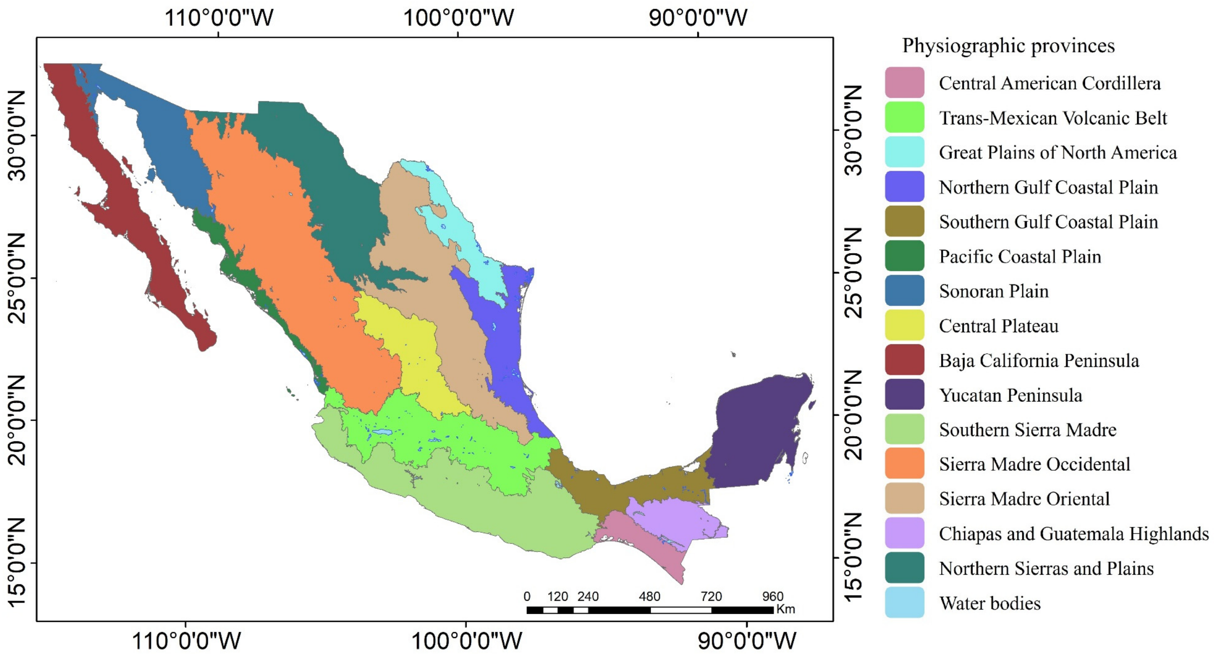

Figure 1. Physiographic provinces.

Forest vegetation was extracted from the 2016 Land Use and Vegetation Map, which is available at a scale of 1:250,000 [28] and covers 183 vegetation types in Mexico. This map was processed and classified to focus only on the forest zone, which is divided into nine forest categories [24]: cloud forest, coniferous, mixed forests (coniferous and broadleaved), broadleaved, highland and midland tropical forests, lowland tropical forests, other wooded areas, secondary forest vegetation, and secondary rainforest vegetation). After cross referencing the two maps, a total of 112 forest landscapes were identified (see Supplementary Material Table S1).

2.2. Cartographic Data Processing and Analysis

To ensure the consistency of the maps, a regular grid of 1000 m × 1000 m polygons was implemented, resulting in a total of 668,546 spatial units covering the entire forest area of the country. In order to construct the database, data extraction was carried out at the centre of each polygon, assigning key variables essential to the analysis. In addition to forest regions, the following variables were taken into account: SOC content, altitude, slope, Lang index, soil bulk density, soil depth and texture class. A diagram illustrating this process is shown in Figure 2. Each of these variables is broken down below to provide a more detailed understanding of their relevance to the study.

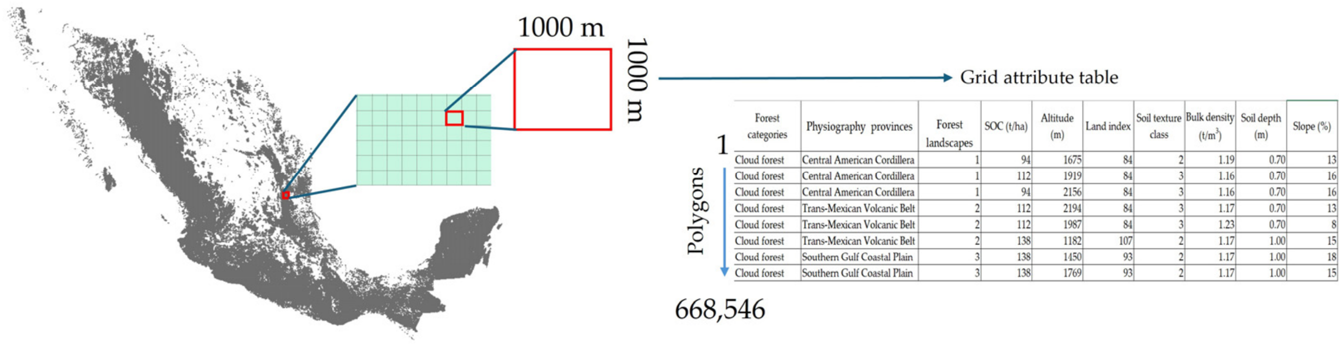

Figure 2. Cartographic data processing and analysis.

2.3. Soil Organic Carbon

Base period. For the base period, the information reported in Mexico's first biennial report was used [29], which included SOC (%) for the years 2001 and 2016. This analysis was based on a representative sample of all ecosystems in Mexico, with a total of 26,220 points. The percentage of SOC per vegetation type was then calculated (Supplementary Material Table S2). From these data, an SOC map was generated for each year by applying Equation (1) to each forest category.

$$SOC = \%SOC \times BD \times 30 \quad (1)$$

where SOC is soil organic carbon stock (t/ha), %SOC is percentage of SOC, BD is bulk density (t/m^3) and 30 is the soil depth (cm). Note that a depth of 30 cm was used, as recommended by the IPCC [30], because microbial activity is more active at this depth [3]. An average was taken between the two years to obtain the SOC for the base period, which reflects the conditions for the period 2001–2016.

Independent variables. In order to build models, the relationship between SOC and six soil and environmental variables was considered.

Lang index. The mean temperature (T in °C) and annual precipitation (P in mm) data for Mexico were obtained from the WorldClim database [31]. To represent the relationship between temperature and precipitation, the Lang index was calculated for the years 2001 and 2016 according to Equation (2):

$$Lang\ index = \frac{P}{T} \quad (2)$$

Terrain altitude and slope. Altitude (masl) was obtained from the Continuo de Elevaciones Mexicano (CEM) with a resolution of 15 m [32]. Slope (%) was derived from the above map in the ArcMap 10.8.1 application [33].

Soil texture class, bulk density and soil depth. Soil texture class, bulk density (t/m^3) and soil depth (m) were obtained from the Series II Soil Profile dataset, scale 1:250,000 [34], which contains a spatial distribution of 16,820 soil profiles.

SOC modelling. Models were constructed for each of the 112 forest landscapes. Linear (Equation (3)) and exponential (Equation (4)) regression models were used with base period SOC as the dependent variable:

$$SOC = \beta_0 + \beta_1 * Lang\ index + \beta_2 * altitude + \beta_3 * Slope + \beta_4 * BD + \beta_5 * texture\ class + \beta_6 * soil\ depth \quad (3)$$

$$\log(SOC) = \beta_0 + \beta_1 * Lang\ index + \beta_2 * altitude + \beta_3 * Slope + \beta_4 * BD + \beta_5 * texture\ class + \beta_6 * soil\ depth \quad (4)$$

For each forest landscape, a final model was selected based on the statistical significance ($p < 0.05$) of each variable. The coefficient of determination (R^2), mean square error (MSE), Bayesian information criterion (BIC) and Akaike information criterion (AIC) were obtained to determine which model was the best for each of the 112 forest landscapes. These are all well-known tests of model calibration. These metrics were used to compare the models and select the most representative model for each forest landscape. Priority was given to the model with the highest coefficient of determination (R^2), the lowest MSE and the lowest values of AIC and BIC. This was carried out using RStudio 2023.06.0 Build 421 [35].

Model validation. In order to validate the results obtained in the models, a comparison approach was used between the observed and predicted values. This was conducted by applying the same data used to construct the models, so that two raster maps were produced: one with the baseline and the other with the values resulting from the application of the models. Six statistical tests were performed to assess errors and statistical metrics and to analyse bias: (1) Root Mean Square Error (RMSE) and (2) Mean Absolute Error (MAE) to quantify the accuracy of the models in terms of differences, (3) coefficient of determination (R^2) to assess the proportion of variability in the observed data, (4) Mean Absolute Percentage Error (MAPE) to obtain a relative perspective of the errors, (5) Lin's concordance index for direct interpretation of the degree of similarity between predictions and observations, and (6) bias analysis (mean difference) to identify any systematic deviations in model predictions, helping to detect trends of under- or over-estimation. Analyses were performed using RStudio 2023.06.0 Build 421 [35].

2.4. Projections with Climate Change

The climate change scenarios were constructed by replacing the Lang index values of the baseline scenario with the future projections. The applied mean temperature (°C) and annual precipitation (mm) were obtained from the climate models HadGEM3-GC31-LL, MIROC6 and MPI-ESM1-2-HR, according to the common socio-economic path (SSP) 585 for the horizon 2081–2100. The information was obtained from the WorldClim database [31].

From this information, the Lang index was calculated to develop SOC projections under climate change conditions. The results of the Lang index were incorporated into each of the 112 models developed.

3. Results

3.1. Forest Landscapes and Ecosystems in Mexico

In summary, the results show that 71% of the country is covered by primary vegetation, of which 33% is coniferous forest, mixed forest, deciduous forest, cloud forest, highland and midland tropical forest, lowland tropical forest and other wooded areas (Figure 3). In contrast, 29% of the land area has been converted for agricultural, urban or other human uses, of which 36% is classified as secondary forest and secondary rainforest vegetation. This is reflected in the Report on the State of the Environment in Mexico, which reports that 354,000 hectares of forest were deforested annually between 1990 and 2000 and 92,000 hectares annually between 2010 and 2015 [36]. While the National Forestry Commission reported that the conversion of forest land to pasture reached its peak in 2014, the conversion of forest land to agricultural land showed its highest intensity in 2016 [37].

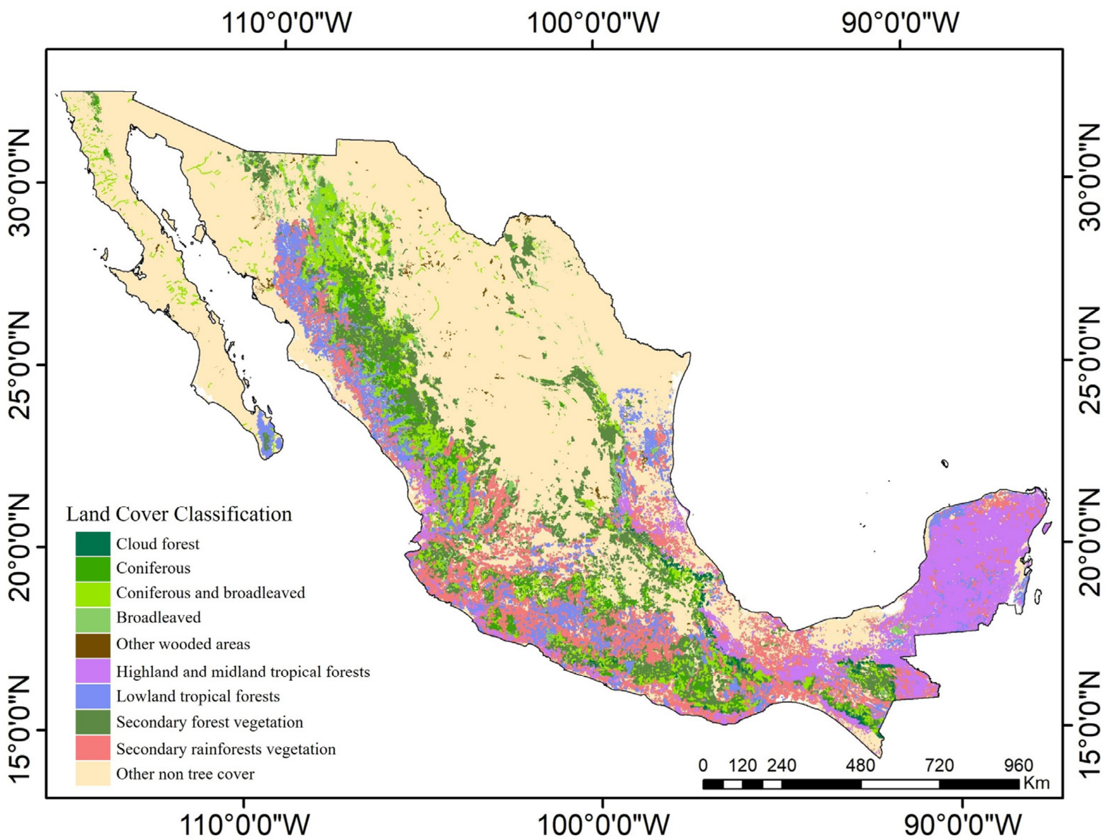

Figure 3. Forest distribution in Mexico.

Specifically, 5.5% of the national territory is covered by high and cloud forest, 5.3% by coniferous and broadleaved forests, 5% by lowland tropical forests, 3.8% by broadleaved forests and 3.1% by coniferous forests. It should be noted that secondary forest vegetation accounts for 5.2% and mixed forest vegetation for 5.1%. Cloud forest and other wooded areas together account for barely 1%.

Forest ecosystems in Mexico vary greatly across the country. In combination with the physiographic provinces (Figure 4), 112 areas were obtained.

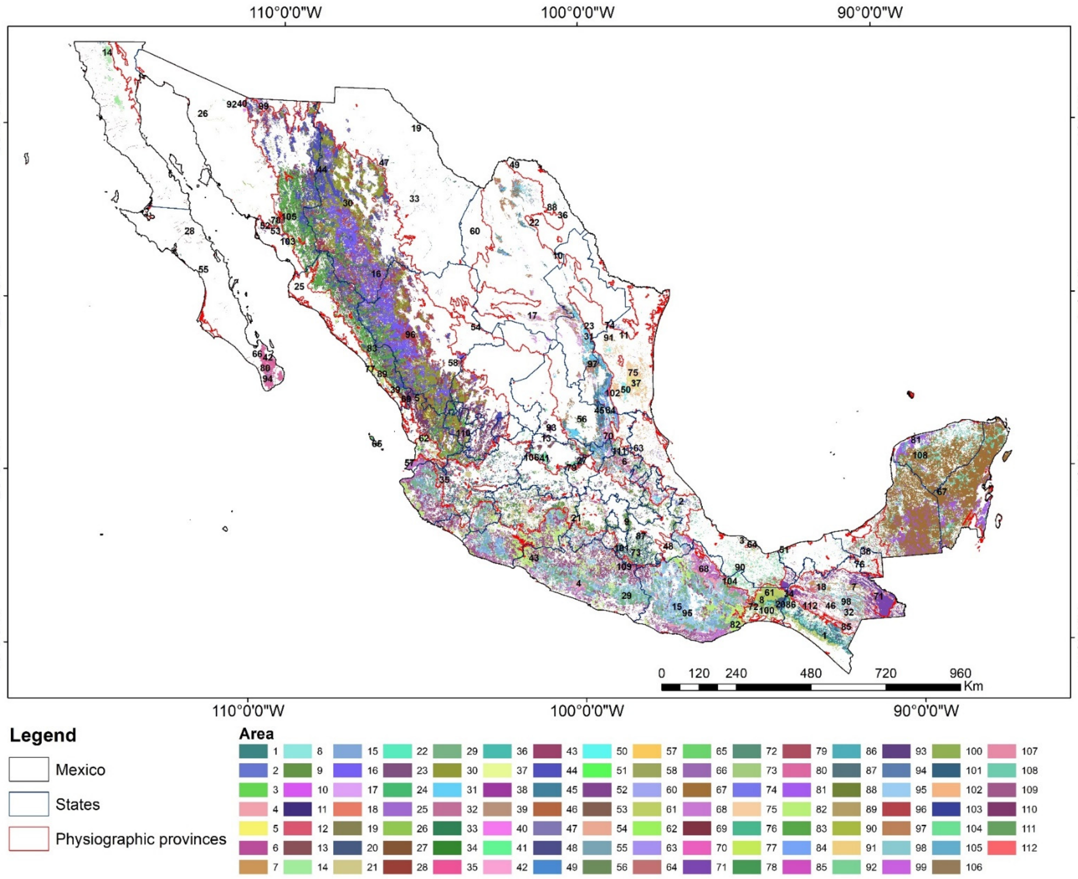

Figure 4. Distribution of areas used for SOC modelling.

In terms of forest cover, the provinces with more than 50% forest are, from largest to smallest, Yucatan Peninsula > Southern Sierra Madre > Sierra Madre Occidental > Central American Cordillera > Chiapas and Guatemala Highlands.

3.2. Soil Organic Carbon Stored in Forest Systems

Values of less than 50 t/ha SOC cover 1% of the forest area. SOC levels of 50–75 t/ha are found in the north-west of the country, covering 4.7% of the forest area. The largest area is found in the Sonoran plain province. A wider distribution, between 75 to 100 t/ha and 100 to 150 t/ha SOC, concentrates 19.5% and 45.6% of the forest area, respectively. This is the case in the provinces of Sierra Madre Occidental, Southern Sierra Madre, Trans-Mexican Volcanic Belt, Central American Cordillera, Chiapas and Guatemala Highlands, Southern Gulf Coastal Plain and Pacific Coastal Plain. SOC levels above 150 t/ha are mainly found in the Yucatan Peninsula. To a lesser extent, they are also found in provinces such as Sierra Madre Occidental, Southern Sierra Madre, Central American Cordillera, Chiapas and Guatemala Highlands. This category covers 29% of the forest area (Figures 3 and 5).

The forest types with the highest SOC content are woodland (highland and midland tropical forests and low forest). However, cloud forests in the Southern Gulf Coastal Plain Province have the highest SOC values, followed by highland and midland tropical forests in the Central American Cordillera. On the other hand, the lowest SOC content was found in the broadleaf forests of the Sonoran plains, followed by other wooded areas in the northern sierras and plains province. This can be seen in Figure 6, which shows the averages of SOC obtained by forest cover type and physiographic province in Mexico.

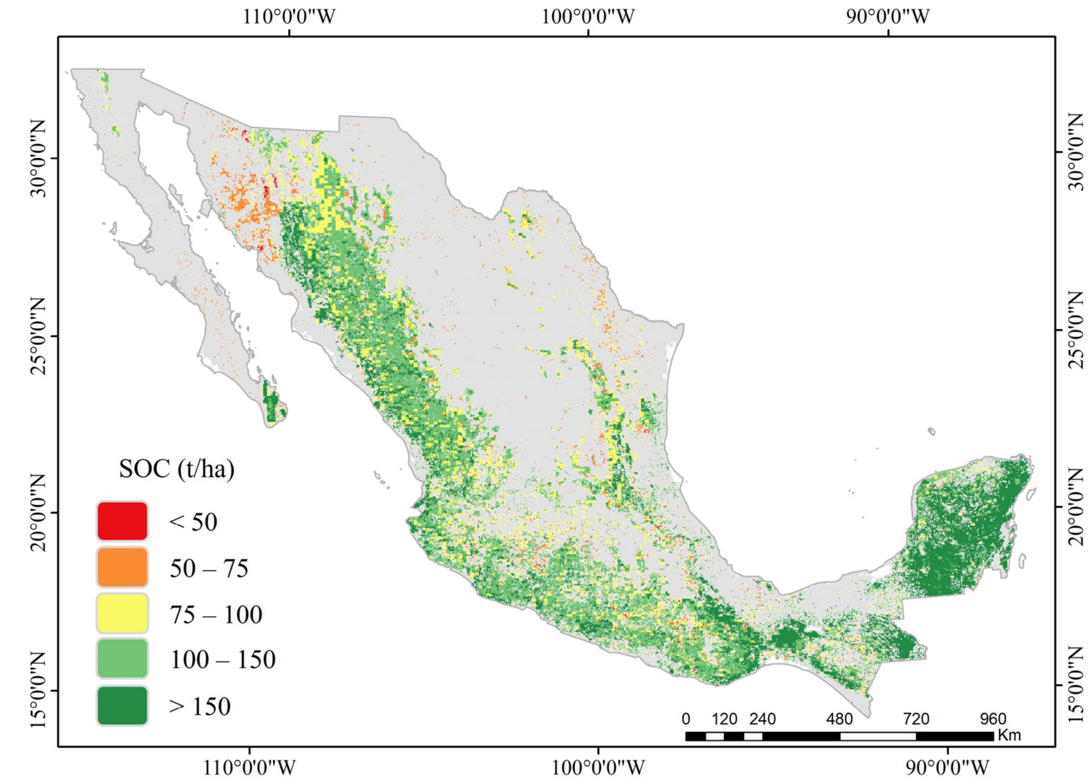

Figure 5. Baseline SOC content.

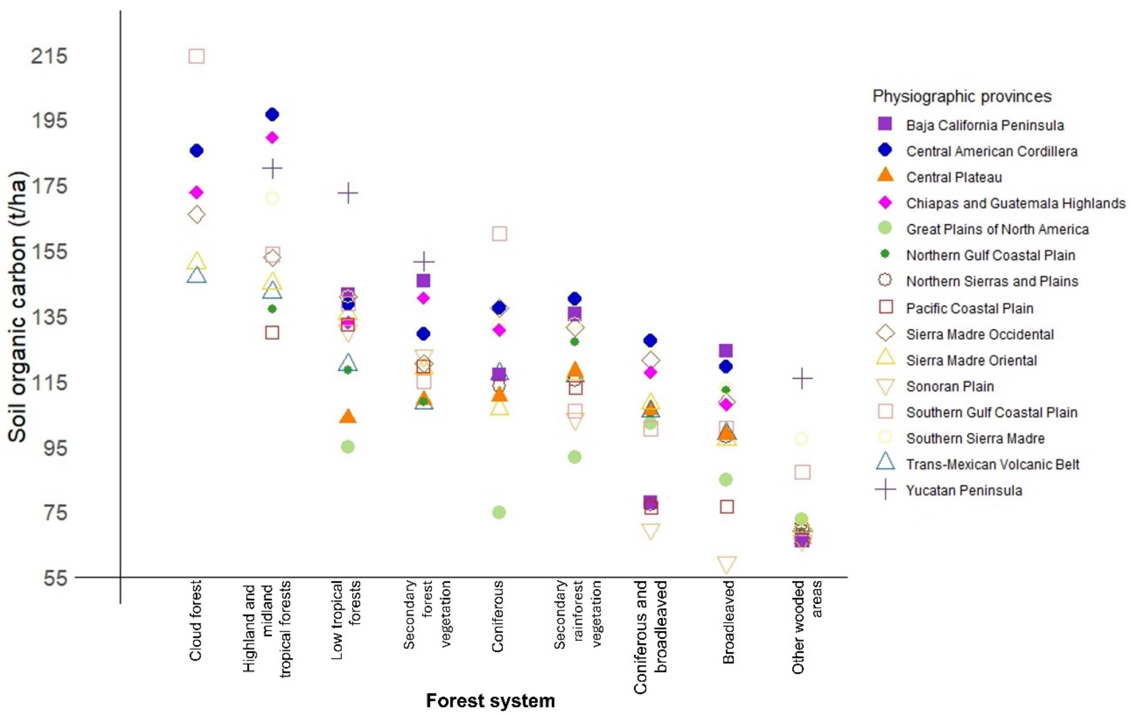

Figure 6. Spatial distribution of soil organic carbon by forest cover and physiographic province.

3.3. Validation of SOC Models

For the 112 forest landscapes, it was possible to obtain 107 models, as for 5 landscapes, insufficient values were obtained to generate the model (Supplementary Material Table S3). For the 107 forest landscapes, linear and exponential models were compared, resulting in 214 models evaluated (107 linear and 107 exponential). According to the metrics evaluated, the best models are 63 linear and 44 exponential (Supplementary Material Table S3).

Once applied to the models with the same data used to build them, an output map reflecting the values predicted by the models was generated. The results reflect a reasonable accuracy in predicting SOC, although they have errors, as expected, as indicated by the RMSE, MAE and MAPE indicators (Figure 7 and Table 1). The RMSE indicates that, on average, the model predictions differ from the observations by this amount. The MAE, on the other hand, shows that the average absolute error of the predictions is about 22 units. The coefficient of determination explains about 52% of the variability in the SOC. The MAPE shows that the predictions deviate from the observed values by about 18.83%. On the other hand, a bias of −0.81 indicates that the model tends to slightly underestimate the SOC values. Finally, Lin's concordance index of 0.685, together with a narrow confidence interval (0.682 to 0.688), suggests a good but not perfect agreement between the predicted and observed values.

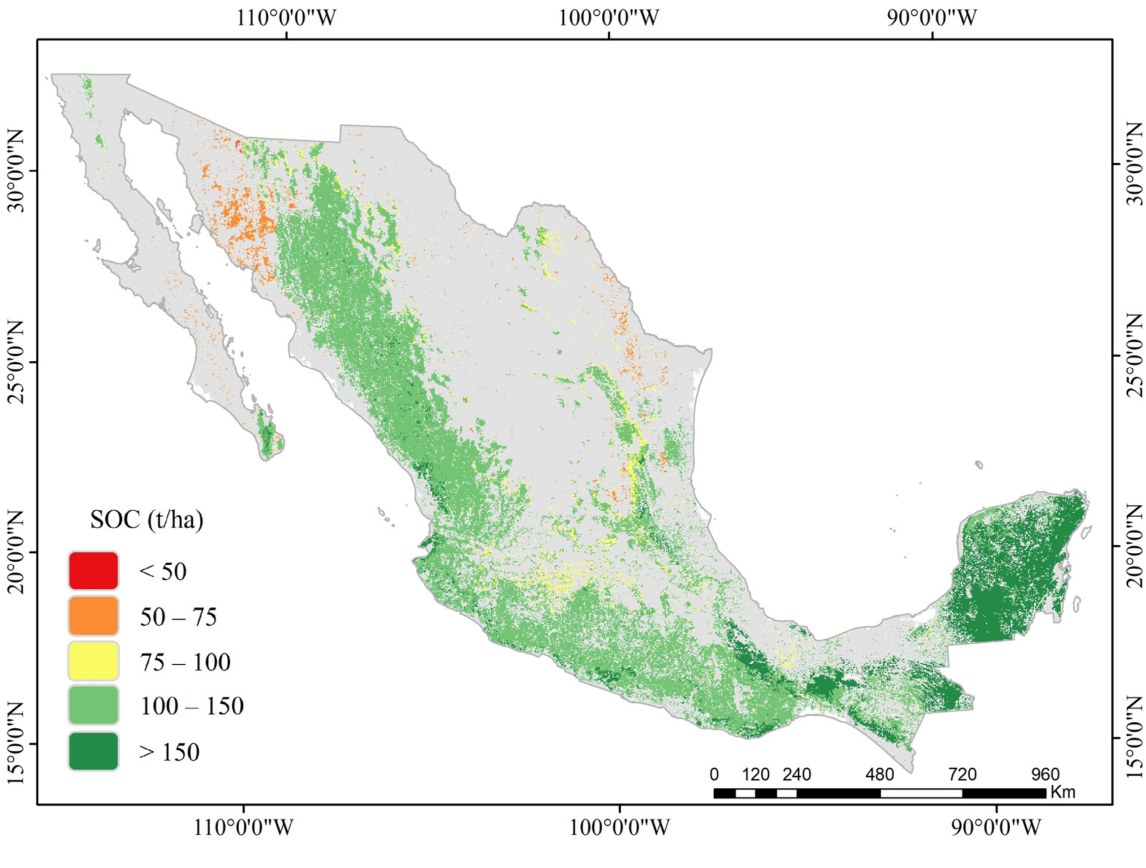

Figure 7. Projected SOC content by model.

Table 1. Validation results: base map versus SOC projections.

Metric	Value
Error evaluation and statistical metrics	
Root Mean Square Error (RMSE)	27.43
Mean Absolute Error (MAE)	22.02
Coefficient of determination (R^2)	0.52
Mean Absolute Percentage Error (MAPE) (%)	18.83

Table 1. *Cont.*

Metric	Value
Lin's Concordance Index	0.685
Lower limit of confidence interval	0.682
Upper limit of confidence interval	0.688
Bias analysis	−0.81

3.4. SOC Projection with Climate Change Scenarios

In the context of climate change, all three models analysed show significant temperature increases, with HadGEM showing the highest values and MPI the lowest. Among the forest types, broadleaved forests stand out with the largest projected increases, ranging from 7.86 °C to 9.71 °C. In contrast, lowland tropical forests have projected increases ranging from 3.58 °C to 5.55 °C. On the other hand, precipitation projections show differences between forest types. High and middle forests are expected to decrease by 16% according to HadGEM and by 15% according to MPI. Meanwhile, other forest areas would experience a 13% increase in HadGEM and a 20% decrease in MPI.

The climate change projection suggests that 60% of the forest area will experience SOC losses of up to 50%. In contrast, 40% of the forest area could reach SOC levels above 60%, although this would only occur on 3% of the total area.

Figure 8 shows the behaviour of the SOC projections, where the orange and red areas indicate a decrease in SOC, while the blue areas show an increase. In all three maps, the trend of decreasing SOC is maintained, although some areas show possible moderate increases in SOC. A significant decrease in SOC is highlighted in many parts of the country, especially in the north and in areas of the Sierra Madre Occidental, although with a slightly different spatial distribution, showing more areas with significant losses in the centre and south-east.

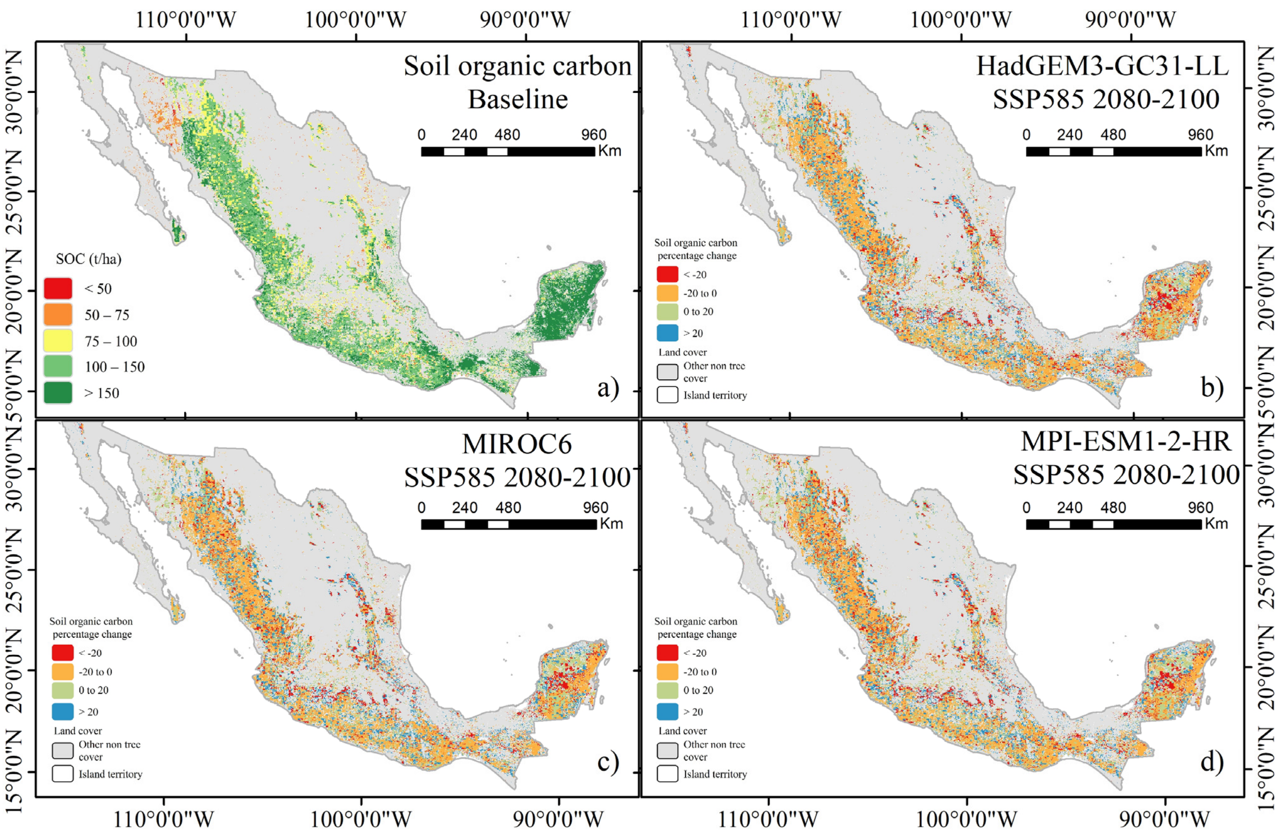

Figure 8. Soil organic carbon map: current state (**a**) and projected SOC in percent change (**b**–**d**) under climate change scenarios.

All three climate models project reductions in lowland tropical forests, coniferous forests, broadleaved forests, mixed coniferous and broadleaved forests and other wooded areas. In particular, mixed coniferous and broadleaved forests are expected to experience the largest SOC losses, with reductions of up to −11% according to MPI, −10% according to HadGEM and −8% according to MIROC6 (Figure 9). In contrast, all three models suggest that mesophyll forests could benefit from changes in temperature and precipitation, with increases in SOC of up to 3%.

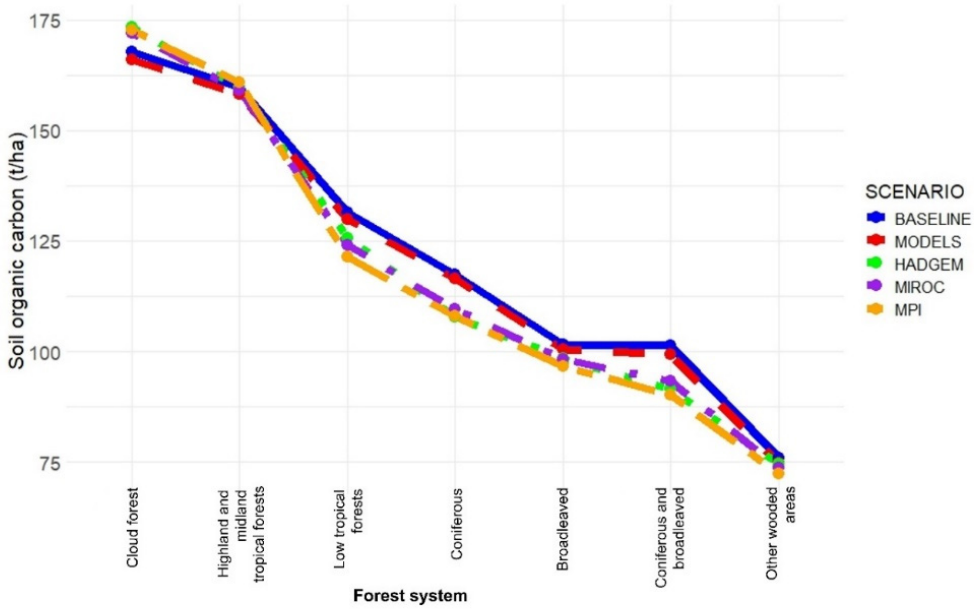

Figure 9. Soil organic carbon dynamics: comparison between baseline and climate change scenarios.

4. Discussion

4.1. Landscape Influence on SOC

SOC is influenced by several interrelated factors such as soil management practices, physico-chemical properties and local climatic conditions [38]. Although the same region can have significant differences in SOC, these differences are due to factors such as soil texture, topography, land use and climatic conditions [39,40]. To understand how these factors affect SOC and to predict carbon sequestration under different land use and climate change scenarios, it is essential to use models that integrate all relevant variables [41]. These models should provide a holistic view, allowing more accurate modelling and a better understanding of the processes that regulate carbon cycling in different ecosystems.

For example, clay soils, with their finer materials, tend to have higher SOC content than sandy soils, which affects water infiltration and retention as well as soil structure [42,43]. In a field trial, after five months, carbon rates were found to be higher in silty soils than in sandy soils, and fine-textured soils tended to have better moisture-holding capacity and favoured organic matter mineralisation during periods of drought [44].

Furthermore, the Lang index is closely related to SOC, soil health and climate change mitigation [8]. This index directly influences organic matter decomposition processes and thus SOC dynamics [9,10]. In regions with a high Lang Index, indicating wetter conditions, soils tend to retain more carbon due to a lower rate of organic matter decomposition. In contrast, in areas with a low Lang index, indicating drier conditions, decomposition is accelerated and carbon storage decreases [45,46]. In a study conducted in native forests in Argentina, SOC stocks were modelled and climatic variables such as annual precipitation and temperature were found to directly influence soil carbon accumulation [47].

In addition, soil depth and bulk density are critical factors influencing SOC content. Deeper soils tend to have higher SOC stocks due to the accumulation of organic matter along the soil profile, facilitating greater carbon storage [48]. On the other hand, greater soil depth AND bulk density, which increases soil compaction, reduces porosity and limits the space available for organic matter, negatively affects the soil's ability to sequester carbon [49,50]. In a broadleaved forest, soil bulk density was found to increase with depth, while it had an inverse relationship with the amount of SOC [51].

Finally, altitude and slope also affect microclimate and soil erosion, which in turn affect carbon storage. On sloping terrain, runoff can carry away carbon and nutrients, reducing their storage. However, SOC generally increases with altitude because higher elevations tend to provide better moisture conditions for organic matter accumulation [13,14]. Understanding these processes associated with changes in land use and management regimes enables the predictive use of models of soil organic carbon dynamics to anticipate how the soil will respond to different interventions [41]. In temperate forests in Poland, SOC stocks in the organic and mineral horizons were reported to increase significantly with altitude. Specifically, an increase of about 40 t/ha C was documented when moving from 300 to 1000 m asl [52].

4.2. Soil Organic Carbon Concentrations

In Mexico, forest cover stores approximately 8992 million tonnes of soil organic carbon (8.9 Pg), of which 51% is stored in tropical forests (4.5 Pg), 46% in temperate forests (4 Pg) and 3% in cloud forest (2.2 Pg). This is similar to what was reported in 2015, where temperate forests stored 4.4 Pg C [53]. At the same time, tropical forests were reported to store 148.75 t C/ha, while forests in Chiapas were reported to store 183.9 t C/ha in 2022 [54]. In contrast, globally, tropical forests store lower concentrations of SOC than temperate forests [55], but Amazonian forests have been reported to store two to five times more than temperate forests [56].

In temperate forests, the order of SOC concentration from highest to lowest is coniferous < coniferous and broadleaved (mixed) < broadleaved, whereas in tropical forests, the order of SOC concentration is highland and midland tropical forests < lowland tropical forests. In temperate forests around the world, the order is reported to be coniferous and broadleaved (mixed forest) < coniferous < broadleaved [57], while in tropical forests, the same trend has been reported [58].

By forest type, coniferous forests store 130 t/ha SOC stock. This is slightly lower than the range reported in other studies, where carbon storage in coniferous forests in Mexico ranges from 160 to 280 t/ha [26]. In comparison, broadleaved forests are reported here to store 106 t/ha. However, studies using organic matter oxidation methods show a discrepancy in the data: 73 t/ha of carbon storage is reported for conifers, while 140 t/ha is reported for broadleaves in the state of Nayarit [59]. Coniferous forests generally have lower SOC concentrations than broadleaved forests, mainly due to slower litter decomposition rates related to the biochemical properties of organic debris and climate [60].

On average, the models obtained project losses in SOC storage of 0.18 Gt and 0.14 Gt for temperate forests and rainforests in Mexico, with a temperature increase of 7 °C and 5 °C, respectively. On a global scale, however, it has been reported that a global temperature increase of 4 °C coupled with land use change is expected to result in losses among 11 and 200 Gt of carbon, which could significantly exacerbate climate change [61].

This study focuses exclusively on the effects of temperature and rainfall variability. However, if the trend of deforestation in Mexico continues, which has reached 668,000 hectares per year since 1997 and 534,707 hectares per year in 2007 [37], the problem could worsen considerably. In 2015, SEMARNAT-INECC reported that deforestation in Mexico had released 5129 million tonnes of carbon into the atmosphere [24], highlighting the vulnerability of these soil organic carbon (SOC) stocks and the potential additional negative impacts of continued forest cover loss.

4.3. Effects of Climate Change on SOC Storage

The climate models HadGEM3-GC31-LL, MIROC6 and MPI-ESM1-2-HR predict significant variations in temperature and precipitation among different forest cover types.

HadGEM3-GC31-LL predicts a temperature increase of up to 4.4 °C by the end of the 21st century, accompanied by a decrease in precipitation in subtropical areas. MIROC6 projects a moderate global temperature increase and an increase in extreme precipitation intensity, while MPI-ESM1-2-HR projects a temperature increase of between 2.5 °C and 3.5 °C, with precipitation increasing in humid regions and decreasing in arid regions [62].

The results indicate that the effects of climate change will lead to a decrease in SOC content. The increasing risk of carbon losses in ecosystems could substantially raise the level of atmospheric carbon dioxide [61]. Temperate forests, such as coniferous, broadleaved and mixed coniferous and broadleaved forests, show a higher increase in temperature compared to forests (highland and midland tropical forests and lowland tropical forests) and a lower decrease in precipitation compared to cloud forests, which could exacerbate SOC loss in these areas. Elevated temperatures can accelerate the decomposition of organic matter by increasing microbial network complexity and bacterial diversity, leading to a significant reduction in SOC stocks [63,64]. Additionally, changes in precipitation can affect soil moisture levels, which in turn influence microbial respiration rates and SOC stability [65]. However, long-term warming in temperate forests will lead to a reduction in microbial carbon necromass, indicating that while microbial activity may increase, the overall carbon pool may decrease due to imbalances in microbial biomass production and decomposition [63].

Importantly, SOC loss is projected to be 8% for coniferous forests and 4% for broadleaved forests. This change is partly due to the expected conversion of coniferous forests to broadleaved forests in the period 2041–2060 [66]. Climate change will not only directly affect soil organic carbon but will also promote vegetation change, which may be one reason for the decrease in soil organic carbon. This phenomenon could have negative consequences for local communities dependent on coniferous forests and for forestry companies by reducing the environmental and economic benefits that these forests provide.

With the expected rise in temperatures, soil temperatures will also increase, leading to a significant loss of SOC by facilitating its mineralisation. This, in turn, leads to a decrease in fine root production and plant biomass, which alters biogeochemical cycles and ecosystem functionality, thus affecting the soil's ability to store carbon in the long term. Overall, soil warming has a negative impact on both SOC and vegetation [67].

The loss of SOC weakens soil structure and reduces its capacity to retain nutrients and water, which has a negative impact on the productivity and resilience of natural ecosystems. This loss can lead to further soil degradation and contribute to desertification [68]. Ecosystems with depleted SOC are particularly vulnerable to the effects of climate change, such as droughts, as they lack the resilience provided by healthy organic matter [69].

Therefore, proper management of SOC is necessary, especially as it is essential for combating desertification, preventing biodiversity loss and achieving land degradation neutrality by storing carbon in the soil [70]. Although SOC reduction poses significant challenges, proactive management strategies can mitigate these effects by promoting resilient ecosystems capable of maintaining productivity [71,72]. Strategies include restoration of degraded land, agroforestry, crop rotation and conservation agriculture practices such as minimum tillage and the use of cover crops. These measures not only help maintain or increase SOC but also enhance biodiversity, improve water retention and reduce erosion [72]. In addition, the implementation of integrated soil and landscape management systems based on natural approaches can increase resilience to the effects of climate change [73].

Finally, the modelling of SOC content can be improved in the future. The combination of Diffuse Reflectance Infrared Fourier Transform Spectroscopy (DRIFT-FTIR) with machine learning models such as Partial Least Squares Regression (PLSR) has been investigated. This approach has shown superior performance in SOC estimation compared to other models such as Artificial Neural Networks (ANNs), Support Vector Regression (SVR) and Random Forests [74]. The integration of hyperspectral data with feature selection methods such as the Successive Projection Algorithm (SPA) and regression algorithms such as Partial Least Squares (PLS) has also yielded promising results in SOC prediction. These advances underline the importance of accurate SOC prediction for ensuring global food security and environmental sustainability [75].

5. Conclusions

It is possible to model SOC content by taking into account different soil and environmental variables. Models are able to capture the capacity of soils to store carbon and the complex interactions among soil, climatic conditions and topographic features. Understanding these interactions is fundamental to developing sustainable management practices that not only optimise soil carbon sequestration but also contribute significantly to greenhouse gas mitigation.

Projections of SOC under climate change scenarios suggest that coniferous and broadleaved forests will be most affected, with up to 40% of their area experiencing a loss of among 10% and 20% of their current SOC content (MPI model). It is clear that the effects of climate change are not uniform, as some areas may be more exposed to degradation while others may benefit. This knowledge is essential for designing ecosystem-specific adaptation strategies.

The research concludes that soil organic carbon is highly sensitive to changes in temperature and precipitation. These changes can significantly affect both the accumulation and stability of SOC. Future research opportunities include the need to integrate interdisciplinary models and knowledge to better understand the mechanisms regulating SOC dynamics in the context of climate change. Artificial intelligence applications combined with field validation work may be encouraging.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land13101711/s1, Table S1. Forests landscapes in Mexico: forest cover overlay with physiographic provinces. Table S2: Bulk density and % SOC by vegetation type. Table S3: Evaluation metrics and models for each area identified.

Author Contributions: Supervision, A.I.M.-R.; Data curation, L.C.L.-T.; investigation, L.C.L.-T. and A.I.M.-R.; methodology, L.C.L.-T. and A.I.M.-R.; software, L.C.L.-T.; conceptualization, L.C.L.-T. and A.I.M.-R.; formal analysis, L.C.L.-T. and A.I.M.-R.; validation, L.C.L.-T. and A.I.M.-R.; visualisation, L.C.L.-T. and A.I.M.-R.; writing—original draft, L.C.L.-T. and A.I.M.-R.; writing—review and editing, L.C.L.-T. and A.I.M.-R. All authors have read and agreed to the published version of the manuscript.

Funding: Dr Lopez (with CVU number 494222) is supported by the Consejo Nacional de Humanidades, Ciencias y Tecnologías (CONAHCYT) during her postdoctoral position in the Postgraduate Programme in Forestry and Environmental Sciences at the Universidad Autonoma Chapingo.

Data Availability Statement: The original contributions presented in the study are included in the article and Supplementary Materials, further inquiries can be directed to the corresponding author.

Acknowledgments: CONAHCYT for financial support, DGIP, CIRENAM and the Department of Forest Sciences of Universidad Autonoma Chapingo, and the anonymous reviewers.

Conflicts of Interest: The authors declare no conflicts of interest.

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