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Soil organic carbon loss in agricultural systems of Mexico due to climate change

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Abstract

Soil organic carbon (SOC) plays a key role in ecosystem health, influencing soil's physical, chemical, and microbiological properties, such as water retention, fertility, and microbiome diversity. SOC modeling, using machine learning and remote sensing, enables the prediction of how agricultural practices and climate change affect its storage. This study aimed to model and project variations in SOC reserves in rainfed and irrigated agricultural soils in Mexico, under current conditions and future climate change scenarios. Therefore, models were developed to relate SOC to variables such as Lang's index (precipitation and temperature), altitude, slope, bulk density, texture type, and soil depth. These models captured the land relief characteristics and their relationship with agricultural practices and SOC content in soils. The highest SOC levels were observed in irrigated agricultural systems. However, under climate change scenarios, SOC losses of up to 7 % are projected, along with temperature increases of up to 6 °C and precipitation increases of 12%. The reduction in SOC could increase greenhouse gas emissions and diminish the soil's carbon storage capacity. This study highlights the importance of implementing sustainable management practices and promoting multidisciplinary research to mitigate adverse effects. Additionally, it demonstrates the potential for simulating SOC behavior and generating models useful for evaluating scenarios and supporting decision-making.

Keywords: COS stocks, climate variability, agriculture, spatial modeling, degradation, COS reduction.

Introduction

Soil organic carbon (SOC) is essential for agricultural sustainability, and modeling is a crucial tool for understanding the carbon cycle in agricultural systems and evaluating its impact on environmental sustainability (Dionizio et al., 2020). SOC plays a crucial role in soil productivity by improving soil structure, enhancing water and nutrient retention, and stimulating microbial activity (Meena et al., 2024). Globally, agriculture has been identified as one of the activities with the greatest influence on SOC loss, due to intensive practices such as tillage, deforestation, and excessive use of chemical fertilizers (Canaza et al., 2023; Lal, 2004). Therefore, having accurate predictions of SOC dynamics in agricultural soils is crucial for designing management strategies that help mitigate climate change and improve the resilience of agricultural ecosystems (Paz et al., 2016; Smith & Olesen, 2010).

In recent years, the development of predictive models of SOC has become increasingly important due to the need to assess the impact of agricultural practices on the soil's ability to sequester carbon (Guo et al., 2023; Mundada et al., 2024). These models integrate key variables such as soil texture and land use, management practices, and climate conditions, and allow the generation of scenarios on carbon storage in both the short and long term (Paz et al., 2016). Modeling also identifies areas of risk, where carbon stored in the soil could be lost more rapidly, which would help prioritize conservation interventions on vulnerable agricultural lands (Vannier et al., 2022).

Advances in machine learning and remote sensing techniques have improved the accuracy of SOC models (Zayani et al., 2023). In particular, tools such as spectral analysis, the integration of satellite data, and the application of machine learning algorithms (such as random forests and artificial

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neural networks) have been successful in predicting SOC changes at different spatial scales (Hateffard et al., 2023). These techniques enhance the accuracy of soil carbon content estimation and facilitate the assessment of the impact of climate change and agricultural practices on a global scale (Abdoli et al., 2023).

Understanding and modeling the impact of agricultural practices on SOC is essential for developing sustainable agricultural policies. The aim of this study was to model and project variations in SOC stocks in rainfed and irrigated agricultural soils in Mexico under current conditions and future climate change scenarios. The main hypothesis is that future changes in temperature and precipitation will cause significant alterations in environmental conditions, notably affecting SOC stocks. This study contributes to the understanding of carbon storage patterns in Mexican soils and emphasizes the importance of integrating physiographic and climate variables into predictive SOC models.

Materials and methods

The projection of COS under different climate change scenarios was carried out in two stages: 1) delimitation of agricultural regions and 2) modeling and calculation of COS in base period and climate change scenarios.

Delimitation of agricultural regions in Mexico

The delimitation of agricultural regions in Mexico was carried out by integrating the physiography of the territory with the main agricultural systems of the country. The physiography of Mexico is divided into fifteen provinces and mapped at a scale of 1:250 000 (Instituto Nacional de Estadística y Geografía [INEGI], 2001). Agricultural systems were defined based on the land use and vegetation map for the year 2016, also at a scale of 1:250 000 (INEGI, 2021). This map was processed and classified to identify agricultural areas, which were further divided into rainfed and irrigated systems according to the criteria set by the United Nations Convention to Combat Desertification (UNCCD), as applied in Mexico by the Comisión Nacional de Zonas Áridas-Universidad Autónoma Chapingo (CONAZA-UACh, 2023).

To integrate the information, the tool ArcMap 10.8.1 (ESRI, 2020) was used, and a spatial intersection was applied between the physiographic map and the classified agricultural systems map. This procedure generated a layer that identified 30 agricultural regions per physiographic province and system type (rainfed or irrigated).

Spatial data analysis and processing

To ensure consistency in the generated maps, a regular grid composed of 1 000 × 1 000 m polygons was used. This approach resulted in 325 166 spatial units covering the entire agricultural area of the country. For constructing the database, information was extracted from each polygon, and fundamental variables for the analysis were assigned. In addition to the agricultural regions, the following variables were considered: SOC, altitude, slope, Lang index, soil bulk density, soil profile depth, and soil texture classification.

Soil organic carbon

For the baseline period, data reported in Mexico's First Biennial Report (Instituto Nacional de Ecología y Cambio Climático-Secretaría de Medio Ambiente y Recursos Naturales [INECC-SEMARNAT], 2015) was used. This report included the breakdown of SOC (%) for 2001 and 2016, according to the type of vegetation (Table 1). Using this information, an SOC map for each year was generated using the following equation (1):

$$SOC = \%SOC \times BD \times SD \tag{1}$$

where SOC represents soil organic carbon($t \cdot ha^{-1}$), BD is bulk density ($t \cdot m^{-3}$), SD is soil depth (cm), and $\%SOC$ is the percentage of SOC. A soil depth of 30 cm was assumed based on the Intergovernmental Panel on Climate Change (IPCC, 2006) guidelines, as microbial activity is most active at this depth (Paz & Etchevers, 2016). To determine the representative SOC value for the baseline period, the average of the values for 2001 and 2016 was calculated.

The SOC values derived were classified into five ranges: lower than 40 $t \cdot ha^{-1}$, 40 to 50 $t \cdot ha^{-1}$, 50 to 60 $t \cdot ha^{-1}$, 60 to 70 $t \cdot ha^{-1}$, and higher than 70 $t \cdot ha^{-1}$. This classification allows for a more detailed evaluation of SOC and facilitates the interpretation of potential variations in SOC stocks under different climate change scenarios.

Independent variables

Six soil and environmental variables were selected to model the relationship with SOC:

Lang index. Mean temperature (T, °C) and annual precipitation (P, mm) data for Mexico were sourced from the WorldClim database (2024). To assess the relationship between T and P, the Lang index for the years 2001 and 2016 was calculated using the following equation:

$$Lang\ index = \frac{P}{T} \tag{2}$$

Land slope and altitude. Altitude (m a. s. l.) was sourced from the Continuo de Elevaciones Mexicano (CEM) with a 15 m resolution (INEGI, 2013b). Using this data, the land slope map (%) was generated with the ArcMap 10.8.1 tool (ESRI, 2020).

Table 1. Bulk density (BD) and soil organic carbon (SOC) per type of vegetation.

Type of vegetation	BD ($t \cdot m^{-3}$)	SOC (%) 2001	SOC (%) 2016
Annual cropland	1.23	3.07	1.27
Permanent cropland	1.22	4.96	1.85
Water	1.25	2.26	0.85
Settlements	1.22	0.98	1.21
Cultivated forest	1.23	2.90	0.88
Primary coniferous forest	1.17	5.25	3.12
Secondary coniferous forest	1.19	3.38	3.02
Primary oak forest	1.18	2.22	3.2
Secondary oak forest	1.19	1.64	2.79
Primary cloud forest	1.17	6.67	5.03
Secondary cloud forest	1.16	9.63	6.59
Other primary woody types	1.27	1.48	1.23
Other secondary woody types	1.21	4.79	3.49
Other non woody primary types	1.55	1.70	0.3
Primary xerophilous scrub (woody)	1.25	1.12	1.37
Secondary xerophilous scrub (woody)	1.21	1.84	1.82
Primary xerophilous scrub (non-woody)	1.25	1.27	1.03
Secondary xerophilous scrub (non-woody)	1.24	1.8	0.91
Primary dry forest	1.21	2.86	2.35
Secondary dry forest	1.2	2.16	2.3
Primary evergreen forest	1.12	7.95	6.52
Secondary evergreen forest	1.19	4.56	3.94
Primary tropical deciduous forests	1.14	4.13	4.53
Secondary tropical deciduous forests	1.2	1.89	2.35
Primary hydrophytic vegetation (woody)	1.24	8.92	6.41
Primary hydrophytic vegetation (non-woody)	1.23	5.24	1.56
Other lands	1.3	0.93	0.39
Grasslands	1.22	2.78	1.45

Source: adapted from INECC-SEMARNAT (2015).

Soil texture class, bulk density, and soil depth. Soil texture, bulk density ($t \cdot m^{-3}$), and soil depth (m) were obtained from the "Series II: Soil Profile Dataset" at a scale of 1:250 000 (INEGI, 2013a).

SOC modeling. Models were developed for each of the 30 agricultural regions. Linear regression models (Equation 3) and exponential regression models (Equation 4) were used, with SOC from the baseline period considered as the dependent variable:

$$SOC = \beta_0 + \beta_1 \times Lang\ index + \beta_2 \times altitude + \beta_3 \times slope + \beta_4 \times BD + \beta_5 \times texture\ class + \beta_6 \times soil\ depht \quad (3)$$

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

The final model for each agricultural region was selected based on the statistical significance ($P < 0.05$) of the variables. To identify the best model, the coefficient of determination (R^2), mean squared error (MSE), and the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were calculated using RStudio 2023.06.0 Build 421 (Posit team, 2023).

Model validation

The validation was conducted by comparing the observed values from the baseline period with those predicted by the models to assess accuracy and reliability. Six statistical tests were applied to analyze errors and biases: 1) Root mean square error (RMSE) and 2) Mean absolute error (MAE) to quantify accuracy, 3) Coefficient of determination (R^2)

to evaluate variability, 4) Mean absolute percentage error (MAPE) to provide a relative perspective of the error, 5) Lin's concordance correlation coefficient to measure the agreement between predictions and observations, and 6) Bias analysis (mean differences) to detect potential systematic deviations. These analyses were performed using RStudio 2023.06.0 Build 421(Posit team, 2023).

Projections under climate change scenarios

To project future scenarios under climate change conditions, the Lang index values from the baseline period were replaced with future projections (2081–2100). These projections were derived from mean temperatures (°C) and annual precipitation (mm) data from the climate models HadGEM3-GC31-LL, MIROC6, and MPI-ESM1-2-HR, based on the Shared Socioeconomic Pathway SSP5-8.5 (WorldClim, 2024).

Results and discussion

Distribution of agricultural regions in Mexico

In Mexico, 17.4% of the territory is designated for agricultural use (Table 2). Of this area, 68 % is dedicated to rainfed agriculture, while 32 % supports irrigated agriculture (Figure 1a). Maize and beans are the primary crops grown under rainfed conditions (Comisión Nacional del Agua [CONAGUA], 2021; INEGI, 2023). In contrast, irrigated agriculture is dominated by maize, wheat, sorghum, alfalfa, sugarcane, and beans (INEGI, 2024). During the reference period, 15 025 424.96 ha were harvested nationwide in the agricultural year, with 75% of this area dedicated to rainfed agriculture (Servicio de Información Agroalimentaria y Pesquera [SIAP], 2023). Maize production under rainfed conditions is crucial for most Mexican farmers, emphasizing the importance of precipitation for the sustainability of rainfed agriculture (Conde et al., 2006).

The Pacific Coastal Plain allocates 54 % of its land area to irrigated agriculture. This region includes the states of Sinaloa and Nayarit and extends to the south, including parts of Jalisco and Colima. It is characterized by its flat terrain and proximity to the Pacific Ocean. In contrast, the Trans-Mexican Volcanic Belt dedicates 36 % of its land area to rainfed agriculture and primarily encompasses the states of Jalisco, Michoacán, Estado de México, Puebla, and Veracruz.

Organic carbon stored in agricultural systems

The analysis of SOC in agricultural systems revealed that values exceeding 70 $t\cdot ha^{-1}$ account for 37 % of the Mexican agricultural land. Ranges between 50 to 60 and 60 to 70 $t\cdot ha^{-1}$ cover 13 % and 14 % of the agricultural area, respectively, and are predominant in the Pacific Coastal Plain. Values ranging from 40 to 50 $t\cdot ha^{-1}$ are primarily concentrated in the central region of the country, specifically in the Trans-Mexican Volcanic Belt, covering 35 % of the agricultural area. Values below 40 $t\cdot ha^{-1}$ have a limited distribution, covering only 1 % of the agricultural land (Figure 1b).

The highest SOC values were recorded in the Yucatán Peninsula for both types of agriculture: 116 $t\cdot ha^{-1}$ in rainfed crops and 112 $t\cdot ha^{-1}$ in irrigated systems. Followed by Sierras de Chiapas, with 84 $t\cdot ha^{-1}$ for rainfed and 81 $t\cdot ha^{-1}$ for irrigation (Figure 2). The southern region of the country is distinguished by its remarkable crop diversity (INEGI, 2007). For example, in the Yucatan Peninsula, milpa systems store up to 58.39 $t\cdot ha^{-1}$ of SOC (Flores-Delgadillo et al., 2011; González-Molina et al., 2008; Shangl & Tiessen, 2003), while in the Sierra de Chiapas and Guatemala, milpa, maize, coffee, and agroforestry systems have been documented to store up to 90.8 $t\cdot ha^{-1}$ (de Jong et al., 1999; Flores-Delgadillo et al., 2011; Mendoza et al., 2003).

SOC projections under future climate change scenarios

Out of the 30 agricultural regions evaluated, models were developed for 27 agricultural regions, as three regions lacked sufficient data to construct them. According to basic

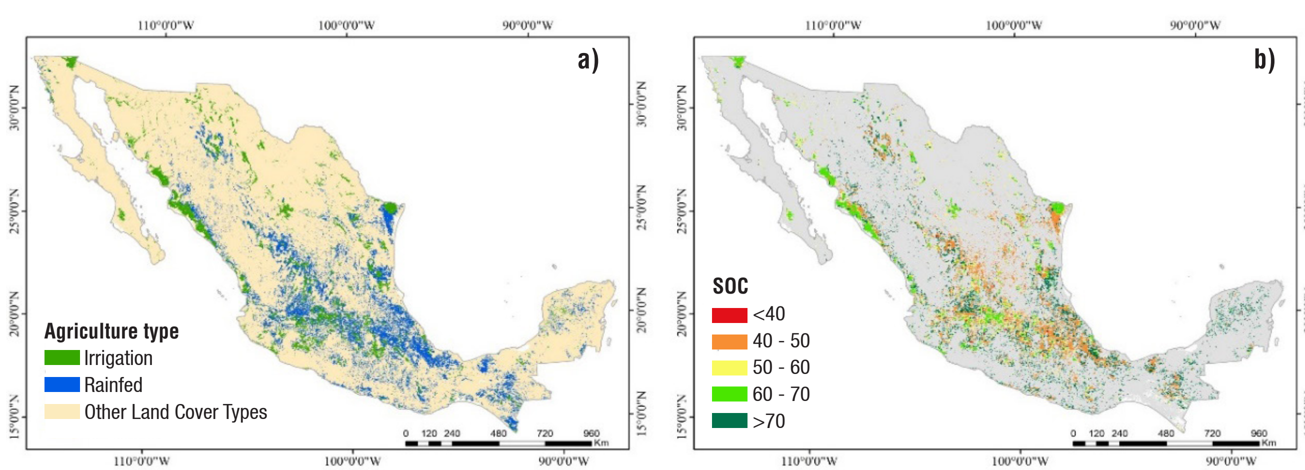

Figure 1. a) Distribution of agriculture in Mexico and b) soil organic carbon (SOC) content in the baseline period.

Table 2. Agricultural regions and land area.

Agriculture	Physiographic province	Area (ha)
Irrigation	Pacific Coastal Plain	1 683 000
	Baja California Peninsula	292 200
	Mexican Plateau	621 100
	Southern Gulf Coastal Plain	188 200
	Sonoran plains	700 300
	Sierra Madre Occidental	757 700
	Northern Gulf Coastal Plain	1 014 100
	Yucatán Peninsula	207 900
	Sierra Madre del Sur	698 200
	Sierras de Chiapas and Guatemala	75 000
	Sierra Madre Oriental	410 600
	Central American Cordillera	79 200
	The Great Plains	267 800
	Northern Sierras and Plains	1 211 400
	Trans-Mexican Volcanic Belt	2 355 300
Rainfed	Sierra Madre Occidental	2 949 500
	Mexican Plateau	2 017 200
	Northern Gulf Coastal Plain	2 095 800
	Baja California Peninsula	101 900
	Sonoran plains	38 800
	Pacific Coastal Plain	348 300
	Sierra Madre del Sur	2 571 000
	Trans-Mexican Volcanic Belt	5 526 000
	Central American Cordillera	656 600
	Sierras de Chiapas and Guatemala	934 700
	The Great Plains	259 500
	Sierra Madre Oriental	1 783 600
	Northern Sierras and Plains	155 200
	Southern Gulf Coastal Plain	1 742 500
	Yucatán Peninsula	778 900
Agricultural area		32 521 500
Total land area		187 079 200

Note: The Mexican coastal area and uncharted insular territory were not included in the total land area.

modeling criteria, at least three data points are required to establish a relationship between variables and achieve a basic statistical fit (Montgomery et al., 2021). For each of the 27 regions, linear and exponential models were compared, resulting in a total of 54 models (27 of each type).

The models developed showed reasonable accuracy in predicting SOC, although they did exhibit expected errors. The statistical indicators indicated that, despite some limitations, the results are sufficiently reliable for interpreting SOC content trends. RMSE value implies that, on average, the model predictions differ by 23 units from the observed values. The MAE shows that the mean absolute error in the predictions is around 17 units. The MAPE indicates that predictions deviate by approximately 26 % from the observed values. R^2 explains about 25 % of the SOC variability, suggesting that a significant portion of the variability is not captured by the models, while a bias of -0.61 indicates a slight underestimation of SOC content by the models. Lastly, Lin's concordance index of 0.685, with a narrow confidence interval (0.409 to 0.420), suggests moderate agreement between predicted and observed values.

The low R^2 value reflects the influence of factors affecting SOC dynamics that are not currently accounted for in the models. While a low R^2 does not invalidate the models, it

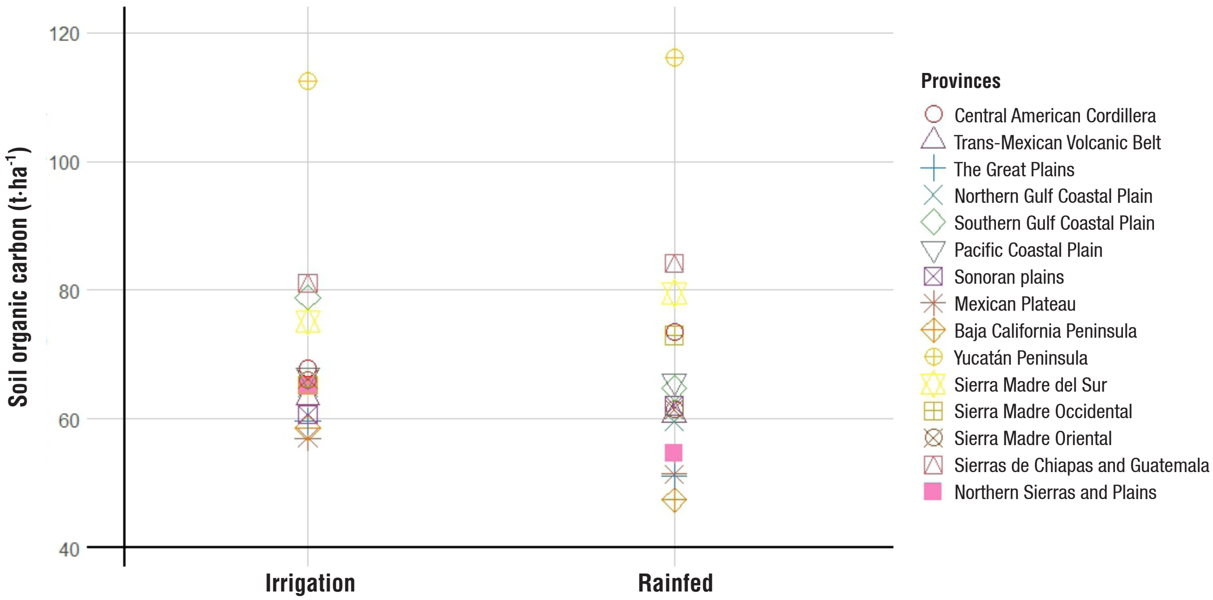

Figure 2. Spatial distribution of soil organic carbon content per type of agriculture and physiographic province.

highlights the need to integrate them with other relevant factors. For example, soil management practices such as crop rotation, vegetative cover, and fertilization, as well as land-use changes like the conversion of agricultural land to urban areas, have been shown to significantly impact SOC levels (Qiu et al., 2013). Additionally, soil erosion can diminish the soil's capacity to store carbon (Gómez et al., 2020), and microbial activity –driven by climatic factors, nutrient availability, and soil type– may not be adequately represented in the current modeling approach (Zsolt et al., 2020).

The effectiveness of the models, despite their limitations, is further supported by complementary metrics such as MAE (Li, 2017). For instance, in India, MAE values of up to 52 and RMSE values reaching 130 were reported for various predicted climate models (Rashiq et al., 2024). Similarly, in Iran, models predicting SOC content in agricultural soils amended with calcareous materials yielded MAE and RMSE values of 0.0056 and 0.62 % of the actual measurements, respectively (Abdoli et al., 2023).

Figure 3 shows the predicted changes in the Lang index, highlighting a potentially significant impact on SOC reserves in Mexico. Projections indicate a decline in the index across northern and central regions of the country, associated with rising temperatures and decreasing precipitation. These variations directly influence the processes of organic matter decomposition and, consequently, the dynamics of SOC (Chen et al., 2020; Jia et al., 2020).

Future climate scenarios indicate a general trend toward increasingly unfavorable conditions for carbon accumulation across most of Mexico. Regions with a declining Lang index often exhibit reductions in SOC, suggesting that rising temperatures and potential decreases in moisture may accelerate soil degradation and the release of stored carbon (Luković et al., 2024; Wiesmeier et al., 2019). This underscores the importance of utilizing multiple climate models to assess soil vulnerability and to develop adaptive strategies aimed at mitigating impacts on both agricultural and natural systems.

With temperature increases of up to 6 °C, models predict a 7 % reduction in SOC for irrigated agriculture systems and a 6 % reduction for rainfed agriculture systems (Figure 4). Despite these negative trends, precipitation is projected to rise by 12 % in irrigated agriculture areas and decline by 12 % in rainfed agriculture areas. High temperatures may accelerate the decomposition of organic matter and reduce SOC reserves by promoting microbial activity and thus enzyme activity (Liu et al., 2024a; Liu et al., 2024b).

On the other hand, variations in precipitation directly influence soil moisture levels, a key factor in the decomposition process and microbial respiration rates. When precipitation increases, as in irrigated areas, soil moisture levels also increase, which favors greater SOC mineralization due to intensified microbial activity (Zhao et al., 2021). However, excess moisture can generate anaerobic conditions and promote the release of greenhouse gases such as methane (da Cunha-Santino & Bianchini, 2023). In contrast, decreased precipitation in rainfed areas can limit microbial activity by reducing soil moisture, thereby decreasing SOC respiration and decomposition rates (Liu et al., 2017). The complex interaction between tem-

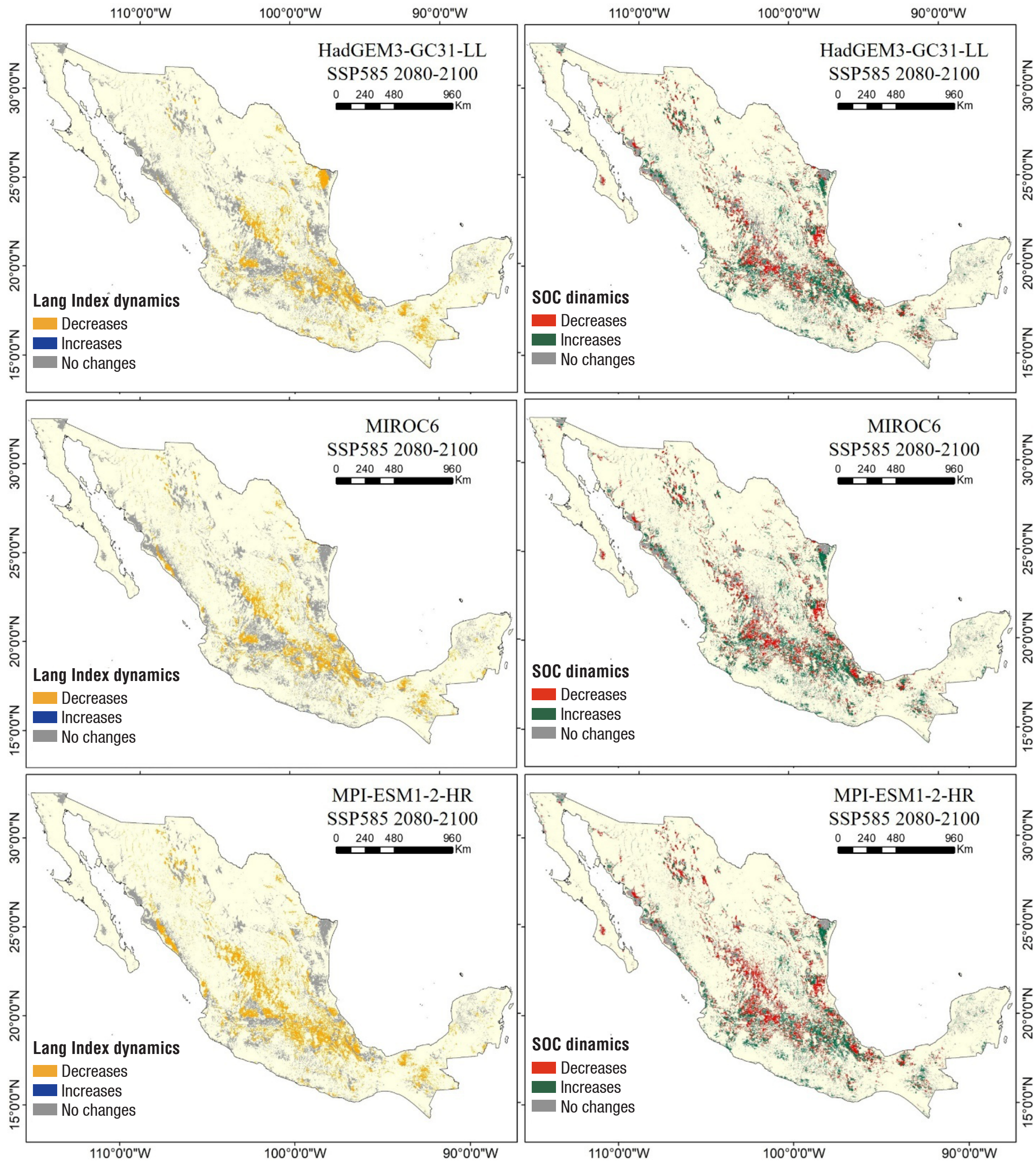

Figure 3. Projections changes in the Lang Index and soil organic carbon (SOC) in agricultural areas.

perature, precipitation, moisture, and microbial activity is critical for understanding how future climate conditions could modify SOC stability (Wang et al., 2025).

A global analysis suggests that agricultural soils have lost an average of 2.5 to 3.9 % of SOC since 1919, which is attributed to changes in climate conditions (Poeplau & Dechow, 2023). For example, in China, a 4 °C increase was reported to cause a 17 % decrease in SOC stocks in agricultural soils (Wang et al., 2023).

This study focuses exclusively on the impact of temperature and precipitation variation; however, in Mexico, 13 300 Gt of carbon have been lost in cropland from 1990 to 2015 (SEMARNAT-INECC, 2018). In addition, agricultural practices have reduced SOC stocks on arable land by 21 %, highlighting the influence of land management on SOC dynamics (Stolbovoy & Fil, 2023).

It is important to note that variations in temperature and precipitation directly impact crop development and yields by increasing their vulnerability against adverse conditions (IPCC, 2022; Wheeler & von Braun, 2013). Arce-Romero et al. (2020) and Monterroso-Rivas et al. (2018) note that crops such as beans and wheat could experience reductions of up to 40 % in some regions of Mexico due to cli-

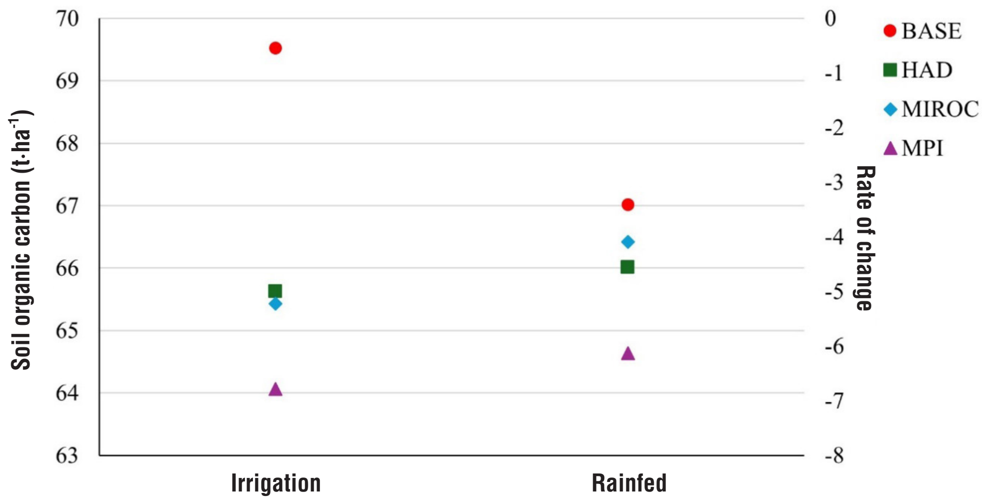

Figure 4. Soil organic carbon dynamics: comparison between baseline and future climate change scenarios using different models.

mate change. These potential losses represent a significant challenge for food security and agricultural sustainability (Food and Agriculture Organization of the United Nations [FAO], 2020).

Implementing sustainable land management practices has great potential to recover SOC reserves. This increase not only improves soil fertility, but also stabilizes crop yields (Page et al., 2020). Techniques such as soil and water conservation, composting, and crop rotation increase soil organic matter, improve soil structure and water retention, and help counteract the adverse effects of climate change (Frelih-Larsen et al., 2022; Mu et al., 2024). It has also been noted that the adoption of agroforestry systems and restoration of degraded lands can reverse SOC losses and contribute to climate resilience. These interventions are key to sequestering additional carbon in soil and generating long-term benefits for agricultural sustainability and climate change mitigation (Naba et al., 2024).

Conclusions

The study was able to model and project variations in SOC reserves in agricultural soils in Mexico under different climate scenarios. The results obtained provide valuable information for decision making in soil management. Although no specific areas of risk were identified, the findings may be useful for guiding conservation interventions.

Climate change, due to increased temperature and precipitation variability, will negatively affect SOC reserves. Both irrigated and rainfed soils could experience significant carbon loss, which could increase greenhouse gas emissions and reduce soil carbon storage capacity.

The projections generated allow us to anticipate the behavior of SOC, although they present an inherent margin of uncertainty. Although the models included climate and edaphic factors, it is important to consider that other variables, such as agricultural practices, also influence the results.

Although no high-risk areas were identified, the results can help prioritize conservation actions in vulnerable agricultural soils. These findings provide a basis for designing policies and practices to mitigate the effects of climate change.

The study highlights the need to adopt sustainable agricultural practices to preserve soil carbon. Projections indicate a loss of SOC in future scenarios, which underlines the importance of implementing conservation measures to mitigate the effects of climate change on agriculture.

Finally, to make the model more consistent, it is suggested to include more explanatory variables, such as microbial activity and agricultural practices, as well as to apply nonlinear models to better capture interactions between variables, use higher temporal and spatial resolution data, perform cross-validation, and optimize parameters to improve accuracy and reduce uncertainty.

References

Abdoli, P., Khanmirzaei, A., Hamzeh, S., Rezaei, S., & Moghimi, S. (2023). Use of remote sensing data to predict soil organic carbon in some agricultural soils of Iran. *Remote Sensing Applications: Society and Environment, 30*, 100969. https://doi.org/10.1016/j.rsase.2023.100969

Arce-Romero, A., Monterroso-Rivas, A. I., Gómez-Díaz, J. D., Palacios-Mendoza, M. Á., Navarro-Salas, E. N., López-Blanco, J., & Conde-Álvarez, A. C. (2020). Crop yield simulations in Mexican agriculture for climate change adaptation. *Atmosfera, 33*(3), 215-231. https://doi.org/10.20937/ATM.52430

Canaza, D., Calizaya, E., Chambi, W., Calizaya, F., Mindani, C., Cuentas, O., Caira, C., & Huacani, W. (2023). Spatial distribution of soil organic carbon in relation to land use, based on the weighted overlay technique in the high Andean Ecosystem of Puno-Peru. *Sustainability, 15*(13), 10316. https://doi.org/10.3390/su151310316

Chen, Q., Niu, B., Hu, Y., Luo, T., & Zhang, G. (2020). Warming and increased precipitation indirectly affect the composition and turnover of labile-fraction soil organic matter by directly affecting vegetation and microorganisms. *Science of the Total Environment, 714*, 136787. https://doi.org/10.1016/j.scitotenv.2020.136787

Comisión Nacional del Agua (CONAGUA). (2021). *Estadísticas agrícolas de los distritos de temporal tecnificado, año agrícola 2020-2021*. CONAGUA. https://www.gob.mx/conagua/documentos/estadisticas-agricolas-de-los-distritos-de-temporal-tecnificado

Comisión Nacional de Zonas Áridas-Universidad Autónoma Chapingo (CONAZA-UACh). (2023). *Informe nacional 2022 de acciones contra la desertificación, degradación de tierras y sequía en México*. CONAZA-UACh.

Conde, C., Ferrer, R., & Orozco, S. (2006). Climate change and climate variability impacts on rainfed agricultural activities and possible adaptation measures. A Mexican case study. *Atmósfera, 19*(3), 181-194. https://www.redalyc.org/pdf/565/56519303.pdf

da Cunha-Santino, M. B., & Bianchini, I. (2023). Reviewing the organic matter processing by wetlands. Acta Limnologica Brasiliensia, 35, e19. https://doi.org/10.1590/S2179-975X3423

de Jong, B., Cairns, M., Haggerty, P., Ramírez, N., Ochoa, S., Mendoza, J., González, M., & March, I. (1999). Land-use change and carbon flux between 1970s and 1990s in central highlands of Chiapas, Mexico. *Environmental Management, 23*(3), 373-385. https://doi.org/10.1007/s002679900193

Dionizio, E. A., Pimenta, F. M., Lima, L. B., & Costa, M. H. (2020). Carbon stocks and dynamics of different land uses on the Cerrado agricultural frontier. *PLoS ONE, 15*(11), e0241637. https://doi.org/10.1371/journal.pone.0241637

ESRI. (2020). *ArcMap Desktop 10.8.1* [Software]. https://desktop.arcgis.com/es/arcmap/latest/get-started/installation-guide/installing-on-your-computer.htm

Flores-Delgadillo, L., Fedick, S. L., Solleiro-Rebolledo, E., Palacios-Mayorga, S., Ortega-Larrocea, P., Sedov, S., & Osuna-Ceja, E. (2011). A sustainable system of a traditional precision agriculture in a Maya homegarden: Soil quality aspects. *Soil and Tillage Research, 113*(2), 112-120. https://doi.org/10.1016/j.still.2011.03.001

Food and Agriculture Organization of the United Nations (FAO). (2020). *The state of food and agriculture. Overcoming water challenges in agriculture*. FAO. https://doi.org/10.4060/cb1447en

Frelih-Larsen, A., Riedel, A., Hobeika, M., Scheid, A., Gattinger, A., & Niether, W. (2022). *Role of soils in climate change mitigation*. German Environment Agency

Gómez, J. A., Guzmán, G., Toloza, A., Resch, C., García-Ruíz, R., & Mabit, L. (2020). Variation of soil organic carbon, stable isotopes, and soil quality indicators across an erosion-deposition catena in a historical Spanish olive orchard. *Soil, 6*(1), 179-194. https://doi.org/10.5194/soil-6-179-2020

González-Molina, L., Etchevers-Barra, J. D., & Hidalgo-Moreno, C. (2008). Carbono en suelos de ladera: factores que deben considerarse para determinar su cambio en el tiempo. *Agrociencia, 42*(7), 741-751. https://www.redalyc.org/articulo.oa?id=30211207001

Guo, Y., Zeng, Z., Wang, J., Zou, J., Shi, Z., & Chen, S. (2023). Research advances in mechanisms of climate change impacts on soil organic carbon dynamics. *Environmental Research Letters 18*(10), 103005. Institute of Physics. https://doi.org/10.1088/1748-9326/acfa12

Hateffard, F., Szatmári, G., & Novák, T. J. (2023). Applicability of machine learning models for predicting soil organic carbon content and bulk density under different soil conditions. *Soil Science Annual, 74*(1), 165879. https://doi.org/10.37501/soilsa/165879

Instituto Nacional de Ecología y Cambio Climático-Secretaría de Medio Ambiente y Recursos Naturales (INECC-SEMARNAT). (2015). *Primer Informe Bienal de Actualización ante la Convención Marco de las Naciones Unidas sobre el Cambio Climático*. INECC-SEMARNAT https://www.gob.mx/inecc/documentos/primer-informe-bienal-de-actualizacion-ante-la-convencion-marco-de-las-naciones-unidas-sobre-el-cambio-climatico

Instituto Nacional de Estadística y Geografía (INEGI). (2001). *Conjunto de datos vectoriales fisiográficos. Continuo nacional serie I. Provincias fisiográficas* [Conjunto de datos]. INEGI https://www.inegi.org.mx/app/biblioteca/ficha.html?upc=702825267575

Instituto Nacional de Estadística y Geografía (INEGI). (2007). *Censo agrícola, ganadero y forestal 2007*. INEGI. https://www.inegi.org.mx/programas/cagf/2007/default.html#Tabulados

Instituto Nacional de Estadística y Geografía (INEGI). (2013a). *Conjunto de datos de perfiles de suelos. Escala 1:250 000. Serie II*. INEGI. https://www.inegi.org.mx/app/biblioteca/ficha.html?upc=702825266707

Instituto Nacional de Estadística y Geografía (INEGI). (2013b). *Continuo de elevaciones mexicano y modelos digitales de elevación*. INEGI. https://www.inegi.org.mx/app/geo2/elevacionesmex/

Instituto Nacional de Estadística y Geografía (INEGI). (2023). *Resultados definitivos del censo agropecuario 2022*. INEGI. https://www.inegi.org.mx/contenidos/saladeprensa/boletines/2023/CA_Def/CA_Def2022.pdf

Instituto Nacional de Estadística y Geografía (INEGI). (2024). *Estadísticas a propósito del día mundial del agua: desafíos y oportunidades en el uso agrícola en México*. INEGI. https://www.inegi.org.mx/app/saladeprensa/noticia.html?id=8942

Intergovernmental Panel on Climate Change (IPCC). (2006). *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. IPCC. https://www.ipcc-nggip.iges.or.jp/public/2006gl/

Intergovernmental Panel on Climate Change (IPCC). (2022). *Climate change 2022: Impacts, adaptation and vulnerability*. Cambridge University Press. https://doi.org/10.1017/9781009325844

Jia, Y., Kuzyakov, Y., Wang, G., Tan, W., Zhu, B., & Feng, X. (2020). Temperature sensitivity of decomposition of soil organic matter fractions increases with their turnover time. *Land Degradation and Development, 31*(5), 632-645. https://doi.org/10.1002/ldr.3477

Lal, R. (2004). Soil carbon sequestration impacts on global climate change and food security. *Science, 304*, 1623-1627. https://doi.org/10.1126/science.1097396

Li, J. (2017). Assessing the accuracy of predictive models for numerical data: Not r nor r^2, why not? Then what?. *PLoS ONE, 12*(8), e0183250. https://doi.org/10.1371/journal.pone.0183250

Liu, G., Sun, J., Xie, P., Guo, C., Zhu, K., & Tian, K. (2024a). Climate warming enhances microbial network complexity by increasing bacterial diversity and fungal interaction strength in litter decomposition. *Science of the Total Environment, 908*, 168444. https://doi.org/10.1016/j.scitotenv.2023.168444

Liu, X., Tian, Y., Heinzle, J., Salas, E., Kwatcho-Kengdo, S., Borken, W., Schindlbacher, A., & Wanek, W. (2024b). Long-term soil warming decreases soil microbial necromass carbon by adversely affecting its production and decomposition. *Global Change Biology, 30*(6), e17379. https://doi.org/10.1111/gcb.17379

Liu, Z., Zhang, Y., Fa, K., Qin, S., & She, W. (2017). Rainfall pulses modify soil carbon emission in a semiarid desert. *Catena, 155*, 147-155. https://doi.org/10.1016/j.catena.2017.03.011

Luković, J., Burić, D., Mihajlović, J., & Pejović, M. (2024). Spatial and temporal variations of aridity-humidity indices in Montenegro. *Theoretical and Applied Climatology, 155*(6), 4553-4566. https://doi.org/10.1007/s00704-024-04893-y

Meena, R. S., Singh, A. K., Jatav, S. S., Rai, S., Pradhan, G., Kumar, S., Mina, K. K., & Jhariya, M. K. (2024). Significance of soil organic carbon for regenerative agriculture and ecosystem services. In K. Singh, M. C. Ribeiro, & Ö. Calicioglu (Eds.), *Biodiversity and Bioeconomy* (pp. 217-240). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-323-95482-2.00010-9

Mendoza, J., Karltun, E., & Olsson, M. (2003). Estimations of amounts of soil organic carbon and fine root carbon in land use and land cover classes, and soil types of Chiapas highlands, Mexico. *Forest Ecology and Management, 177*(1-3), 191-206. https://doi.org/10.1016/S0378-1127(02)00439-5

Monterroso-Rivas, A. I., Conde-Álvarez, A. C., Pérez-Damian, J. L., López-Blanco, J., Gaytan-Dimas, M., & Gómez-Díaz, J. D. (2018). Multi-temporal assessment of vulnerability to climate change: insights from the agricultural sector in Mexico. *Climatic Change, 147*(3-4), 457-473. https://doi.org/10.1007/s10584-018-2157-7

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2021). *Introduction to linear regression analysis.* John Wiley & Sons, Inc.

Mu, Y., Ye, R., Xiong, K., Li, Y., Liu, Z., Long, Y., Cai, L., & Zhou, Q. (2024). Response of soil organic carbon to land-use change after farmland abandonment in the karst desertification control. *Plant and Soil, 501*, 595-610. https://doi.org/10.1007/s11104-024-06541-w

Mundada, S., Jain, P., & Kumar, N. (2024). Prediction of soil organic carbon using machine learning techniques and geospatial data for sustainable agriculture. *Journal of Intelligent & Fuzzy Systems*, 1-14. https://doi.org/10.3233/JIFS-240493

Naba, C., Ishidaira, H., Magome, J., & Souma, K. (2024). Exploring the potential of soil and water conservation measures for climate resilience in Burkina Faso. *Sustainability, 16*(18), 7995. https://doi.org/10.3390/su16187995

Page, K. L., Dang, Y. P., & Dalal, R. C. (2020). The ability of conservation agriculture to conserve soil organic carbon and the subsequent impact on soil physical, chemical, and biological properties and yield. *Frontiers in Sustainable Food Systems, 4*(31), 1-17. https://doi.org/10.3389/fsufs.2020.00031

Paz, F., Covaleda, S., Hidalgo, C., Etchevers, J., & Matus, F. (2016). Modelación simple y operativa de la distribución del carbono orgánico por fracciones físicas en los suelos. *Terra Latinoamericana, 34*(3), 321-337. https://www.terralatinoamericana.org.mx/index.php/terra/article/view/152

Paz, F., & Etchevers, J. (2016). Distribución a profundidad del carbono orgánico en los suelos de México. *Terra Latinoamericana, 34*(3), 339-355. https://www.terralatinoamericana.org.mx/index.php/%20terra/article/view/153/132

Poeplau, C., & Dechow, R. (2023). The legacy of one hundred years of climate change for organic carbon stocks in global agricultural topsoils. *Scientific Reports, 13*(1), 7483. https://doi.org/10.1038/s41598-023-34753-0

Posit team. (2023). *RStudio: Integrated Development Environment for R* [Software]. http://www.posit.co/

Qiu, L., Zhu, J., Zhu, Y., Hong, Y., Wang, K., & Deng, J. (2013). Land use changes induced soil organic carbon variations in agricultural soils of Fuyang County, China. *Journal of Soils and Sediments, 13*(6), 981-988. https://doi.org/10.1007/s11368-013-0684-4

Rashiq, A., Kumar, V., & Prakash, O. (2024). A spatiotemporal assessment of the precipitation variability and pattern, and an evaluation of the predictive reliability, of global climate models over Bihar. *Hydrology, 11*(4), 50. https://doi.org/10.3390/hydrology11040050

Secretaría de Medio Ambiente y Recursos Naturales-Instituto Nacional de Ecología y Cambio Climático (SEMARNAT-INECC). (2018). *Sexta Comunicación Nacional y Segundo Informe Bienal de Actualización ante la Convención Marco de las Naciones Unidas sobre el Cambio climático*. SEMARNAT-INECC. https://www4.unfccc.int/sites/SubmissionsStaging/NationalReports/Documents/69287541_Mexico-BUR2-NC6-2-MEX_6aNC_Revisada.pdf

Servicio de Información Agroalimentaria y Pesquera (SIAP). (2023). *Anuario estadístico de la producción agrícola*. SIAP. https://nube.siap.gob.mx/cierreagricola/

Shang, C., & Tiessen, H. (2003). Soil organic C sequestration and stabilization in karstic soils of Yucatan. *Biogeochemistry, 62*(2), 177-196. https://doi.org/10.1023/A:1021123728639

Smith, P., & Olesen, J. E. (2010). Synergies between the mitigation of, and adaptation to, climate change in agriculture. *Journal of Agricultural Science, 148*(5), 543-552. https://doi.org/10.1017/S0021859610000341

Stolbovoy, V. S., & Fil, P. P. (2023). Assessment of the carbon content in agricultural soils of the European Russia for climate projects. *Izvestiâ Rossijskoj Akademii Nauk. Seriâ GeografičEskaâ, 87*(4), 568-583. https://doi.org/10.31857/S2587556623040143

Vannier, C., Cochrane, T. A., Reza, P. Z., & Bellamy, L. (2022). An analysis of agricultural systems modelling approaches and examples to support future policy development under disruptive changes in New Zealand. *Applied Sciences, 12*(5), 2746. https://doi.org/10.3390/app12052746

Wang, S., Zhang, X., Adhikari, K., Wang, Z., Shi, D., Jin, X., & Qian, F. (2023). Impact of future climate warming on soil organic carbon stocks in Inner Mongolia, China. *Ecological Indicators, 156*, 111208. https://doi.org/10.1016/j.ecolind.2023.111208

Wang, X., Chen, F., Zeng, J., Wang, Z., Feng, Y., Wang, X., Ren, C., Yang, G., Zhong, Z., & Han, X. (2025). Divergent responses of soil glomalin and microbial necromass to precipitation reduction: New perspectives from soil aggregates and multi-trophic networks. *Soil Biology and Biochemistry, 200*, 109638. https://doi.org/10.1016/j.soilbio.2024.109638

Wheeler, T., & von Braun, J. (2013). Climate change impacts on global food security. *Science, 341*(6145), 508-513. https://doi.org/10.1126/science.1239402

Wiesmeier, M., Urbanski, L., Hobley, E., Lang, B., von Lützow, M., Marin-Spiotta, E., van Wesemael, B., Rabot, E., Ließ, M., Garcia-Franco, N., Wollschläger, U., Vogel, H. J., & Kögel-Knabner, I. (2019). Soil organic carbon storage as a key function of soils - A review of drivers and indicators at various scales. *Geoderma, 333*, 149-162. https://doi.org/10.1016/j.geoderma.2018.07.026

WorldClim. (2024, January 23). *WorldClim - Global Climate Data*. https://worldclim.org/

Zayani, H., Fouad, Y., Michot, D., Kassouk, Z., Baghdadi, N., Vaudour, E., Lili-Chabaane, Z., & Walter, C. (2023). Using machine-learning algorithms to predict soil organic carbon content from combined remote sensing imagery and laboratory Vis-NIR spectral datasets. *Remote Sensing, 15*(17), 4264. https://doi.org/10.3390/rs15174264

Zhao, F., Wu, Y., Hui, J., Sivakumar, B., Meng, X., & Liu, S. (2021). Projected soil organic carbon loss in response to climate warming and soil water content in a loess watershed. *Carbon Balance and Management, 16*(1), 24. https://doi.org/10.1186/s13021-021-00187-2

Zsolt, S., Tállai, M., Kincses, I., László, Z., Kátai, J., & Vágó, I. (2020). Effect of various soil cultivation methods on some microbial soil properties. *DRC Sustainable Future: Journal of Environment, Agriculture, and Energy, 1*(1), 14-20.