Assessing the Impact of Climate Change on Mineral-Associated Organic Carbon (MAOC) Using Machine Learning Models*

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Abstract

This study examines the impact of climate change on Soil Organic Carbon (SOC) stocks, with a particular focus on Mineral-Associated Organic Carbon (MAOC)—a stable fraction of soil organic matter critical for long-term carbon sequestration. This study aims to develop a predictive tool for estimating MAOC at a finer spatial resolution, addressing gaps in current models and enabling cost-effective climate change mitigation strategies..

Using an extensive dataset from the Zenodo repository, augmented with detailed meteorological data, machine learning techniques were employed—specifically, the Random Forest (RF) Regressor and Support Vector Machine (SVM) Regressor. The RF model not only outperformed the SVM in predictive accuracy but also identified key factors influencing MAOC content under various climate change scenarios.

These findings deepen our understanding of soil carbon sequestration potential in future climate conditions, offering actionable insights for sustainable soil management and cost-effective climate change mitigation strategies.

Keywords

Soil Organic Carbon (SOC), Mineral-Associated Organic Carbon (MAOC), Predictive Modeling

1. Introduction

Soil organic carbon (SOC) is an indispensable component of the global carbon cycle that strongly influences soil health, agricultural productivity and the climate system in general. SOC makes up a significant part of the organic matter in soils and serves as the main source of nutrients for plants and microorganisms. It improves soil structure, water retention, and resistance to erosion, making it a cornerstone of sustainable agricultural practices. In addition to the immediate benefits to soil and crop health, SOC plays a central role in the global carbon budget by sequestering carbon that would otherwise contribute to increasing atmospheric carbon dioxide (CO2) levels, one of the main drivers of climate change. The global carbon cycle is a complex network of processes in which carbon is exchanged between the Earth's atmosphere, the oceans, the biosphere, and the geosphere. Within this cycle, soils are the largest terrestrial reservoir of organic carbon and contain more carbon than the atmosphere and vegetation combined. The ability of soils to store carbon therefore has a significant impact on climate regulation. When properly managed, soils can act as a carbon sink by absorbing more CO_2 from the atmosphere than they release, thus helping to mitigate climate change. Conversely, poor land management practices or changing environmental conditions can turn soils into carbon sources, releasing stored carbon back into the atmosphere and exacerbating global warming. A crucial aspect of SOC is its stabilization within the soil matrix, which determines how long the carbon remains sequestered in the soil. One of the most important mechanisms for the stabilization of SOC is its

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association with soil minerals, resulting in the so-called mineral-associated organic matter (MAOM). MAOM is a part of organic matter that binds tightly to soil minerals, protecting them from microbial decomposition and physical disturbance. This binding traps the carbon in the soil, making it less likely to be released back into the atmosphere as CO2. The carbon fraction of MAOM, known as mineral-associated organic carbon (MAOC), is particularly important because it represents a stable and long-term storage form of SOC.

By understanding the dynamics of MAOC, we can better predict the long-term carbon storage potential of soils and develop strategies to enhance this process. The stability of MAOC is influenced by various factors, including soil type, mineralogy, and environmental conditions. However, one of the most pressing questions in current research is how climate change will impact MAOC stability and, by extension, the broader SOC stock. So, even if we shall devise a good method in the context of the prediction, the topic we deal with here shall be subject of several investigations in the climate change studies.

Climate change, in fact, introduces a new level of complexity to the study of SOC and MAOC. Rising global temperatures, changing precipitation patterns, the increasing frequency of extreme weather events, and shifts in vegetation cover are just some of the ways in which climate change can affect soil processes. These changes *can accelerate* the decomposition of organic matter, *disrupt* the formation of MAOM and *alter the balance* between carbon input and output in soil ecosystems. For example, higher temperatures can increase microbial activity, leading to faster decomposition of organic matter and potentially reducing the amount of carbon that is stabilized as MAOC. Changing precipitation patterns can affect soil moisture, which is crucial for microbial processes and the decomposition of organic matter. In some regions, increased precipitation could promote the formation of MAOM by facilitating the movement of organic matter into the soil where it can bind with minerals. In other regions, droughts could reduce plant growth and the supply of organic matter, limiting the formation of new MAOM. Given these potential impacts, it is crucial to understand how MAOC will respond to future climate scenarios.

Beyond understanding these changes in MAOM in general and MAOC in particular, lies one point that could make the mitigation process effective: the ability to reduce the cost of the mitigation initiatives. This can be done when we shall be able to detect the raster of the area where we need to provide the initiative as small as possible. Scientists and policymakers will be able to predict changes in SOC stocks and develop effective land management practices that can enhance soil carbon sequestration under changing environmental conditions. This study utilizes Random Forest and Support Vector Machine regression models to explore the intricate relationship between climate change and MAOC dynamics. These models were selected for their ability to handle complex, non-linear interactions within large, multifactorial datasets.

This study employs RF and SVM regressors to predict MAOC content, leveraging environmental and climatic variables, including temperature, precipitation, soil type, and land use. The models' ability to handle non-linear relationships and interactions between variables makes it particularly useful for identifying the most important factors that influence MAOC stability. Additionally, RF can provide insights into the relative importance of different climatic factors, helping to pinpoint which aspects of climate change are most likely to impact SOC stocks.

The rest of this paper is organized as follows: Section 2 provides references to relevant literature, while Section 3 discusses the experimental design. Section 4 presents the results of the experiments, and Section 5 introduces a discussion of the key findings. Finally, Section 6 takes some conclusions and sketches further work.

2. Related Work

In this section, we review the current literature at the intersection of agronomy and climate change. This review is motivated by the limited forecasting methods based on machine learning, which is the central focus of this study. In contrast to studies applying Neural Networks and XGBoost to soil carbon dynamics [2], this study focuses on Random Forest for its balance of accuracy and interpretability, which is critical for ecological and policy decision-making.

The effectiveness of agricultural methods enhanced by artificial intelligence on a large scale has been examined in prior studies. For instance, Tomazzoli et al. [3] explored the role of robotics in agriculture, while Cristani et al. [4] investigated the application of drones in modernizing agriculture, particularly in developing countries.

The relationship between climate change and Soil Organic Carbon (SOC) has been extensively researched over recent decades. Many studies have examined the effects of rising temperatures, shifting precipitation patterns, and land use changes on SOC dynamics. However, the specific impacts of climate change on Mineral-Associated Organic Carbon (MAOC)—a stable fraction of SOC—remain underexplored. Studies like Golchin et al. [5] demonstrated that increased temperatures accelerate the decomposition of organic matter, leading to SOC loss. Wan et al. [6] highlighted that shifts in precipitation patterns affect soil moisture, influencing microbial activity and SOC dynamics.

This study builds upon the dataset described by Whalen et al. [7], which provides foundational insights into MAOM dynamics under changing climate conditions. By extending this dataset, our work utilizes machine learning models to predict MAOC stability at a finer spatial resolution. Whalen et al[7]. emphasize the importance of soil mineralogy, climate conditions, and microbial traits in determining the long-term stability of soil organic matter, with significant implications for carbon sequestration and climate change mitigation.

SOC levels are influenced by various factors, both positive and negative, that must be considered when forecasting the effects of climate change. While currently minor, shifts in agricultural practices, such as increased adoption of plant-based diets and reduced meat consumption, could significantly alter SOC dynamics, emphasizing the need for accurate predictive models.

MAOC, being more resistant to decomposition than other SOC fractions, plays a critical role in soil stability. Xu et al. [8] highlighted the role of mineral-organic interactions in stabilizing MAOC. However, the long-term stability of MAOC under changing climatic conditions remains uncertain. Machine learning has recently gained prominence in soil science. For example, Matinfar et al. [9] successfully applied machine learning to predict SOC content based on environmental variables, while Bouslihim et al. [10] identified soil stability zones using similar methods.

Despite these advancements, several gaps persist in the literature. Research specifically addressing the effects of climate change on MAOC stability is limited. While machine learning has been widely applied to study SOC dynamics, its application in predicting MAOC stability and behavior remains relatively unexplored. Furthermore, most studies focus on individual climatic factors, with few integrating multiple variables to assess the overall impact of climate change on SOC and MAOC.

This study addresses these gaps by focusing on MAOC stability under climate change scenarios. It employs machine learning techniques, specifically Random Forest and Support Vector Machines (SVM), to model and predict MAOC content. Additionally, the study aims to identify the most critical environmental factors influencing MAOC stability, classify soil samples into stability zones, and assess their resilience to climate change. By exploring the non-linear relationships between climatic variables and SOC dynamics, this research contributes to a nuanced understanding of soil carbon sequestration potential under future climate conditions. Ultimately, it offers valuable insights for sustainable soil management and climate change mitigation strategies.

3. Methodology

This study utilized machine learning techniques, specifically Random Forest (RF) and Support Vector Machine (SVM) regressors, to enhance predictive modeling of Mineral-Associated Organic Carbon (MAOC) stability. The methodology comprises several critical steps: data sourcing and preprocessing, feature selection, model training and evaluation, and model interpretation. These steps are detailed below.

3.1. Data Source and Preprocessing

The dataset used in this study was sourced from the Zenodo repository[1], containing comprehensive information on soil properties such as Soil Organic Carbon (SOC), Mineral-Associated Organic Carbon (MAOC), and various climatic variables. To address the dataset's initial limitations in climatic data representation, additional meteorological variables were integrated from the Open-Meteo Historical Weather API[2]. This process leveraged geographic coordinates to fetch variables like temperature, precipitation, and soil moisture.

The final dataset, encompassing 1,231 entries and 396 columns, included a mix of climatic, land use, and soil factors. Key attributes comprised Latitude, Longitude, SOC, MAOC, year of observation, temperature-related variables, and vegetation types. Data preprocessing steps included:

- **Handling Missing Values**: Statistical imputation methods were applied to ensure data completeness.
- **Normalization**: Continuous variables were normalized to improve model performance and convergence.

The enriched dataset forms a robust foundation for analyzing climate change's impact on soil carbon dynamics.

3.2. Feature Selection

Feature importance analysis was performed using Random Forest to identify variables most influential in predicting MAOC stability. This process revealed that SOC, MAOC-to-SOC ratio, and climatic factors (e.g., temperature and precipitation) were the most significant predictors. These features were subsequently selected for model training to enhance prediction accuracy.

3.3. Model Training and Evaluation

Both RF and SVM regressors were employed for model training. The training process involved:

- **Hyperparameter Tuning**: Grid search and cross-validation were utilized to optimize model performance.
- **Performance Metrics**: Models were evaluated using Mean Squared Error (MSE) and R-squared (R^2) values. The RF model outperformed the SVM model due to its superior ability to capture non-linear interactions among features.

3.4. Model Interpretation

The RF model provided feature importance scores, offering insights into how various climatic and soil variables influence MAOC stability. This interpretability is essential for understanding ecological drivers and identifying actionable strategies for land management. The findings underline the importance of SOC and climatic factors in determining long-term carbon sequestration potential.

3.5. Analysis Steps

The following analysis steps were undertaken:

1. **Feature Importance Analysis**: Random Forest was used to identify significant features impacting MAOC stability in the original dataset.
2. **Climatic Influence Analysis**: The enriched dataset was analyzed to determine how specific climatic variables affect SOC dynamics and to identify climatic zones most influenced by MAOC.

[1]The data can be accessed via the following link: https://zenodo.org/record/5987644#.Y-53q3aZPIX
[2]API documentation: https://open-meteo.com/en/docs/historical-weather-api

3. **SOC Impact Analysis**: Zones with exceptionally high SOC levels were examined for their contribution to CO_2 emissions.
4. **Model Predictions and Comparisons**: The developed RF and SVM models were compared to assess their predictive accuracy and performance.

4. Results and Analysis

In this section, we present the results of the analysis we conducted, which employed two regression methods -Random Forest Regressor and Support Vector Machine Regressor— to predict the stability of Mineral-Associated Organic Carbon (MAOC). We assessed the performance of these models using regression metrics, specifically Mean Squared Error (MSE) and R-squared (R^2). Additionally, we identified key climatic factors influencing Soil Organic Carbon (SOC) dynamics.

The analysis yielded four main insights:

1. **Identification of Significant Features:** We determined the most significant features impacting MAOC stability using the original dataset from the Zendro repository. This identification helps in understanding which factors are most influential in predicting MAOC stability.
2. **Understanding Climatic Influences on SOC Dynamics:** We gained insights into how specific climatic variables contribute to variations in SOC dynamics. The analysis also highlighted which climatic zones are most affected by MAOC, providing a clearer picture of the relationship between climate and MAOC stability.
3. **SOC Levels and CO2 Emissions:** We observed that SOC levels are exceptionally high in certain zones. This finding has significant implications as it indicates a substantial contribution to CO2 emissions, underscoring the importance of these zones in the global carbon cycle.
4. **Model Predictions and Comparisons:** We predicted MAOC stability using the developed models and compared their performance. The results, including graphical representations, illustrate the effectiveness of each model and provide a visual comparison of their predictions.

These insights underscore the critical role of SOC in the global carbon cycle and its potential impact on climate change.

4.1. Key Analyses

1 **Feature Importance Analysis((Original Dataset): Random Forest regression was used to rank features by their predictive power. Variables like SOC, MAOC-to-SOC ratio, and climatic conditions were assessed for their contribution to MAOC predictions)**. The dataset includes variables that capture the geographical coordinates (latitude and longitude), time (year), and ecological context (biome, natural vegetation management, and climatic zone) of specific locations. It also includes detailed soil measurements (depth, soil organic carbon, mineral-associated organic carbon) critical for assessing soil health and carbon storage. The MAOC-to-SOC ratio serves as a key metric for assessing the stability of soil organic carbon, offering valuable insights into long-term sequestration potential and ecosystem resilience.Model performance metrics indicate that Random Forest significantly outperformed SVM in predicting MAOC stability . Consequently, feature importance analysis focuses on Random Forest results due to its superior accuracy. SOC and the MAOC-to-SOC ratio emerged as the most influential predictors of MAOC stability, highlighting the central role of SOC in soil carbon sequestration. (Table 1). Table 1 and Figure 1 shows the correlations between all features(right). Understanding these features allows researchers to focus on the environmental factors that most strongly influence the stability of MAOC in soils.
To explore the relationships between Mineral-Associated Organic Carbon (MAOC) content and various climate zones, categorized as B (dry), C (temperate), D (continental), and E (polar), we

Table 1
Top 10 Most Important Features for MAOC Stability

Rank	Feature	Importance
1	SOC	0.741136
2	MAOCtoSOC	0.231405
3	Lon	0.006446
4	Lat	0.004193
5	Biome_Grassland	0.000607
6	Biome_Temperate Forest	0.000589
7	Climzone_D	0.000321
8	Climzone_C	0.000265
9	Biome_Shrubland	0.000219
10	Natvman_Natural	0.000174

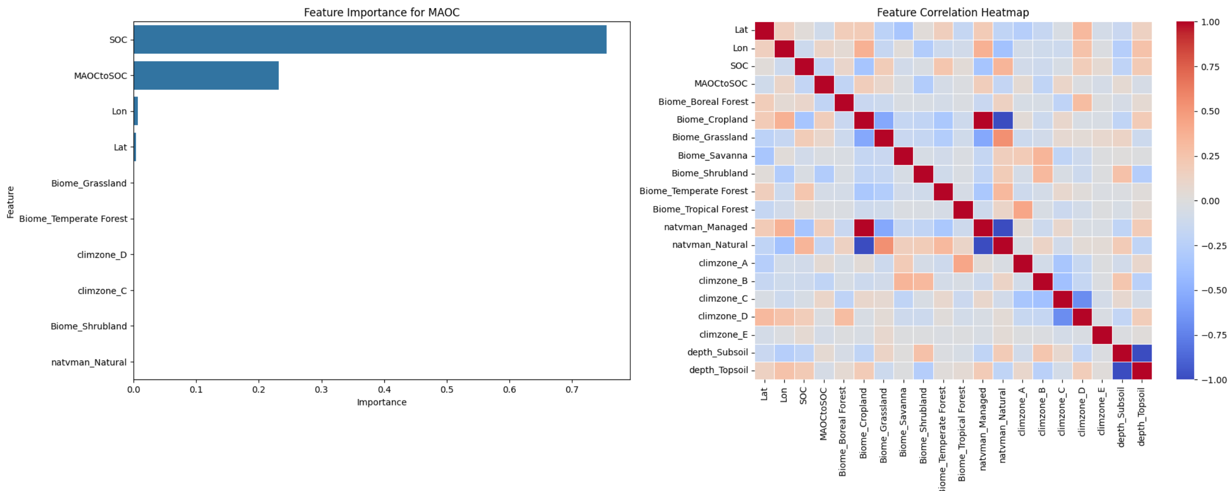


Figure 1: This combined visualization presents a side-by-side comparison of the top 10 features influencing MAOC stability (left) and the correlations between all features (right). Together, they offer insights into the importance of individual features and how they interact.

investigated how these climatic conditions correlate with a range of environmental and soil-related variables. These variables include temperature, precipitation, and Soil Organic Carbon (SOC) levels. The goal of this analysis is to explore how MAOC content fluctuates across different biomes and climate zones, thereby identifying potential patterns in carbon storage within mineral-associated organic carbon across diverse ecosystems. By examining these correlations, we aim to gain a deeper understanding of how varying climatic conditions influence the distribution and stability of MAOC, which could provide insights into the broader implications for carbon sequestration and soil health across different environmental contexts.

2 **Climatic Influence Analysis(Extended Dataset)** Random Forest regression on the enriched dataset with additional meteorological variables was conducted to evaluate how climatic factors (e.g., precipitation, temperature) affect SOC and MAOC dynamics. Temperature and moisture levels are critical factors in determining the rate of organic matter decomposition and, consequently, MAOC stability. Higher temperatures can accelerate decomposition rates, while soil moisture levels influence the microbial activity that breaks down organic matter. However, the interaction between temperature and moisture can be complex—e.g., very wet or dry conditions can slow down decomposition. We analyze the interaction between temperature, soil moisture, and MAOC stability. we analyzed to see important factors that impact MAOC stability in the extended dataset. Table 2 shows the top 10 parameters affecting MAOC value in the extended dataset(the dataset that includes all meteorological data). i.e The table ranks features based on their importance

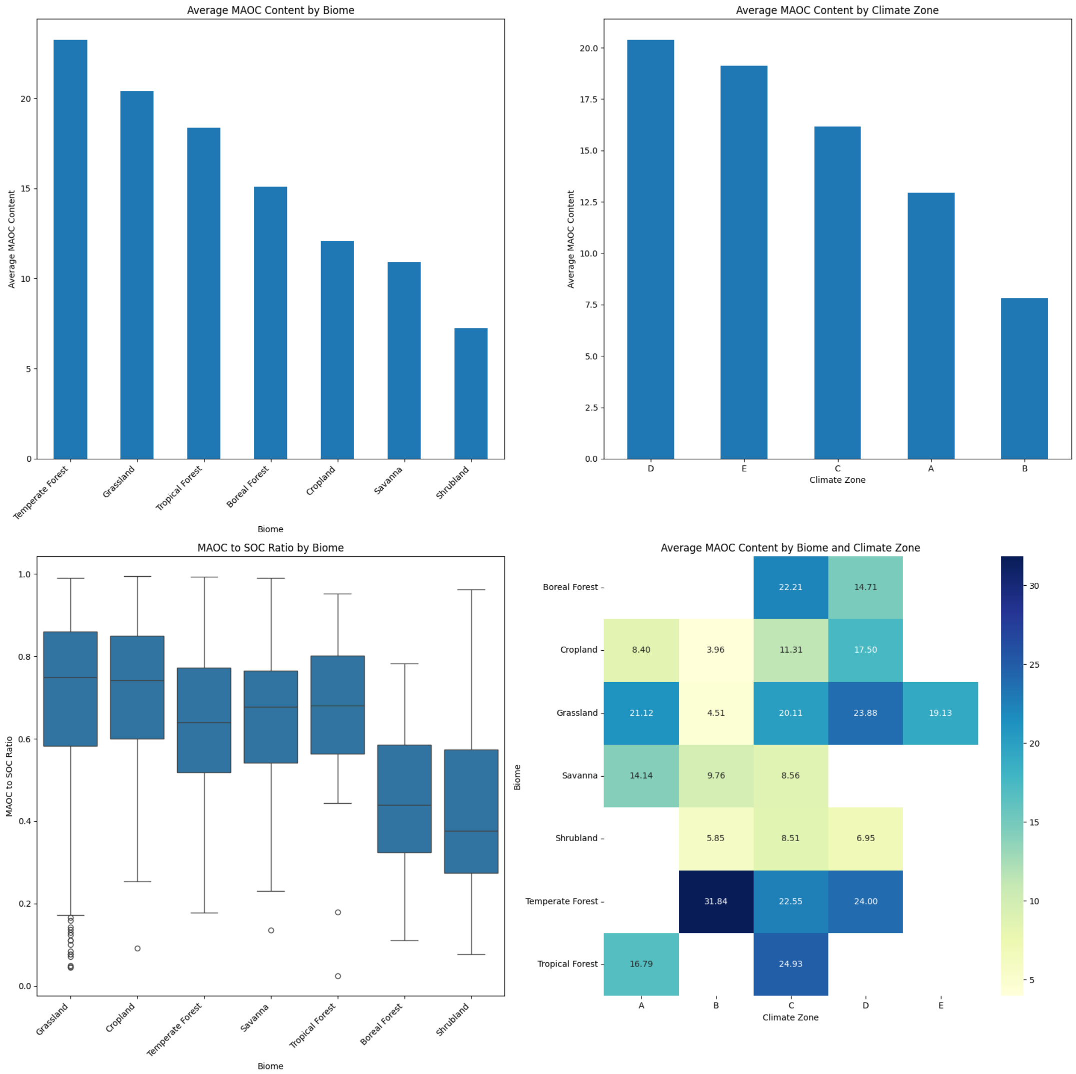


Figure 2: Comprehensive analysis of MAOC content, including bar plots of average MAOC by biome, average MAOC by climate zone, and the MAOC-to-SOC ratio distribution by biome, to illustrate spatial and environmental variability. This figure includes: (1) *Bar Plot of Average MAOC Content by Biome* showing the average MAOC content across various biomes. (2) *Average MAOC content across climate zones (A-E), highlighting significant variations in carbon sequestration potential among zones.* illustrating the average MAOC content across different climate zones. (3) *Boxplot of MAOC to SOC Ratio by Biome* indicating the relationship between MAOC and SOC across biomes. (4) *Heatmap of Average MAOC Content by Biome and Climate Zone* combining biome and climate zone data to visualize their interaction effect on MAOC content.

scores, with SOC being the most significant factor.. whereas Figure 2 shows Feature importance for predicting MAOC stability and 3 shows the comparison of the top 10 features influencing MAOC stability (left) and the correlations between all features (right). Together, they offer insights into the importance of individual features and how they interact

In Figure4 the correlation heatmap (a) reveals the interdependencies between variables, while the average values plot (b) displays the mean metrics across various climzone,i.e Tropical Climates (A), Arid Climates (B), Temperate Climates (C), Continental Climates (D), Polar Climates (E), 4a Correlation heatmap showing the relationships between different variables. i.e between the climzone(i.e A, B, C, D, E) and Top 10 parameters influencing the MAOC and 5 show the distribution of various soil and climate-related variables across different climate zones

3 **SOC Impact Analysis**: In this analysis, we investigate zones with exceptionally high Soil Organic Carbon (SOC) levels and their contribution to CO_2 emissions. SOC is a crucial component of

Rank	Feature	Importance
1	SOC	0.743450
2	MAOCtoSOC	0.214718
3	soil_temperature_100_to_255cm (°C) - min	0.004954
4	dewpoint_2m (°C) - min	0.004788
5	Lon	0.003179
6	dewpoint_2m (°C) - max	0.002164
7	soil_temperature_100_to_255cm (°C) - max	0.001746
8	precipitation (mm) - max	0.001657
9	temperature_2m (°C) - max	0.001585
10	relativehumidity_2m (%) - min	0.001546

Table 2
Feature importance for predicting MAOC stability.

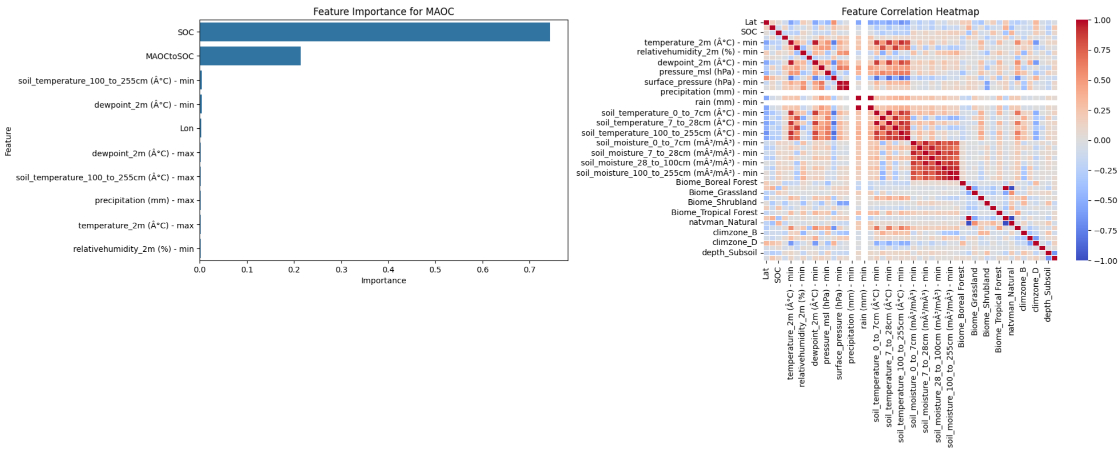
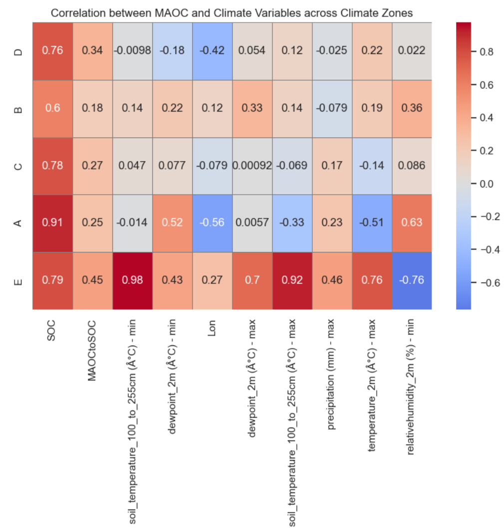


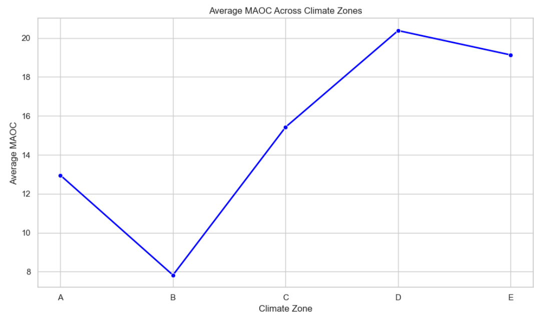
Figure 3: This combined visualization presents a side-by-side comparison of the top 10 features influencing MAOC stability (left) and the correlations between all features (right)

soil health, playing a significant role in the global carbon cycle. While SOC is vital for soil fertility and ecosystem functioning, it is also a major carbon reservoir. When SOC levels are disturbed—whether through land use changes, deforestation, agricultural practices, or climate change—this stored carbon can be released into the atmosphere as carbon dioxide (CO_2), a potent greenhouse gas. Consequently, areas with high SOC levels have the potential to significantly contribute to CO_2 emissions if not managed sustainably. The investigation aims to identify these high SOC zones, assess their current carbon storage capacity, and evaluate their potential risk of CO_2 emissions. By understanding the relationship between SOC levels and CO_2 emissions, we can better inform land management practices and climate change mitigation strategies. This analysis is critical in guiding policies that balance the need for agricultural productivity with the urgency of reducing atmospheric CO_2 levels. In figure6, shows the contribution of each climate zone to potential CO_2 emissions and the correlation between SOC levels and key environmental variables.

- **Model Predictions and Comparisons** The Random Forest model outperformed the SVM model in predicting MAOC stability, as shown in Figure X. This suggests that ensemble methods are better suited for capturing the non-linear relationships inherent in soil carbon dynamics. In figure 7 and 8, we showed the correlation between SOC levels and key environmental variables and the Comparison of the Random Forest Regressor and Support Vector Regressor models respectively.



(a) Correlation heatmap showing relationships between climatic zones (A, B, C, D, E) and the top 10 parameters influencing MAOC.



(b) Average MAOC values across different climatic zones (A, B, C, D, E).

Figure 4: (a) Correlation heatmap and (b) average MAOC values for different climatic zones.

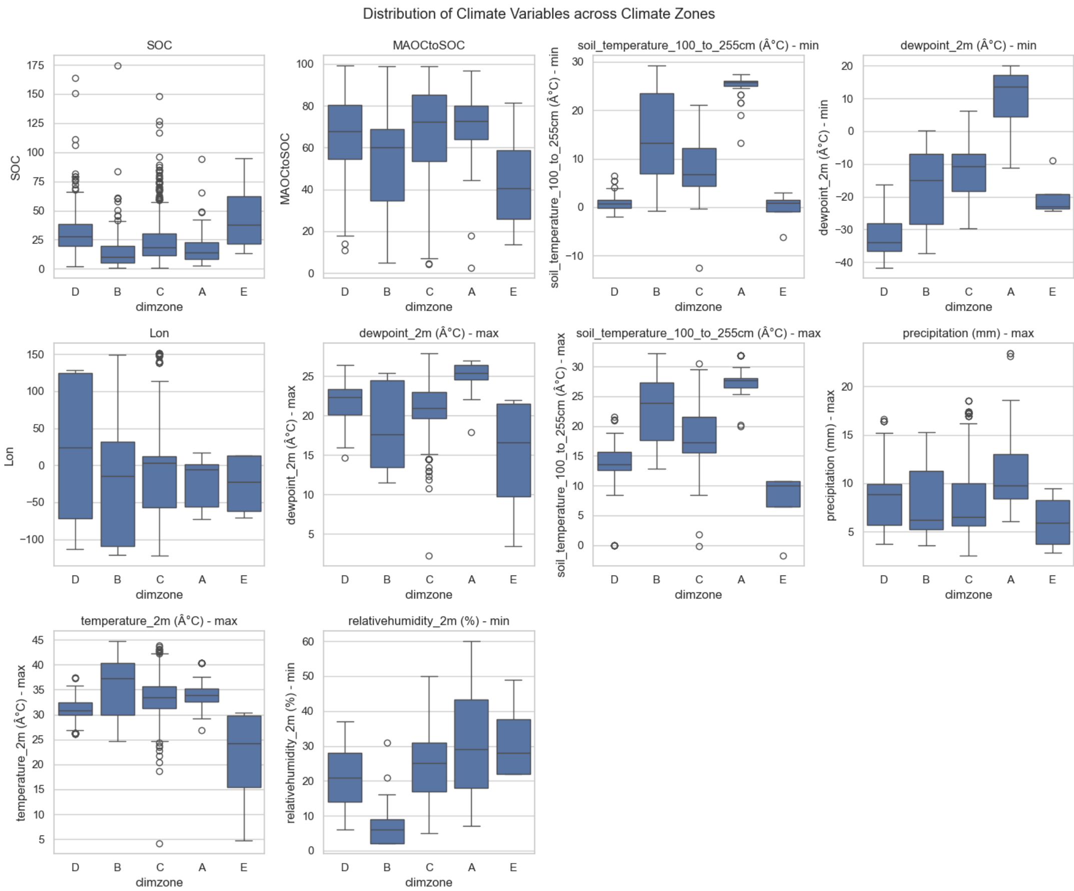


Figure 5: Distribution of various soil and climate-related variables across different climate zones (A, B, C, D, and E). The x-axis represents the climate zones, while the y-axis shows the respective values for each variable.

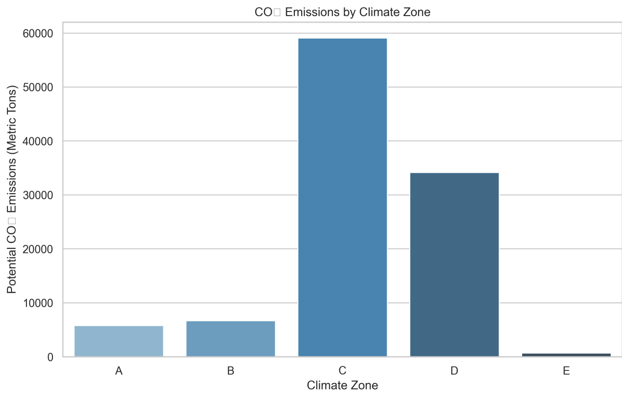


Figure 6: Contribution of each climate zone to potential CO_2 emissions. This visualization highlights the proportional impact of climate zones on emissions.

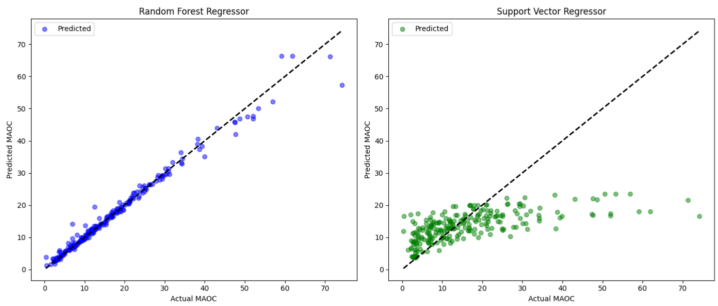


Figure 7: A heatmap showing the correlation between SOC levels and key environmental variables, indicating how other factors influence SOC levels.

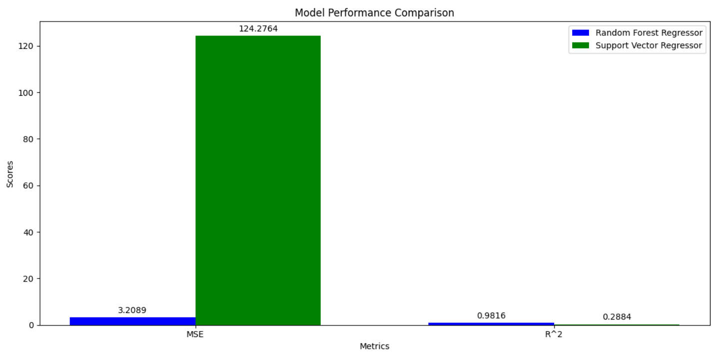


Figure 8: Comparison of the Random Forest Regressor and Support Vector Regressor models based on Mean Squared Error (MSE) and R^2 scores, highlighting the performance differences between the two models.

5. Key Findings' Discussion

This section synthesizes the insights gained from the analysis and discusses their implications in the broader context of soil carbon dynamics, climate change, and model performance. To ensure clarity and readability, the key findings and their broader implications are structured into subsections.

5.1. Key Findings

5.1.1. Significant Features in Predicting MAOC Stability

The analysis revealed that Soil Organic Carbon (SOC) and the ratio of Mineral-Associated Organic Carbon to Soil Organic Carbon (MAOC to SOC) are the most critical factors in predicting MAOC stability. This underscores the direct relationship between SOC levels and the stability of organic carbon within soils, highlighting the importance of maintaining high SOC levels to ensure long-term carbon sequestration. Other features, such as geographic coordinates (latitude and longitude), biomes, and climate zones, were found to have a lesser but still notable impact. These results suggest that while local environmental conditions are less influential, they still play a role in determining MAOC stability.

5.1.2. Climatic Influence on SOC Dynamics

Climatic factors, particularly temperature and moisture, have a significant impact on SOC dynamics. Higher temperatures and varying moisture regimes affect organic matter decomposition rates, which in turn influence the stability of MAOC. The complex interaction between these factors, as reflected in the model's interaction terms, suggests that extreme dryness and excessive moisture can limit decomposition, thereby affecting MAOC stability. This finding highlights the necessity of accounting for local climatic conditions in any assessment of carbon sequestration potential.

5.1.3. SOC Levels and CO_2 Emissions

The identification of zones with exceptionally high SOC levels reveals a dual-edged sword: while these zones serve as crucial carbon reservoirs, they also pose a significant risk for CO_2 emissions if disturbed. Specific climate zones, such as temperate and continental regions, were highlighted as areas with high SOC levels. This underscores the importance of sustainable land management practices in these regions to prevent the release of stored carbon and contribute to climate change mitigation.

5.1.4. Model Performance Comparison

The Random Forest Regressor and Support Vector Machine Regressor models demonstrated differing levels of accuracy in predicting MAOC stability. The Random Forest model outperformed the Support Vector Machine model in both Mean Squared Error (MSE) and R^2 metrics. This suggests that ensemble methods like Random Forest are better suited for capturing the complex, non-linear relationships inherent in soil carbon dynamics. The superior performance of the Random Forest model also implies that it could be a more reliable tool for policymakers and scientists working on soil carbon management.

5.2. Discussion

5.2.1. Model Effectiveness and Future Directions

While the Random Forest model demonstrated superior performance, future work could explore advanced methods such as XGBoost or deep neural networks to further enhance accuracy. However, Random Forest's interpretability and feature importance capabilities make it ideal for understanding the ecological drivers of MAOC stability. Compared to existing approaches, our method offers finer spatial resolution and greater clarity in identifying key climatic influences on MAOC dynamics. The identification of SOC as a critical factor in MAOC stability underscores the need for targeted conservation efforts to preserve and enhance SOC levels, particularly in regions identified as high-risk for CO_2 emissions.

5.2.2. Climatic Factors and Carbon Dynamics

The interaction between climatic variables and SOC underscores the complexity of soil carbon processes. Climate change, through alterations in temperature and moisture regimes, could significantly impact the stability of soil carbon stocks. This finding aligns with broader concerns about feedback loops between climate change and carbon cycling, where warming temperatures could lead to increased carbon release from soils, further exacerbating global warming.

5.2.3. Applications of Model Insights

The analysis provides data that can be utilized to refine forecasting processes and reduce raster sizes for targeted interventions. For example, by identifying areas prone to MAOC instability, actions such as seeding or other mitigation strategies can be more effectively implemented. This approach not only enhances precision but also supports cost-effective land management strategies.

5.2.4. Summary of Implications

The comparison of model performances adds another layer of understanding. The effectiveness of the Random Forest model in predicting MAOC stability suggests that it can serve as a powerful tool for future research and practical applications. Its ability to handle complex interactions and non-linearities makes it particularly well-suited for environmental modeling, where such complexities are common.

In summary, this study provides robust evidence that SOC plays a pivotal role in the stability of MAOC and, by extension, the global carbon cycle. It also emphasizes the importance of climatic factors in shaping these dynamics. The findings highlight the pivotal role of SOC in ensuring MAOC stability and emphasize the need for region-specific land management practices. The demonstrated efficacy of the Random Forest model underscores the potential of machine learning in advancing predictive accuracy for soil carbon dynamics, enabling more targeted and cost-effective mitigation strategies.

6. Conclusion

This study provides a novel approach to understanding soil carbon dynamics by integrating Random Forest-based predictive modeling with feature importance analysis. By identifying key predictors of MAOC stability, such as SOC and MAOC-to-SOC ratio, and refining predictions to a finer spatial resolution, this research contributes actionable insights for sustainable land management and climate change mitigation. By providing insights at a finer spatial resolution, our approach offers actionable data for climate change mitigation and sustainable land management. By identifying the key variables that affect soil carbon, such as SOC, climate, and geographic conditions, this research provides a foundation for more targeted conservation and land management efforts aimed at mitigating climate change. The superior performance of the Random Forest model further suggests that advanced machine learning techniques can play a crucial role in environmental research, offering accurate and actionable insights into complex ecological processes.

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