Reviewer 4:

General Evaluation:

This manuscript presents a 100-meter resolution global soil organic carbon (SOC) map at 30 cm and 100 cm depths, built using a harmonized collection of over 120,000 point measurements and remote sensing covariates. The authors use random forest (RF) models, with special treatment of peatlands and mangroves through ecosystem-specific models, and provide uncertainty maps based on bootstrap ensembles.

The development of a globally consistent, fine-resolution SOC map is highly relevant and potentially valuable for applications in carbon accounting, land restoration planning, and natural climate solutions. However, while the dataset is promising in scope and spatial granularity, the manuscript currently lacks structural completeness, spatial transparency, and modeling rigor necessary for scientific reproducibility and policy relevance.

I recommend major revision before the manuscript is considered for publication. Below are my detailed comments.

Author Response:

We thank the reviewer for their constructive feedback. In response, we have revised our manuscript and refined the modeling approach stratifying across 14 distinct biomes and ecosystems. We trained separate machine learning models for each, allowing for more localized SOC predictions. Updated raster data for the revised SOC predictions have been uploaded to the Zenodo repository.

Major Comments

1. **Biome- and Region-specific SOC Estimates, Uncertainty, and Validation Are Missing**

While the authors emphasize the use of biome-specific models and regionally tuned data inputs (e.g., for mangroves, peatlands), they do not provide SOC estimates, confidence intervals (CI), or model performance metrics at these spatial units. Readers cannot evaluate whether modeling SOC separately by biome or region has indeed improved performance.

Additionally, there is no validation of these outputs against either prior SOC products (e.g., GSOCmap, SoilGrids, WISE30sec) or independent in-situ observations within these biomes or regions.

Recommendation:

- Present SOC maps, uncertainty maps, and model metrics stratified by biome and/or key geographic regions (e.g., Amazon, SE Asia, Congo Basin).
- Compare SOC estimates for each biome with existing datasets and, if available, ground truth values.
- Consider including these outputs in main figures or supplementary materials.

Author Response:

Thank you for these important points. We have addressed them as follows:

- **Biome-level performance metrics: Table 2** presents the performance of the biome-specific RF models at 30 cm and 100 cm. **Figures 2** and **3** show predicted vs. observed SOC density per biomes. Results are discussed in **Section 3.4** of the Results section (*Final model performance across biomes*).

- **Biome-level SOC estimates and associated total uncertainty: Table 3** reports biome area, biome-level average SOC density (t C/ha) and SOC stocks (Pg C), and the associated total uncertainty at 30 cm and 100 cm depths. Total uncertainty combines model variance and residual variance, as described in **Section 2.10**. Results are discussed in **Section 4.1.2**.

- **Comparison of biome-level SOC estimates with existing datasets: Figure 1** compares our global SOC output with seven widely used global SOC maps (WISE30secv.3, HWSDv1.21, GSDE, GSOCmap v1.5, Sanderman et al. (2017) and SoilGrids250m v.1 and v.2). **Table 3** provides biome-level comparisons of SOC estimates with existing datasets. Results are discussed in **Section 4.1.1**. (*Comparison with existing global maps*).

- **Uncertainty: Figure 1** and **Table 3** summarize total propagated uncertainty in biome-level SOC stocks.

2. Model Accuracy is Low and Methodological Alternatives Are Not Explored

The global model shows modest predictive accuracy (R^2 = 0.35-0.38) and suffers further degradation post bias-correction. Yet, only a single modeling method - random forest - is used, with no evaluation of alternative algorithms or ensemble strategies.

This is concerning given the complexity of SOC drivers and the goal of high-accuracy mapping at fine resolution.

Recommendation:

- Compare multiple modeling approaches (e.g., XGBoost, LightGBM, Cubist) and report their relative performance.
- Explore ensemble or stacked models to increase generalization and reduce bias.

- Report R^2, RMSE, and MAE for each biome or region and for each model tested.

Author Response:

Thank you for this important comment. We added the following methods section to the manuscript. It details our model selection approach, the evaluation of alternative algorithms and their relative performance.

2.5 Model selection and biome-level framework

“We initially developed a single global model, with test R^2 values of 0.35 at 30 cm and 0.38 at 100 cm depth (before histogram-based bias correction; model trained using an 80/20 split and evaluated on the held-out test set). We tested alternative global model configurations. The initial global Random Forest model with 300 trees and no hyperparameter tuning achieved $R^2 = 0.35$. Adding latitude and longitude as predictors slightly increased R^2 to 0.37. Increasing the number of trees to 500 without latitude and longitude yielded the same R^2 of 0.37. A Gradient Boosted Trees (GBT) model performed worse ($R^2 = 0.29$), and hyperparameter tuning (i.e. two trials) increased performance only marginally to $R^2 = 0.34$.

We then explored spatially stratified models based on different levels of ecological classification, using the WWF biomes classification, which delineates the following biomes globally (Olson et al., 2001): TMB-Tropical and subtropical moist broadleaf forests; TDB-Tropical and subtropical dry broadleaf forests; TCF-Tropical and subtropical coniferous forests; TeBF-Temperate broadleaf and mixed forests; TeCF-Temperate coniferous forest; BoF-Boreal forests/taiga; TUN-Tundra; TrG-Tropical and subtropical grasslands, savannas, and shrublands; TeG-Temperate grasslands, savannas, and shrublands; FGr-Flooded grasslands and savannas; MtG-Montane grasslands and shrublands; MeF-Mediterranean forests, woodlands, and scrub; DES-Deserts and xeric shrublands.

For each biome, we tested model performance when biomes were subdivided by continent or region (e.g., TMB in South America vs. Africa vs. Asia). While this biome-by-continent approach often produced high R^2 values in certain regions, it also introduced considerable variability and data imbalance. Some biome-continent combinations had strong performance (e.g., $R^2 > 0.7$), while others suffered from limited sample size or overfitting. For example, TMB reached R^2 of 0.53 in South America, 0.77 in Africa, and 0.49 in Asia and TeBF achieved R^2 of 0.31 in the Americas, 0.85 in Asia, and 0.47 in Europe. Based on these findings, we selected a consistent set of 12 biome models that maintained ecological specificity while preserving sufficient data volume and geographic breadth for each model.”

Regarding histogram-based bias correction, we clarified the following in **Section 2.6:**

“The biome-specific approach inherently reduces systematic bias, allowing each model to better capture local patterns. Consequently, no additional bias correction (i.e. histogram-based bias correction) was applied, and the reported values reflect the direct outputs of the biome-specific models.”

Further, we included model performance metrics (R^2, RMSE, and MAE) for each biome model in **Tables S9** and **S10**. These metrics are reported in the main text and in the Supplementary Information.

Biome/Ecosystem soc30		Train Count	Train R^2	Test Count	Test R^2	Full Count	Full R^2
Forests							
Tropical and subtropical moist broadleaf forests	TMB	7,864	0.84	1,966	0.62	9,830	0.84
Tropical and subtropical dry broadleaf forests	TDB	2,750	0.73	688	0.52	3,438	0.74
Tropical and subtropical coniferous forests	TCF	987	0.78	247	0.43	1,234	0.79
Temperate broadleaf and mixed forests	TeBF	19,947	0.73	4,988	0.33	24,935	0.72
Temperate coniferous forest	TeCF	7,055	0.68	1,765	0.43	8,820	0.71
Boreal forests / taiga and tundra	BoF-TUN	3,675	0.59	920	0.12	4,595	0.60
Mangroves - based on Global Mangrove Watch (2020) extent	MG	1,261	0.79	316	0.57	1,577	0.80
Grasslands and shrublands							
Tropical and subtropical grasslands, savannas and shrublands	TrG	3,259	0.82	815	0.65	4,074	0.83
Temperate grasslands, savannas and shrublands	TeG	6,932	0.73	1,735	0.49	8,667	0.74
Flooded grasslands and savannas	FGr	1,038	0.77	260	0.42	1,298	0.76
Montane grasslands and shrublands	MtG	334	0.93	84	0.12	418	0.73
Other biomes							
Mediterranean forests, woodlands and scrub	MeF	5,632	0.79	1,410	0.43	7,042	0.79
Deserts and xeric shrublands	DES	7,232	0.70	1,809	0.33	9,041	0.70
Peatlands - based on UNEP classification (2022)	P	2,697	0.66	675	0.22	3,372	0.67

Biome/Ecosystem soc30		Train Count	Train RMSE	Test Count	Test RMSE	Full Count	Full RMSE
Forests							
Tropical and subtropical moist broadleaf forests	TMB	7,864	38	1,966	67	9,830	39
Tropical and subtropical dry broadleaf forests	TDB	2,750	42	688	44	3,438	40
Tropical and subtropical coniferous forests	TCF	987	20	247	33	1,234	20
Temperate broadleaf and mixed forests	TeBF	19,947	60	4,988	100	24,935	62
Temperate coniferous forest	TeCF	7,055	84	1,765	111	8,820	80
Boreal forests / taiga and tundra	BoF-TUN	3,675	143	920	229	4,595	144
Mangroves - based on Global Mangrove Watch (2020) extent	MG	1,261	25	316	34	1,577	24
Grasslands and shrublands							
Tropical and subtropical grasslands, savannas and shrublands	TrG	3,259	31	815	47	4,074	31
Temperate grasslands, savannas and shrublands	TeG	6,932	35	1,735	40	8,667	34
Flooded grasslands and savannas	FGr	1,038	45	260	44	1,298	43
Montane grasslands and shrublands	MtG	334	9	84	54	418	21
Other biomes							
Mediterranean forests, woodlands and scrub	MeF	5,632	24	1,410	35	7,042	24
Deserts and xeric shrublands	DES	7,232	28	1,809	35	9,041	27
Peatlands - based on UNEP classification (2022)	P	2,697	127	675	216	3,372	129

Biome/Ecosystem soc30		Train Count	Train MAE	Test Count	Test MAE	Full Count	Full MAE
Forests							
Tropical and subtropical moist broadleaf forests	TMB	7,864	15	1,966	27	9,830	15
Tropical and subtropical dry broadleaf forests	TDB	2,750	16	688	26	3,438	16
Tropical and subtropical coniferous forests	TCF	987	13	247	24	1,234	13
Temperate broadleaf and mixed forests	TeBF	19,947	23	4,988	39	24,935	23
Temperate coniferous forest	TeCF	7,055	35	1,765	59	8,820	35
Boreal forests / taiga and tundra	BoF-TUN	3,675	67	920	108	4,595	68
Mangroves - based on Global Mangrove Watch (2020) extent	MG	1,261	14	316	25	1,577	14
Grasslands and shrublands							
Tropical and subtropical grasslands, savannas and shrublands	TrG	3,259	11	815	18	4,074	10
Temperate grasslands, savannas and shrublands	TeG	6,932	14	1,735	22	8,667	13
Flooded grasslands and savannas	FGr	1,038	19	260	28	1,298	18
Montane grasslands and shrublands	MtG	334	6	84	15	418	8
Other biomes							
Mediterranean forests, woodlands and scrub	MeF	5,632	13	1,410	22	7,042	13
Deserts and xeric shrublands	DES	7,232	11	1,809	17	9,041	10
Peatlands - based on UNEP classification (2022)	P	2,697	58	675	103	3,372	59

Table S9. Biome-specific model performance metrics for 0-30 cm soil organic carbon (SOC30).

3. Data Sparsity in Key Regions Remains Unresolved

Although the manuscript compiles an impressive collection of point data, it is unclear whether it significantly improves training sample density in previously under-sampled areas (e.g., SE Asia, Amazon peatlands, Congo Basin, boreal permafrost zones).

Recommendation:

- Provide maps or histograms of sample density by region or biome.
- Quantify the number and proportion of new samples added to underrepresented areas.
- Compare data coverage with existing global SOC datasets to clarify how this product advances spatial completeness.

Author Response: Thank you. We have taken several steps to address this.

To show sample density by biome, we have added **Figure S2** to show the distribution of ground-truth SOC observations across biomes. The figure illustrates the global extent of biomes (in orange) and the locations of SOC measurements (in dark grey) at 30 cm and 100 cm depths, and includes summary statistics (number of observations, mean SOC, and standard deviation) for each biome. A subset of representative maps is shown below. **Figure S2** presents the full set of 27 maps in the Supplementary Material.

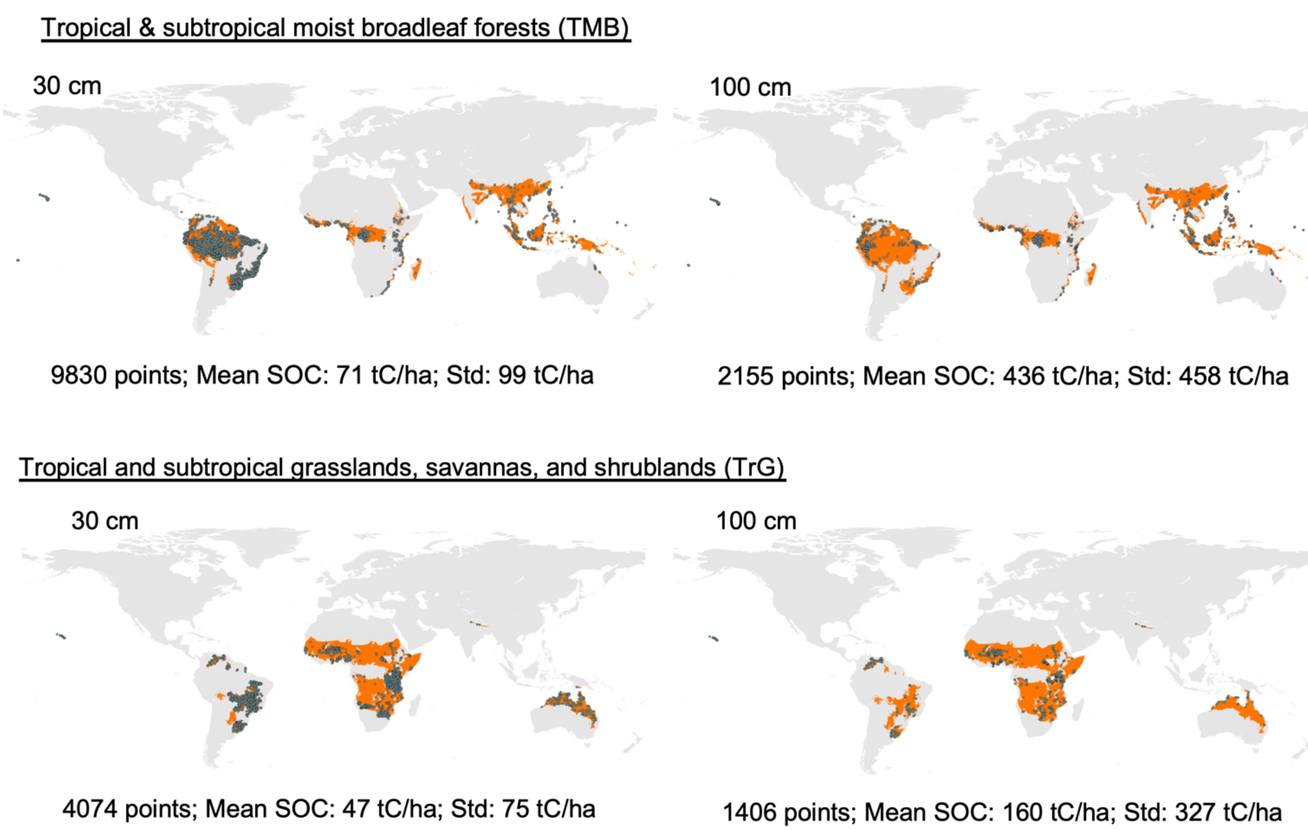


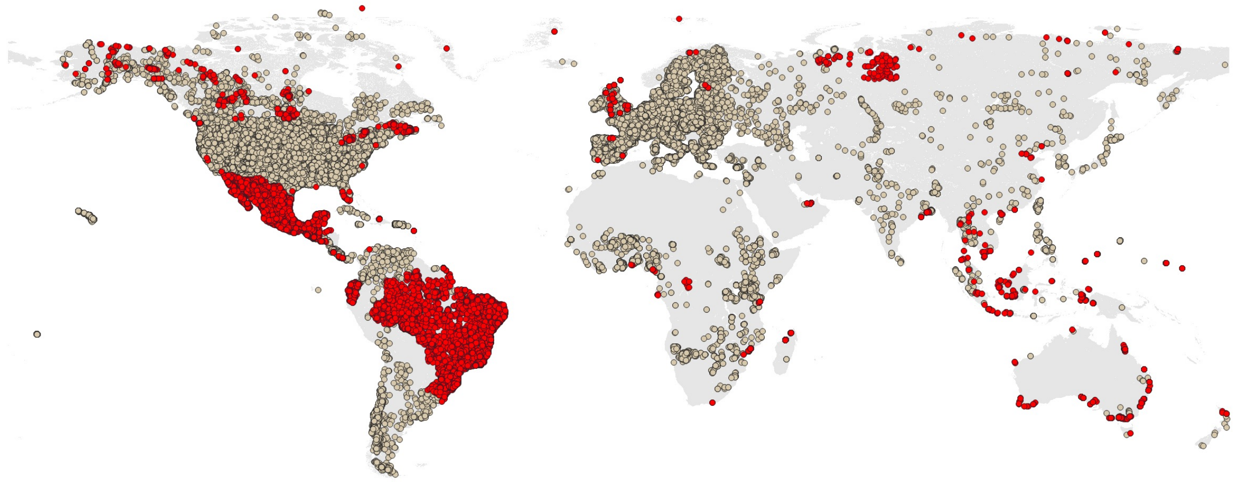
Figure S2 (subsection). Global distribution of biomes and ground-truth soil organic carbon (SOC) data with summary statistics. This figure shows the spatial extent of the biomes in orange and the locations of ground-truth SOC observations for 0-30 cm and 0-100 cm depths, in grey. The number of observations, mean SOC density (t C/ha), and standard deviation are reported for each biome and depth.

Further, we added the following clarification to **Methods Section 2.8**:

"In this study, we integrated multiple global and large regional soil datasets, including Europe-LUCAS 2018, ISCN, ISRIC-WISEv3, RaCA, and the WoSIS snapshot 2023. While previous global SOC maps such as SoilGrids v1/v2, Sanderman et al. (2017), GSOCmap v1.5, WISE30sec, GSDE and HWSD v1.21 relied on earlier versions of these datasets, our study incorporates the latest WoSIS release and additional national and ecosystem-specific datasets (Table S2), many published after 2017. By integrating these diverse inventories, we improve spatial completeness and enhance representation of SOC across biomes and regions (Figure S1)."

We added **Figure S1** to show the global spatial coverage of the main large datasets (Europe-LUCAS 2018, ISCN, ISRIC-WISEv3, RaCA, and WoSIS) and the coverage of regional datasets.

(a) SOC30



(b) SOC100

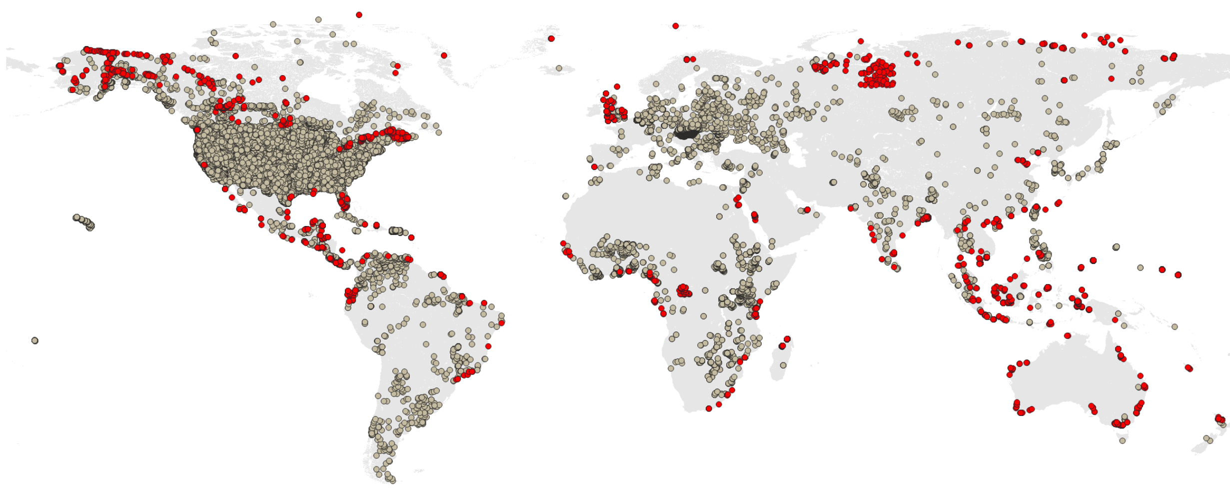


Figure S1. Locations of ground-truth data points for (a) soil depth 0–30 cm (SOC30) and (b) soil depth 0–100 cm (SOC100). Grey points show large regional and global datasets (SOC30: Europe-LUCAS 2018, ISCN, ISRIC-WISEv3, RaCA, WoSIS 2023; SOC100: ISCN, ISRIC-WISEv3, RaCA, WoSIS 2023), while red points indicate additional ground-truth datasets used in this study, excluding sampled gridded datasets.

4. No Connection Between Static SOC Map and Dynamic Carbon Policy Use

The authors claim their product supports natural climate solutions and carbon removal strategies. However, the map reflects a static snapshot of SOC conditions and does not account for management interventions or disturbance effects.

Recommendation:

- Clearly position this dataset as a static SOC baseline and discuss its potential role in MRV (Monitoring, Reporting, Verification) systems.
- Provide examples or scenarios where SOC stocks are compared under different management or fire regimes using model predictions.
- Alternatively, simulate SOC distributions under no-fire or no-agriculture scenarios using the trained models to demonstrate potential use in change detection or policy design.

Author Response:

We greatly appreciate the reviewer's comments and concerns. It is clear that our map serves as a one-time baseline or benchmark for soil organic carbon (SOC) stock at two depths. To clarify the use cases of the SOC maps, we have added the following sections to the manuscript.

4.3.1 Baseline map for research and monitoring

"We present a high-resolution (100 m) soil organic carbon map at two depths, representing baseline SOC stocks circa 2022. Soil profile data collected from the 1950s to the 2020s were combined with contemporary remote sensing covariates, using Landsat 8 bands to capture landscape conditions around 2022. The use of long-term soil datasets aligns with previous global mapping efforts, such as SoilGrids v1-v2 and GSOCmap v1.5, which integrate multi-decadal data to capture large-scale spatial patterns. The primary goal of this work was to represent SOC variation across diverse landscape gradients with a resolution fine enough to capture local differences while maintaining global coverage. The resulting map can support applications in land management, nature-based climate solutions, and future assessments of SOC dynamics.

SOC data inevitably span decades, while Earth observation covariates reflect more recent conditions. In landscapes without major human disturbances, SOC is assumed to remain relatively stable over time, so historical soil measurements can reliably represent baseline stocks when combined with current remote sensing data. In areas affected by land-use change, degradation, or recovery, such as forests regrowing after wildfire, agricultural rotations, or restored wetlands, SOC may have changed since sampling. For instance, samples from western CONUS encompass forests at different successional stages recovering from events such as wildfires or storms. Remote sensing captures spectral signals related to land cover and vegetation recovery, helping to contextualize historical soil measurements. Consequently, the SOC map reflects not only static soil conditions but also the imprints of temporal changes across landscapes. To address potential temporal discrepancies at the pixel level, we generated an uncertainty map alongside the SOC estimates, allowing users to assess confidence in areas where SOC may have changed substantially since sampling.

Our dataset integrates both natural and human-modified landscapes, including agricultural areas, managed forests, wetlands, and coastal ecosystems such as mangroves. By combining long-term soil measurements with remote sensing covariates and machine learning models, the map captures both spatial variation in SOC and the influence of historical land-use changes and recovery processes. Overall, the high-resolution SOC maps represent a valuable tool for carbon management and conservation. The maps enable fine-scale detection of spatial variability, supports assessments of land-use impacts, and provides a foundation for monitoring SOC dynamics over time, even in regions with limited historical soil data."

4.3.2 Policy and management applications

"The baseline SOC map serves as a benchmark with broad relevance across scientific, management, and policy applications. For carbon stock reporting, it enables estimation of SOC across regions, land cover types, and management units, with particularly high precision for areas larger than 1 hectare where pixel aggregation reduces uncertainty. At the policy level, the map provides national and sub-national jurisdictions with a means to assess soil carbon storage and sequestration potential, accounting for spatial variability across land uses and vegetation successional stages. Such information supports the design and implementation of land-use and restoration policies aimed at improving soil carbon conditions. The map also facilitates participation in carbon markets, where project developers require reliable SOC stock data to estimate emissions reductions or removal factors, including avoided losses and potential accumulation rates in disturbed versus natural areas. In addition, the high-resolution benchmark map at multiple depths can be integrated into biogeochemical models to quantify potential changes in soil carbon. Building on this work, we plan to combine repeated SOC measurements with process-based models to advance understanding of SOC dynamics. By leveraging this baseline, carbon management strategies can be refined and climate policies better informed."

5. No Analysis of Predictor Effects Across Biomes or Regions

The manuscript includes no interpretation of model behavior through partial dependence plots (PDPs), SHAP values, or marginal effect visualizations. This is a major weakness given the low model R^2 and the ecological complexity of SOC formation.

Understanding how each covariate influences SOC predictions is critical to evaluate whether the model captures realistic biogeochemical relationships or is driven by spurious correlations.

Recommendation:

- Provide variable importance rankings and partial dependence plots for key predictors (e.g., pH, CEC, clay, NDVI, temperature).
- Stratify these analyses by biome or region to highlight differences in covariate effects.
- Comment on whether the model's response patterns are ecologically interpretable and consistent with known SOC mechanisms.

Author Response:

Thank you. We conducted additional calculations using partial dependence analysis to evaluate feature influence on SOC predictions. These analyses were stratified by biome to highlight differences in covariate effects.

Methods are detailed in the new **Section 2.7** ("Partial dependence analysis"), and results are presented in **Section 3.5** ("Feature effects on SOC predictions"), where we discuss how the models' response patterns are ecologically interpretable.

Full results are provided in **Supplementary Figure S3**.

Minor Comments

1. Abstract (Lines 22–24): Rephrase "can influence SOC by 132 Pg C…" to avoid misinterpretation as quantified changes. Suggest: An estimated 132 Pg C of SOC is located in areas affected by wildfire and 140 Pg C in agricultural areas.

Author Response:

Thank you for this comment. We have revised the sentence to clarify that the reported values represent SOC stocks located in fire-prone and agricultural areas. The sentence in the manuscript now reads:

"Our estimates indicate 134 ± 2 Pg C and 340 ± 5 Pg C sit in fire prone areas at 30 cm and 100 cm depth, and that 140 ± 2 Pg C and 384 ± 8 Pg C are in areas of ongoing agricultural activity at 30 cm and 100 cm depth, representing about 13% of global SOC stocks."

2. Line 505: If the increased Amazon SOC estimate is driven by better mapping of peatlands, please state that explicitly.

Author Response:

Thank you. We have revised this section of the manuscript, which now reads:

"Across the entire Amazon Basin (593 Mha), we estimate 37 ± 1 Pg C at 30 cm and 162 ± 7 Pg C at 100 cm, representing 4 % and 6 % of the global SOC total, respectively. Our results at 100 cm are higher than previous Amazon Basin assessments, including 47 Pg C at 100 cm (Moraes et al., 1995), 46.5 Pg C (Batjes and Dijkshoorn, 1999), and 36.1 Pg C (Gomes et al., 2019), due in part to our use of the recently updated peatland extent dataset that better captures carbon-rich areas."

3. Line 551–555: The difference between SOC estimates with and without fire (28 Pg C at 100 cm) is small (~1%). Confidence intervals should be reported to assess significance. Also clarify whether adding fire improved model performance.

Author Response:

We thank the reviewer for this comment. Regarding the first point, we no longer compare global stock predictions with and without fire as an input layer to the model. Instead, we focus on the results of the fire feature effects on SOC predictions per biome, and find large fire effects in tundra/boreal regions and in peatlands, consistent with known ecological patterns.

Regarding the second point, total uncertainty combining model variance and residual variance has been computed and added to the manuscript.

Regarding the third point, for each biome model and soil depth, we compared the model performance (R^2) on the full dataset with and without the fire variable. Including fire as a predictor had a negligible to very small effect of ~0.01 on model performance across biomes and soil depths. The minimal change in R^2 suggests that adding fire does not introduce artifacts or model instability. Thus, we retain fire as a predictor because it captures an important ecological process influencing soil carbon dynamics. This has been added to the manuscript **Section 2.2**.

4. Figures 1–5: Add consistent color bars, units (e.g., t C/ha), and labels for clarity.

Author response: We have revised **Figures 1–5** to include consistent color bars and clearly labeled units (t C/ha).

5. Line 685 & 689: The phrase “our map shows high fire/agriculture activity” may confuse readers. Clarify that these are input datasets, not part of the new SOC product.

Author Response:

Thank you for this comment. The agricultural land extent and fire activity are derived from external datasets (LGRIP 2015 and MODIS 2000–2023, respectively) rather than generated directly from our SOC mapping effort.

To clarify, we have revised the text to explicitly attribute these datasets to their original sources. The manuscript now reads:

“In Brazil’s Cerrado, our model estimates that soils store 8.7 ± 0.2 Pg C at 30 cm and 28.1 ± 10.8 Pg C at 100 cm across 204 Mha. Although the Cerrado contains moderate SOC stocks compared to other biomes, 38% of the region is classified as fire-prone and 35% as agricultural land, with a 63% spatial overlap with either category, based on LGRIP 2015 and MODIS 2000-2023 datasets (Figure 8). Fire-prone areas contain an estimated 3.3 ± 0.1 Pg C (30 cm) and 10.0 ± 0.6 Pg C (100 cm) across 77 Mha, and agricultural areas contain 3.1 ± 0.1 Pg C (30 cm) and 9.4 ± 0.6 Pg C (100 cm) across 72 Mha. Fire-prone areas and agricultural land show larger SOC contrasts at 100 cm than at 30 cm compared to other areas, which may reflect differential SOC dynamics with depth. High fire activity in regions such as Matopiba could be associated with rapid agricultural expansion. These patterns suggest a combined role of fire and land use in shaping SOC dynamics (LGRIP 2015; MODIS, 2000-2023).”

6. Line 699–703: Discussion of fire impacts here is redundant with earlier sections. Consider consolidating to avoid repetition.

Author Response: Thank you. We have reworked the manuscript outline and consolidated the discussion of fire impacts into a single coherent section. The revised outline now reads:

4.2 Land-use and disturbance

4.2.1 Global fires and agriculture (*now includes a consolidated global fire discussion*)

4.2.2 Regional SOC stocks relative to land-use and fire (*focuses on regional distribution of fire and agriculture*)