Reviewer 2:

The authors utilized 84880 and 44304 field measurements at 30cm depth and 100cm depth and combined with biome-specific machine learning approaches to map SOC at 100m spatial resolution. This novel idea would provide significant spatially explicit information in reducing uncertainties related to SOC estimation. However, there are a few issues that need to be addressed before the paper being accepted. The detailed comments are as follows.

Author Response:

Thank you for your careful review and helpful comments. We hope the changes we made address your suggestions and improve the manuscript.

Line 13, 1-hectare refers to the area, instead of the spatial resolution of the map, please make this consistent with the “100m” spatial resolution that mentioned in the title.

Author Response: Thank you. We have corrected this.

Line 18, What is the “average of prior estimates”, which research?

Author Response:

Thank you for pointing this out. We have clarified the source of the “average of prior estimates” in the revised manuscript.

Revised text:

“We estimate global soil organic carbon stocks of 1,023 ± 20 Pg C at 30 cm and 2,837 ± 57 Pg C at 100 cm, representing increases of 28 % and 46 %, respectively, relative to the average of previous estimates (798 Pg C at 30 cm; 1,947 Pg C at 100 cm) calculated from SoilGrids v1-v2, Sanderman et al. (2017), GSOCmap v1.5, WISE30sec, GSDE, and HWSD v1.21.”

Line 110, Please add a map to provide the spatial distribution of all the field measurements. Also, please add a table describing the basic information of sampled points in each biome, such as the total number of samples, mean and standard deviation values of soil samples in each biome.

Author Response:

Thank you for the suggestion. We have added **Figure S2** to show the spatial 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.

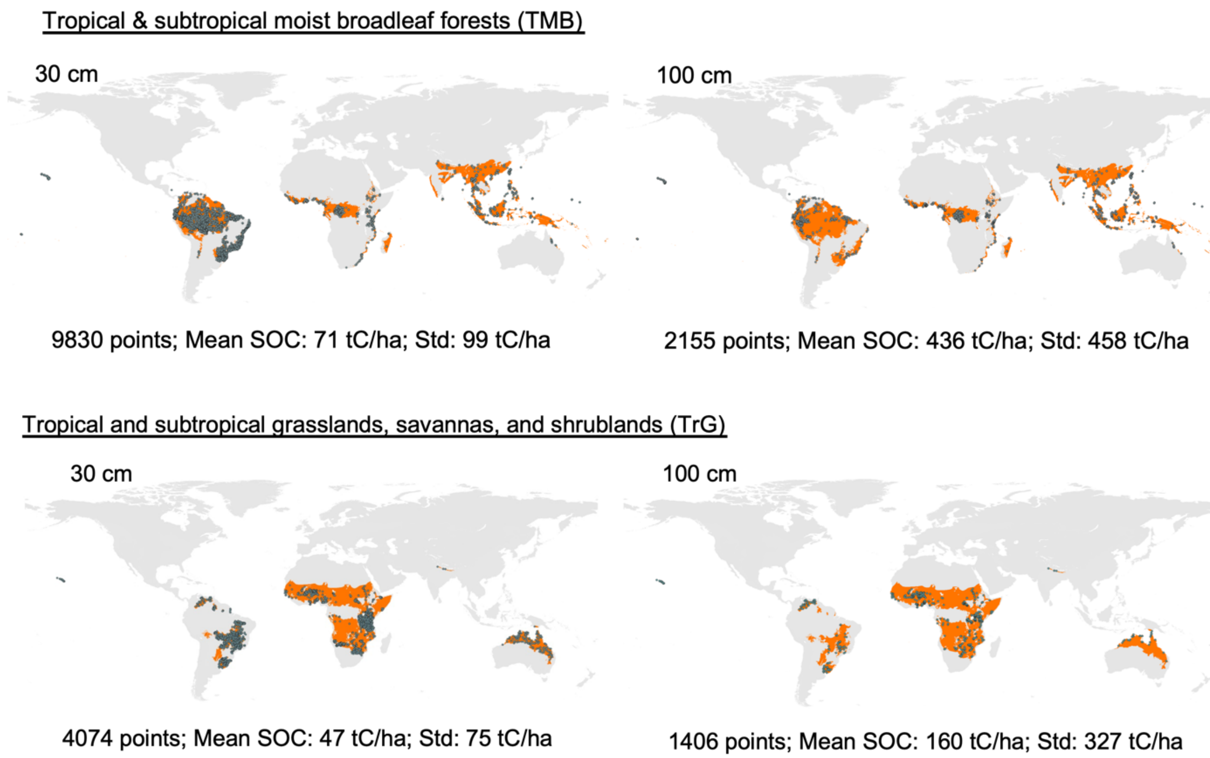

Figure S2 (subsection). Global distribution of biomes and ground-truth soil organic carbon (SOC) data with summary statistics. This figure shows the spatial extent of the biomes in orange and the locations of ground-truth SOC observations for 0-30 cm and 0-100 cm depths, in grey. The number of observations,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

Line 153, This approach may introduce mistakes in treating gridded products as ground truth, leading to biased models, especially in data-scarce regions where underlying map quality is uncertain. Additionally, subsampling and binning may not fully capture spatial or ecological variability, and global performance metrics can obscure significant local errors. I suggest the authors provide (1) analysis that does not include samples that are sampled from these maps (2) model metrics and R^2 that are not including these samples. As samples collected from maps are not ground truth, which will change the model's performance.

Author Response: We thank the reviewer for highlighting this point. We have added detail regarding the inclusion of subsampled data in **Section 2.1.3** of the methodology, which now reads:

"We analysed model performance both with and without subsamples derived from the previously described gridded datasets. The results show that, when subsamples are excluded, model performance remains largely robust, with only minor reductions of 0.01-0.02 in R^2 values across most biomes and ecosystems (Table S8). Montane grasslands are an exception, showing a larger drop in R^2 due to the low number of samples in this biome. At 100 cm depth, removing subsamples similarly preserves model performance, with only marginal changes of 0.02-0.03 in R^2, again with the exception of montane grasslands. These results indicate that, although map-derived samples contribute to model training, they do not fundamentally alter overall model performance or spatial patterns. The model is therefore not overly reliant on these potentially biased samples. We include these samples to improve spatial representativeness, but we have verified that their inclusion does not introduce substantial bias in our predictions. The full biome-level results with and without subsamples are available in Table S8."

	with subsamples		without subsamples	
Biome/Ecosystem soc30	**Full Count**	**Full R^2**	**Full Count**	**Full R^2**
Forests				
Tropical and subtropical moist broadleaf forests	9,830	0.84	9,162	0.82
Tropical and subtropical dry broadleaf forests	3,438	0.74	3,424	0.74
Tropical and subtropical coniferous forests	1,234	0.79	1,232	0.79
Temperate broadleaf and mixed forests	24,935	0.72	24,889	0.73
Temperate coniferous forest	8,820	0.71	8,781	0.71
Boreal forests / taiga and tundra	4,595	0.60	No subsamples	
Mangroves - based on Global Mangrove Watch (2020) extent	1,577	0.80	1,238	0.79
Grasslands and shrublands				
Tropical and subtropical grasslands, savannas and shrublands	4,074	0.83	3,439	0.83
Temperate grasslands, savannas and shrublands	8,667	0.74	8,448	0.74
Flooded grasslands and savannas	1,298	0.76	1,024	0.76
Montane grasslands and shrublands	418	0.73	33	0.40
Other biomes				
Mediterranean forests, woodlands and scrub	7,042	0.79	6,962	0.79
Deserts and xeric shrublands	9,041	0.70	8,493	0.70
Peatlands - based on UNEP classification (2022)	3,372	0.67	2,805	0.67

	with subsamples		without subsamples	
Biome/Ecosystem soc100	**Full Count**	**Full R^2**	**Full Count**	**Full R^2**
Forests				
Tropical and subtropical moist broadleaf forests	2,155	0.90	1,573	0.87
Tropical and subtropical dry broadleaf forests	1,322	0.71	1,295	0.71
Temperate broadleaf and mixed forests	14,516	0.72	14,503	0.72
Temperate coniferous forest	6,919	0.70	6,873	0.70
Boreal forests / taiga and tundra	1,716	0.68	No subsamples	
Mangroves - based on Global Mangrove Watch (2020) extent	1,453	0.80	1,097	0.78
Grasslands and shrublands				
Tropical and subtropical grasslands, savannas and shrublands	1,406	0.90	1,360	0.90
Temperate grasslands, savannas and shrublands	8,236	0.62	8,219	0.62
Flooded grasslands and savannas	1,034	0.77	790	0.75
Montane grasslands and shrublands	385	0.56	21	0.28
Other biomes				
Mediterranean forests, woodlands and scrub	1,298	0.83	1,297	0.83
Deserts and xeric shrublands	4,431	0.66	4,370	0.66
Peatlands - based on UNEP classification (2022)	1,936	0.77	1,286	0.75

Table S8. Model performance (R^2) and sample count per biome and ecosystem for soil organic carbon (SOC) predictions for 0-30 cm and 0-100 cm depths. Results are shown for biome-specific models trained with the full dataset and with or without the inclusion of subsampled gridded datasets.

Line 177, The differences in SOC lab methods (e.g., dry combustion vs. Walkley-Black) are not accounted for. Could this introduce systematic regional bias in SOC predictions?

Author Response:

Thank you for this comment. To address it, we have added the following clarification to **Methods Section 2.1.4** of the manuscript:

"Soil organic carbon was assessed using different methods (e.g., dry combustion or Walkley-Black) across datasets, reflecting the extended timeline over which data were collected. Most datasets compiled in this study had already been internally harmonized using conversion factors, and we did not apply further adjustments for potential method-based discrepancies. Most datasets reported final soil carbon stocks standardized in t C/ha. Older campaigns relied more on loss on ignition (LOI) and Walkley-Black methods, potentially introducing regional differences despite conversions. In contrast, more recent datasets, which we integrated to enhance spatial coverage, were predominantly analysed using dry combustion. Thus, methodological differences remain a potential source of bias in the compiled SOC estimates; however, remaining method-related effects are expected to be relatively minor compared with the overall spatial variability captured by the model."

Line 197, Please replace "Environment" with "environment".

Author Response: Thank you. We corrected this.

Line 213, Please justify why ET was included for SOC estimation.

Author Response:
Thank you. We have updated the manuscript to include a clear justification for including ET. The revised text now reads:

"To account for climate-driven factors influencing soil carbon, we integrated MODIS Evapotranspiration (ET) data (kg/m²/8-day; MODIS/061/MOD16A2GF). ET serves as an indicator of both water availability and ecosystem productivity, which directly affect plant growth, litter input, and soil organic carbon accumulation. By including ET, we capture spatial variations in climate that help explain SOC distribution globally."

Line 219, Is fire frequency also derived from MODIS based products?

Author Response:

Thank you for the comment. In the Discussion section of the manuscript, we clarified the use of MODIS products for fire frequency. Further, we expanded **Methods Section 2.2**. The fire raster used as an input layer was derived from the MODIS/061/MCD64A1 dataset for 2000–2023 and represents the average number of burned days per pixel per year. This raster was then converted into a binary fire mask, with pixels having an average annual burned days ≥1 assigned a value of 1 (fire-prone) and all others assigned 0 (not fire-prone). Zonal statistics were computed using this binary mask.

Line 222, Please specify which years' ALOS2 data have been utilized.

Author Response:
Thank you. This information is provided in the manuscript, which reads:

"We used ALOS-2 PALSAR-2 data for synthetic aperture radar (SAR) backscatter (HH and HV bands) to account for the effects of soil moisture and structure on soil carbon. We calculated the median for the years 2019-2020 for each band."

Line 225, Please replace NiR with "NIR" and justify why these bands in Landsat8 were selected?

Author Response:

Thank you. We have corrected "NiR" to "NIR" and updated the manuscript to justify the selection of these bands. The revised text now reads:

"We processed Landsat 8 data (bands red, NIR, SWIR1, and SWIR2), taking the median for 2022 and gap-filling with data from prior years. These four bands capture vegetation and surface reflectance, providing insight into land cover, vegetation type, and land-use patterns, which are factors closely associated with soil organic carbon distribution at the landscape-scale. Furthermore, these bands capture spectral signals related to vegetation recovery and land cover dynamics, reflecting temporal changes across landscapes. This information helps to contextualize historical soil measurements. Of all Landsat 8 bands, these four are the most informative and commonly used for SOC estimation."

Line 229, The spatial resolution of all the remote sensing data or remote sensing-based products are not the same, how the mismatch in spatial resolution was handled? Please provide more details.

Author Response:

We thank the reviewer for this important comment. We have revised **Methods Section 2.4** to further detail our approach. As described in the manuscript:

"All geospatial input raster layers were reprojected to a standardized spatial reference system and a uniform 100 m spatial resolution prior to model training and inference. The input datasets, described in previous sections, included: Copernicus Global Land Cover (100 m), Landsat 8 bands (30 m), MODIS Land Surface Temperature (1 km), MODIS Evapotranspiration (500 m), ALOS PALSAR (25 m), SoilGrids soil properties (250 m), GPM2.0 global peatland map (1 km), Global Mangrove Watch forest extent (25 m), NCSCDv2 permafrost map (1 km), WRB soil classification (250 m), Congo Basin peatland map (50 m), Peruvian peatland map (50 m), and MarSOC tidal marsh map (10 m). Differences in native spatial resolution among datasets were addressed through interpolation-based resampling. The harmonized 100 m layers were then used as predictor variables in the RF modeling framework to generate the final global 100 m resolution product."

Also, how did the temporal mismatch between different Earth Observation sources and the temporal mismatch between SOC data and EO were handled? SOC maps often combine soil profile data collected over decades with environmental covariates reflecting more recent conditions. This ignores soil property changes over time, particularly in areas affected by land-use change or degradation.

Author Response:

Thank you. To address it, we have added the following section 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."

Line 250, The abstract mentioned a bio-specific machine learning approach for mapping SOC, more details needed to describe the bio-specific approach.

Author Response:
Thank you. We have added the following clarification to **Methods Section 2.5** to clarify the biome-specific approach:

"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.

Peatland (P) and mangrove (MG) ecosystems were modeled separately at both 30 cm and 100 cm depths due to their distinct biophysical characteristics and the importance of their soil carbon stocks. To minimize the inclusion of non-mangrove or non-peatland sites, we relied on the most accurate and spatially explicit global datasets available: the Global Mangrove Watch v3.0 (2020) (Bunting et al., 2022) and the Global Peatland Assessment Database v2 (GPM2.0, 2022) from UNEP, both of which account for small-scale land use changes such as local farming and deforestation. The Global Peatland Assessment Database 2022 v.2 (GPM2.0) from UNEP categorizes peatlands into two primary classes: 'peat dominated', where peat is the dominant land cover, and 'peat-in-soil mosaic', where peat occurs in smaller patches within other land cover types. We combined both classes (GPM2.0 classes 1 and 2) into a single mask to capture the full extent of peat-dominated and peat-in-soil mosaics. To improve regional accuracy, we integrated high-resolution peatland datasets for the Congo Basin and Peruvian Amazon. These higher-resolution regional datasets were prioritized in overlapping areas, such that where both global and regional datasets were available, the regional data replaced the global data, while areas outside these regions retained the GPM2.0 coverage. While not all SOC ground-truth points had land cover metadata, 58% of points within the mangrove extent at 30 cm (71% at 100 cm) were explicitly identified as mangrove, and 14% of points within the peatland extent at 30 cm (35% at 100 cm) were identified as peatland.

To evaluate predictive performance of biome- and ecosystem-models, we conducted k-fold cross-validations with 50 simulations. In each simulation, the dataset was partitioned into training and test subsets. A separate model was trained on the training subset and evaluated on both subsets. Model performance (R^2) was computed for each simulation, and the mean and standard deviation for the 50 simulations are reported (Table 1). In addition, a weighted R^2, which combines training and test performance, is reported in Table 1. Overall, the stratified biome-model approach provided a balance between model complexity and generalizability."

Line 251, How the parameter of "mtry" has been trained and specified in the random forest model?

Author Response:

Thank you. We have clarified this point in **Methods section 2.6** as follows:

"The number of candidate features considered at each split in the Random Forest (mtry) was not explicitly tuned (tuner_num_trials = 0); the TensorFlow Decision Forests (TF-DF) *RandomForestModel* used default regression settings, automatically setting mtry to one-third of the available features."

Line 325, Does the average represent all the aforementioned SOC products? Please consider adding the average SOC of each SOC map.

Author Response:

Thank you for the comment. Yes, the average represents the SOC products mentioned in the text. We have added the SOC value of each map in **Figure 1**, in the table attached below:

	Global Soil Organic Carbon Stocks							
	Digital soil mapping							
	calculate-first			*interpolate-first*		*Taxotransfer method*		
	this study	**SoilGridsv2**	**Sanderman**	**SoilGridsv1**	**GSOCv1.5**	**WISE30sec**	**GSDE**	**HWSDv1.21**
Global (Pg C)		2021	2017	2017	2018	2016	2014	2012
soc30	1023 ± 20	594	869	1,176	684	883	794	588
soc100	2837 ± 57	-	1,960	2,769	-	1,969	1,907	1,130

Line 267, Please provide other model evaluations metrics for mapping SOC such as RMSE instead of only R^2.

Author Response:
Thank you for the suggestion. We have included additional model evaluation metrics to complement R^2. These metrics are presented in the **Supplementary Information** as follows:

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).

Biome/Ecosystem soc100		Train Count	Train R²	Test Count	Test R²	Full Count	Full R²
Forests							
Tropical and subtropical moist broadleaf forests	TMB	1,724	0.89	431	0.79	2,155	0.90
Tropical & subtropical dry broadleaf and coniferous forests	TDB-TCF	1,057	0.73	265	0.27	1,322	0.71
Temperate broadleaf and mixed forests	TeBF	11,612	0.70	2,904	0.36	14,516	0.72
Temperate coniferous forest	TeCF	5,535	0.70	1,384	0.26	6,919	0.70
Boreal forests / taiga and tundra	BoF-TUN	1,372	0.71	344	0.28	1,716	0.68
Mangroves - based on Global Mangrove Watch (2020) extent	MG	1,162	0.78	291	0.52	1,453	0.80
Grasslands and shrublands							
Tropical and subtropical grasslands, savannas and shrublands	TrG	1,124	0.89	282	0.91	1,406	0.90
Temperate grasslands, savannas and shrublands	TeG	6,588	0.58	1,648	0.40	8,236	0.62
Flooded grasslands and savannas	FGr	827	0.76	207	0.45	1,034	0.77
Montane grasslands and shrublands	MtG	308	0.52	77	0.60	385	0.56
Other biomes							
Mediterranean forests, woodlands and scrub	MeF	1,038	0.81	260	0.64	1,298	0.83
Deserts and xeric shrublands	DES	3,544	0.64	887	0.24	4,431	0.66
Peatlands - based on UNEP classification (2022)	P	1,548	0.74	388	0.41	1,936	0.77

Biome/Ecosystem soc100		Train Count	Train RMSE	Test Count	Test RMSE	Full Count	Full RMSE
Forests							
Tropical and subtropical moist broadleaf forests	TMB	1,724	155	431	196	2,155	145
Tropical & subtropical dry broadleaf and coniferous forests	TDB-TCF	1,057	125	265	243	1,322	135
Temperate broadleaf and mixed forests	TeBF	11,612	193	2,904	286	14,516	189
Temperate coniferous forest	TeCF	5,535	201	1,384	258	6,919	193
Boreal forests / taiga and tundra	BoF-TUN	1,372	270	344	478	1,716	288
Mangroves - based on Global Mangrove Watch (2020) extent	MG	1,162	91	291	123	1,453	87
Grasslands and shrublands							
Tropical and subtropical grasslands, savannas and shrublands	TrG	1,124	113	282	82	1,406	105
Temperate grasslands, savannas and shrublands	TeG	6,588	129	1,648	144	8,236	121
Flooded grasslands and savannas	FGr	827	131	207	277	1,034	140
Montane grasslands and shrublands	MtG	308	68	77	37	385	61
Other biomes							
Mediterranean forests, woodlands and scrub	MeF	1,038	91	260	124	1,298	87
Deserts and xeric shrublands	DES	3,544	94	887	134	4,431	91
Peatlands - based on UNEP classification (2022)	P	1,548	283	388	502	1,936	278

Biome/Ecosystem soc100		Train Count	Train MAE	Test Count	Test MAE	Full Count	Full MAE
Forests							
Tropical and subtropical moist broadleaf forests	TMB	1,724	74	431	108	2,155	70
Tropical & subtropical dry broadleaf and coniferous forests	TDB-TCF	1,057	47	265	98	1,322	49
Temperate broadleaf and mixed forests	TeBF	11,612	63	2,904	100	14,516	62
Temperate coniferous forest	TeCF	5,535	83	1,384	128	6,919	80
Boreal forests / taiga and tundra	BoF-TUN	1,372	129	344	232	1,716	135
Mangroves - based on Global Mangrove Watch (2020) extent	MG	1,162	50	291	82	1,453	47
Grasslands and shrublands							
Tropical and subtropical grasslands, savannas and shrublands	TrG	1,124	38	282	45	1,406	35
Temperate grasslands, savannas and shrublands	TeG	6,588	42	1,648	67	8,236	41
Flooded grasslands and savannas	FGr	827	60	207	108	1,034	59
Montane grasslands and shrublands	MtG	308	18	77	27	385	16
Other biomes							
Mediterranean forests, woodlands and scrub	MeF	1,038	42	260	68	1,298	41
Deserts and xeric shrublands	DES	3,544	41	887	67	4,431	41
Peatlands - based on UNEP classification (2022)	P	1,548	126	388	212	1,936	123

Table S10. Biome-specific model performance metrics for 0-100 cm soil organic carbon (SOC100).

Line 356, Please position the captions below the figure, same comment for all the figures.

Author Response: Captions have been placed below the figures.

Line 202, The authors mentioned that they used SoilGrids2 data as the inputs of the models. However, SoilGrids2 itself is a modeled product with known spatial biases and uncertainties. Could the authors clarify what steps were taken to mitigate the risk of error propagation from SoilGrids2 into the final SOC predictions?

Author Response: We used a set of soil characteristics from SoilGrids2 to support global SOC modeling. We recognize that SoilGrids2 is itself a predictive product derived from ground observations and ancillary data, and therefore may contain spatial biases and uncertainties in magnitude. Nevertheless, we chose to include these datasets for three main reasons:

1. **Comparative modeling tests:** We evaluated SOC models with and without SoilGrids2 layers, using only remote-sensing, vegetation, and climate data in the latter case. Treating SOC measurements as independent targets, our results showed that including SoilGrids2 layers substantially improved mapping accuracy at both global and biome scales.
2. **Feature space enrichment:** In principle, any dataset, even if noisy or weakly correlated with SOC, can serve as part of the feature space for SOC prediction. Features that do not contribute meaningfully can simply be excluded during model optimization.
3. **Error characterization:** While SoilGrids2 does not provide pixel-level uncertainty estimates that could propagate through modeling frameworks, our approach relies on cross-validation and pixel-level SOC uncertainty estimates. Consequently, the errors we report represent true prediction uncertainties at both pixel and regional levels. The main limitation is that fine-scale spatial variability, which may reflect SoilGrids2's inherent spatial errors, cannot be fully quantified. However, at larger spatial scales and biome levels, these uncertainties are unlikely to exert a significant effect.