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Global patterns of soil organic carbon dynamics in the 20–100 cm soil profile for different ecosystems: A global meta-analysis

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Abstract

Determining the dynamics of organic carbon in subsoil (SOC, depth of 20–100 cm) is important with respect to the global C cycle and warming mitigation. However, there is still a huge knowledge gap in the dynamics of spatiotemporal changes in SOC in this layer. Combining traditional depth functions and machine-learning methods, we achieved soil β values and SOC dynamics at high resolution for global ecosystems (cropland, grassland, and forestland). First, quantified the spatial variability characteristics of soil β values and driving factors by analyzing 1221 soil profiles (0–100 cm) of globally distributed field observations. Then, based on multiple environmental variables and soil profile data, we mapped the grid-level soil β values with machine-learning approaches. Lastly, we evaluated the SOC density spatial distribution in different soil layers to determine the subsoil SOC stocks of various ecosystems. The subsoil SOC density values of cropland, grassland, and forestland were 63.8, 83.3, and 100.4 Mg ha^{-1}, respectively. SOC density decreased with increasing depth, ranging from 5.6 to 30.8 Mg ha^{-1} for cropland, 7.5 to 40.0 Mg ha^{-1} for grassland, and 9.6 to 47.0 Mg ha^{-1} for forestland. The global subsoil SOC stock was 912 Pg C (cropland, grassland, and forestland were 67, 200, and 644 Pg C), in which an average of 54% resided in the top 0–100 cm of the soil profile. This study provides information on the vertical distribution and spatial patterns of SOC density at a 10 km resolution for areas of Global ecosystems, which providing a scientific basis for future studies pertaining to Earth system models. The dataset is open-access and available at https://doi.org/10.5281/zenodo.10846543 (Wang et al., 2024).

Keyword: Subsoil SOC dynamics; Soil profiles; Random forest; Driving factors; Global ecosystems

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

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1. Introduction

Organic carbon in soil (SOC) plays a critical role in global C cycling, climate change mitigation, reducing greenhouse gas(GHG) emissions, and the health of ecosystems (Bradford et al., 2016; Lal et al., 2021; Griscom et al., 2017) Subsoil, defined here as soil residing below 20 cm in depth, contains more than half of the global SOC stock (Esteban G. Jobbágy. and Jackson., 2000; Poffenbarger et al., 2020; Batjes, 1996). Worldwide, high SOC loss due to crop production and grazing, which contributes significantly to increasing atmospheric CO_2 levels (Beillouin et al., 2023; Lal, 2020; Qin et al., 2023). Complex polymeric carbon in subsoil is vulnerable to decomposition under future warming; specifically, ecological or trophic limitations of SOC biodegradation in deep soil layers can lead to sharp declines in the nutrient supply and biodiversity (Chen et al., 2023). Subsoil is more suited to long-term C sequestration than topsoil. The '4 per 1000' initiative aims to boost SOC storage in agricultural soils by 0.4% each year to help mitigate climate change and increase food security (Chabbi et al., 2017). However, subsoil SOC dynamics, especially across a large scale, remain poorly understood (Padarian et al., 2022), as the measurements are difficult, time-consuming, and labor intensive particularly at deeper depths.

Recent studies have focused on SOC allocation and dynamics at varied depths and the subsoil SOC–climate feedback cycle of terrestrial ecosystems (Luo et al., 2019; Jia et al., 2019; Li et al., 2020). The complexity, uncertainty, and large spatial heterogeneity of SOC stock estimation have limited the ability to accurately quantify the SOC stock distribution (Mishra et al., 2021; Wang et al., 2022a) To date, three main methods are commonly used to estimate large-scale SOC stocks: area-weighted averaging based on vegetation inventories and soil survey data (Tang et al., 2018), machine-learning based on remote-sensing, land-use, and edaphic data and climatic factors as covariates (Ding et al., 2016), and depth distribution function-based empirical analysis (Wang et al., 2023). The first approach provides the most accurate measurement of the SOC stock but is time-consuming and labor intensive and is not practical at the global scale. The latter two do not fully consider the vertical distribution of the soil profile or the soil properties of various ecosystems. The extrapolation to large soil depths, for example, using 0–40 cm or 0–50 cm of surface SOC to predict 0–100 cm or 0–200 cm of subsoil SOC (Wang et al., 2023; Ding et al., 2016), may lead to high uncertainty, thus preventing an accurate assessment of the global subsoil SOC stock.

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

Studies of whole-soil profiles have recorded greater changes in the SOC dynamics of the subsoil under warming (Zosso et al., 2023; Luo et al., 2020; Soong et al., 2021). The amount and quality of C in input soil, such as aboveground litter and root biomass input, could profoundly alter the vertical SOC distribution (Lange et al., 2023; Feng et al., 2022). The β model, in particular, uses simple and flexible functions that capture the relative slope of depth profiles with a single parameter, with the advantage of being able to integrate SOC values from the surface down to a given depth (Esteban G. Jobbágy. and Jackson., 2000). The β model was originally applied to vertical root distributions and has been used to fit the steepest reductions with depth (Gale and Grigal, 1987; Jackson et al., 1997). Some researchers have used the global average β of 0.9786 to calculate deep soil SOC stocks (Yang et al., 2011; Deng et al., 2014), however, the different hydrological conditions, soil type, and ground/underground organic matter have limited the ability to resolve the SOC depth distribution with confidence.

In this study, we produced spatially resolved global estimates of the depth distribution and stocks of subsoil SOC using the β model as a depth distribution function-based empirical approach for evaluating cropland, grassland, and forestland ecosystems on a global scale. First, we collected and analyzed 1221 soil profiles (0–1 m) of globally distributed observations from 478 sites to estimate the SOC vertical distribution (soil β values). Then we developed a random forest (RF) model to estimate the spatial variation in grid-level soil β values in the associated ecosystems to resolve the dynamics of the SOC density in different soil layers and subsoil stocks of the global ecosystems.

2. Methods

2.1. Data collection

We conducted peer-reviewed literatures review of studies previously published on SOC stock or SOC content of soil profile between 1980 and 2022 to obtain a database. The Web of Science and China National Knowledge Infrastructure (CNKI) database were searched (article abstracts and key words) using the terms “Soil organic carbon” AND “subsoil” AND “Soil profile” AND “Deep soil” The criteria were as follows: (1) The research scope is worldwide, (2) the study was conducted in the field, (3) the profiles of multiple sites are reported in the same literature, and the profile of

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

each site is considered as an independent study, (4) profiles with more than three suitable measurements of organic carbon in the first meter were collected from the analysis for there was sufficient detail to characterize the vertical distribution of SOC, (5) the data extracted from included basic site information including location latitude and longitude, soil organic carbon (SOC), total nitrogen (TN), soil bulk density (BD), soil pH and C:N, Microbial biomass carbon and nitrogen (MC), Microbial biomass nitrogen (MN), and MC: MN, soil clay content, climate conditions [mean annual precipitation (MAP) and mean annual temperature (MAT)]. If the SOM rather than SOC was reported, the value was converted to SOC by multiplication with a conversion factor of 0.58 (Don et al., 2011). To extract data presented graphically, the digital software GetData Graph Digitizer 2.25 (getdata-graph-digitizer.com) was used. A total of 161 peer reviewed papers comprising 1221 soil profiles were included in this dataset, with the distribution of locations shown in Figure1. Missing soil and climate factor data from a few sites were either provided by the study authors through direct correspondence, or obtained from the spatial datasets (section 2.2), based on latitude and longitude. These data were analyzed to determine the impact of the environment on soil β values and develop a model to predict global grid-level β values, subsequently, soil profiles SOC density, and calculate SOC stocks.

2.2 Global soil attributes calculation

Since the 0-1 m soil profile has different layers in the row data, mass-preserving spline method (R Package 'mpspline2') was used to divide the soil profiles into 5 layers with 20 cm interval. This function implements for continuous down-profile estimates of soil attributes measured over discrete, often discontinuous depth intervals. In some studies, there was a lack of bulk density data below 20 cm soil layer. Notable differences in global SOC stocks estimations were attributed to the values used for soil bulk density. Therefore, we use the database issued by predecessors to generate bulk density data with 0-1m profile at 20 cm interval (Shangguan et al., 2014). For SOC density, it is necessary to supplement the bulk density data to calculate the SOC content. In order to reveal the variation of SOC dynamic with depth, we first have to calculate the SOC density (see Equation 1). The SOC stocks of each land use is equal to SOC density multiplied by its square (see Equation 2).

$$SOC\ \ \text{density} = SOC * BD * D/10 \qquad [1]$$

$$SOC\ \ stocks = SOC\ \ density * S_{ecosystem} \quad [2]$$

where SOC is the SOC concentration (g kg^{-1}), BD is the soil bulk density (g cm^{-3}), and D is the thickness of the soil layer (at intervals of 20 cm in the first meter), SOC

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

density (Mg C ha^{-1}). $S_{ecosystem}$ is the areas of cropland, grassland or forestland (ha), SOC stocks (Pg C).

2.3 Global soil β values calculation

We obtained soil β data from 160 published studies representing 1221 observations. The original SOC density data the original soil depth available in individual study was converted to SOC density in the top 100 cm soil using the depth functions developed by Yang et al. (2011) according to the following equations:

$$Y = 1 - \beta^{d} \qquad [3]$$

$$X_{100} = \frac{1-\beta^{100}}{1-\beta^{d_0}} * X_{d0} \qquad [4]$$

where Y represents the cumulative proportion of the SOC density from the soil surface to depth d (cm); β is the relative rate of decrease in the SOC density with soil depth; X_{100} denotes the SOC density in the upper 100 cm; d_0 denotes in the 0-20 cm soil (cm); and X_{d0} is the SOC density of the top 20 cm soil depth.

2.4 Spatial gridded datasets

The gridded datasets included forestland, grassland, and cropland areas, climate factors and soil properties. Areas of cropland, forestland, and grassland were obtained from Global Agro-Ecological Zones (GAEZ, https://gaez.fao.org/) at a resolution at 0.083° × 0.083°. The MAP and MAT were acquired from the Climatic Research Unit Time Series (CRU TS ver. 4.05; https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.05/cruts.2103051243.v4.05/).The spatial SOC, total N, soil clay contents, and soil pH were acquired from the Harmonized World Soil Database ver. 1.2 (https://www.fao.org/soils-portal/data-hub/soil-lassification/worldreference-base/en/). MC and MN data were obtained from this study (Xu et al., 2013). The BD dataset of the whole soil profile was acquired from gridded Global Soil Dataset for use in Earth System Models (GSDE) (http://globalchange.bnu.edu.cn/research/soilw), whose resolution is 30 arc-seconds. All data were resampled at 0.083° resolution using the “raster” R package (https://rspatial.org/raster).

2.5 Application of RF modeling to predict global soil β values

We reconstruct the relationships among multiple factors, cropland, grassland and forestland soil β values by RF algorithm. The developed RF models were used to predict grid-level soil β values for each ecosystem. Prior to constructing the RF

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

model, the optimal parameter values of m_{try} and *ntrees* were determined through the bootstrap sampling method, which was performed with the "e1071" R package. Predictions of soil β values derived by RF and random-effects regression models were evaluated by 10-fold cross-validation. The dataset was divided into 10 subsets of equal size, of which 70% were used for model fitting and RF procedures, then predicted with the fitted models using the remaining 30% of the data. The performance of RF models was evaluated based on the coefficient of determination (R^2) and root mean square error (RMSE) according to those following equations:

$$R^2 = 1 - \frac{\sum_{p=1}^{q}(y_p - \hat{y}_p)^2}{\sum_{p=1}^{q}(y_p - \bar{y})^2} \quad [5]$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{p=1}^{q}(y_p - \hat{y}_p)^2}{q}} \quad [6]$$

where y_p represents an observed value (p = 1, 2, 3, …), $\hat{y}_p$ represents the corresponding predicted value (p = 1, 2, 3, …), $\bar{y}$ represents the mean value of observed values , and q represents the total number of observed values.

2.6 Data management and analyses

One-way analysis of variance at $p < 0.05$ was applied to identify significant differences in soil β values using SPSS ver. 20.0 (SPSS, Inc., Chicago, IL, USA) software. we made a database of peer-reviewed publications with Excel 2010 software (Microsoft Corp., Redmond, WA, USA). Weather data analyses were performed using MATLAB R2017a software (MathWorks Inc., Natick, MA, USA). Weather data were analyzed using MATLAB R2017a (MathWorks, Natick, MA, USA). Excel 2010, R software (ver. 3.5.1; R Development Core Team, Vienna, Austria) and SigmaPlot (ver. 12.5; Systat Software Inc., San Jose, CA, USA) software were used to generate graphs. A publicly available map of China was obtained from the Resource and Environment Data Cloud Platform (http://www.resdc.cn). All map-related operations were implemented using ArcGIS 10.2 software (http:/www.esri.com/en-us/arcgis). All algorithms implemented using the random Forest R package in the R software environment (ver. 3.5.1; R Development Core Team, Vienna, Austria).

3. Results

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

3.1 Soil β values of the three global ecosystems based on field measurements

We analyzed 1221 observations (soil profile: 0–1 m): 758 for cropland, 219 for forestland, and 244 for grassland (Figure 1), we also quantified the magnitudes of β (see Methods). Across all observations, the soil β values ranged from 0.9645 to 0.9831 (5th–95th percentile), with a mean of 0.9756 and median of 0.9766. The average value was 0.9761, 0.9750, and 0.9743 for cropland, forestland, and grassland, respectively. The coefficients of variation (CVs) for the three ecosystems were as follows: forestland (CV: 0.72%) > grassland (CV: 0.71%) > cropland (CV: 0.54%). The significant differences in soil β values among the ecosystems were attributed to the different biological vegetation types (Figure S1).

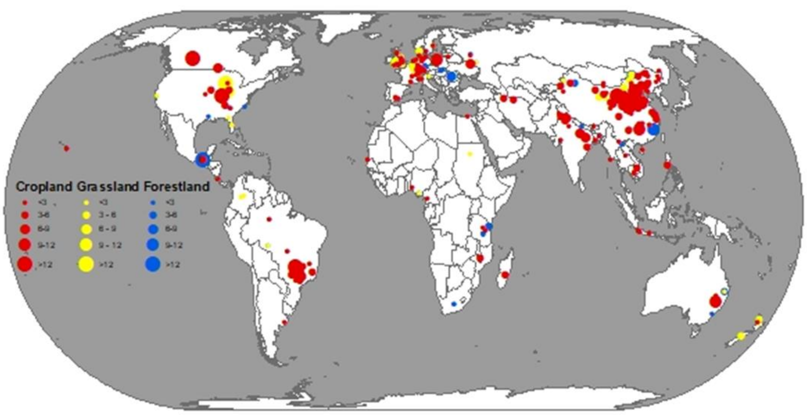

Figure 1. Geographic location of the study sites included in the meta-analysis of the 0–1 m soil profiles. The dot sizes reflect the sample sizes. Red, yellow, and blue dots represent cropland, grassland, and forestland, respectively.

3.2 Impact of soil and climate variables on soil β values

Nonparametric smooth regression was used to determine the direct and indirect relationships between the continuous explanatory variables and soil β values. Among the 13 explanatory variables, SOC, the ratio of SOC to soil total nitrogen (i.e., the C/N ratio), and the mean annual temperature (MAT) had the greatest influence on β values with relative contributions of 35%, 34%, and 28%. A higher MAT corresponded to

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

higher β values, particularly for MAT values greater than 20℃ (Figure 2). The β values decreased with an increase in mean annual precipitation (MAP) up to 1500 mm and increased when the MAP exceeded 1500 mm. These results indicate that higher temperatures and more precipitation promote the rapid decomposition of SOC into CO_2 from its sequestered state.

The effects of SOC, microbial biomass carbon (MC), and microbial biomass nitrogen (MN) on soil β values were strongly significant; the regression fittings of these variables were open downward parabolic, with peaks at about 40 g kg^{-1}, 200 mg kg^{-1}, and 30 mg kg^{-1}, respectively. With increases in the topsoil SOC, MC, and MN, the β values first decreased and then increased. The MC:MN ratio indicated a relatively weak but significant positive effect on β values. The β values decreased with increases in soil total nitrogen (TN) and the C/N ratio, indicating that C in the soil is more likely to be sequestered under high N or a high C/N ratio; the relative rate of decline of the SOC density decreased with increasing depth. A sharp increase was observed at $pH < 6$ or >8, whereas the β value remained stable for pH levels between 6 and 8. Thus, within a reasonable soil pH range, the relative rate of decline in the SOC density with depth tended to be stable. The clay content of the soil had no significant influence on the soil β value.

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

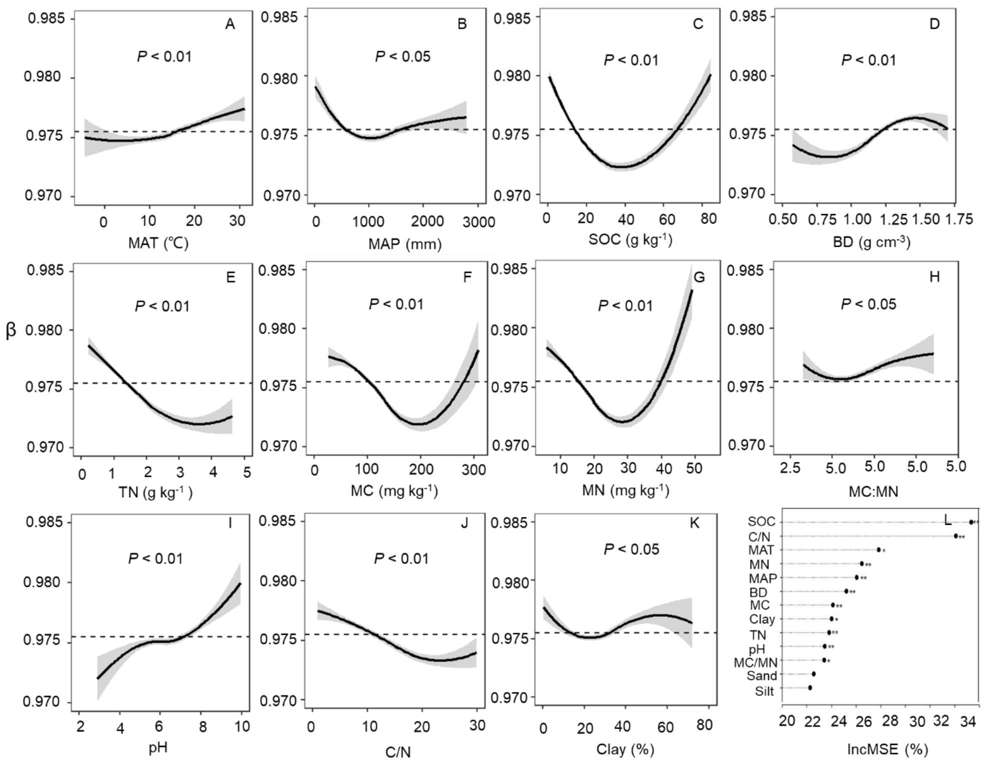

Figure 2. Plots A–K show the variables affecting soil β values. MAT, mean annual temperature; MAP, mean annual precipitation; SOC, soil organic carbon; BD, bulk density; TN, soil total nitrogen; MC, microbial biomass carbon; MN, microbial biomass nitrogen; C/N, soil organic carbon/soil total nitrogen; Clay, soil clay content. Shaded bands indicate 95% confidence intervals, and the dashed lines represent the average soil β values. Relative contributions of the factors to soil β values (L).

3.3 Performance of the random forest regression model

We developed an RF regression model using machine learning techniques to determine grid-level soil β values on a global scale. The model included 11 significant factors (SOC, C/N, MAT, MN, MAP, BD, MC, Clay, TN, pH, MC:MN), as well as the corresponding high-spatial-resolution raster datasets (Figures S2–S4). The model performed well, with an adjusted coefficient of determination (R^2) of 0.80, 0.78, and 0.86 for cropland, grassland, and forestland, respectively (Figure 3). The predictions

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

and measurements of all samples were also distributed close to the 1:1 line. These validations suggest that the trained RF model is capable of capturing and predicting the spatial pattern of the soil β value on a global scale.

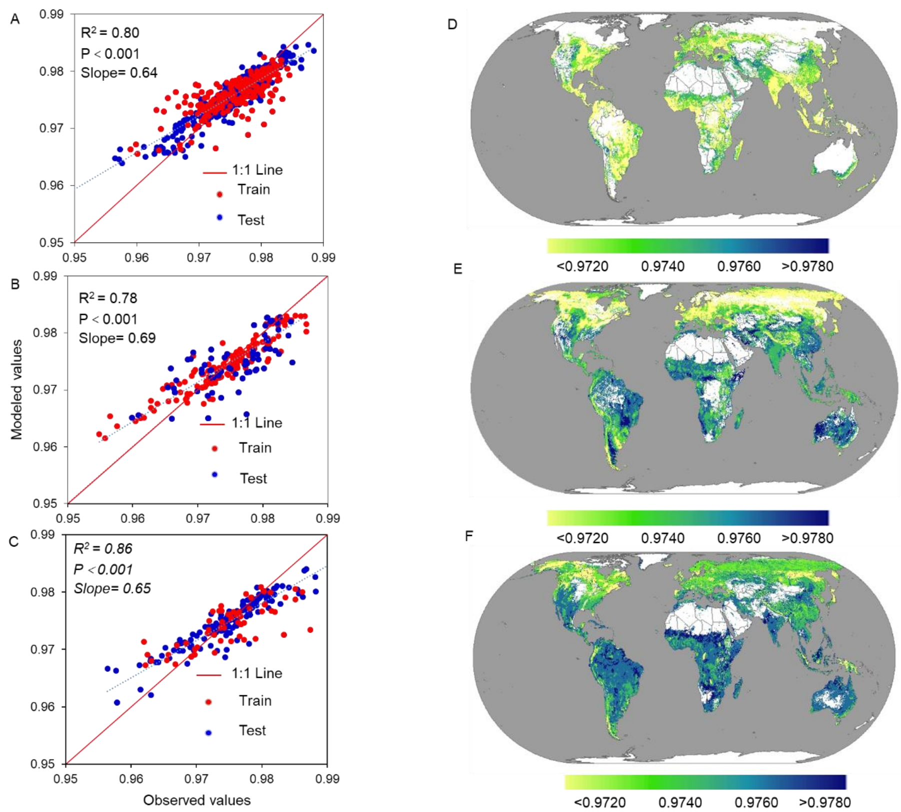

Figure 3. Grid-level maps showing the predicted global soil β values. Plots A–C reflect the performance of the random forest model as evaluated by the correlation between the observed and predicted responses of soil β values. Plots D–F represent the spatial variability of soil β values in cropland, grassland, and forestland, respectively.

3.4 Mapping the global grid-level soil β value

We predicted the global soil β value using the RF model for 4,057,524 integrated

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

grid-level, high-spatial-resolution soil and climate raster datasets (cropland, *n* = 832,827; forestland, *n* = 1,695,053; and grassland, *n* = 1,529,644). The average value was 0.9727, 0.9739, and 0.9751 for cropland, grassland, and forestland, respectively, with CVs of 0.2%, 4.4%, and 3.8%. More than 95% of the grids were less than that (β = 0.9786) reported by the reference (Esteban G. Jobb ágy. and Jackson., 2000). The results of the predicted soil β indicate that the relative rate of decline of SOC stocks was highest for forestland, followed by grassland and cropland.

There was extensive geographic variability in soil β values according to land use. In central North America, cropland, grassland and forestland all had high β values (Figure 3). The large β values for cropland were distributed in Sub-Saharan Africa, central North America, and southern Oceania. The large β values for grassland were distributed mainly in eastern and southern South America and Oceania. For forestland, the large β values were mainly distributed in northern South America, central and southern Africa, Oceania (except for the central region), and northeastern Africa. The low values exhibited similar spatial patterns among land uses and were found mainly in northern and western regions of Europe and in northern and eastern regions of North America.

3.5 Spatial variability of the soil organic carbon (SOC) density in subsoil (20–100 cm soil layer)

The estimated values for the global average SOC density of cropland, grassland, and forestland were 63.8, 83.3, and 100.4 Mg ha^{-1}, respectively, for the 20–100 cm layer (Table S1), with considerable spatial variation on the global scale (Figure 4). The larger the soil β value, the more rapidly the SOC density decreased with an increase in soil depth. Spatially, there was geographic variability in the density depending on ecosystems. The higher values exhibited similar spatial patterns in each ecosystems type and were distributed mainly in northern and western Europe and northern and eastern North America. The highest SOC density and microbial C/N ratios were found at high latitudes in tundra and boreal forests, probably due to the higher levels of organic matter in soils, greater fungal abundance, and lower nutrient availability in cold biomes (Gao et al., 2022).

For cropland, the lower values were distributed in eastern and southwestern Asia,

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

Sub-Saharan Africa, southern Africa, central North America, and southern Oceania. For grassland, the lower values were mainly distributed in eastern and southwestern Asia, eastern, and southern South America, and Oceania. For forestland, the lower values were mainly distributed in northern South America, central, and southern Africa, the central most region of Oceania, and northeastern Africa. The spatial variation in SOC density at multiple standardized depths (20–40, 40–60, 60–80, and 80–100 cm) was also estimated (Figures S5–S7), which exhibited a decreasing trend with increasing depth. The global subsoil SOC stock was estimated to be 912 Pg C, being 67, 200, and 644 Pg C in cropland, grassland, and forestland (Table 1). Subsoil contains more SOC stock; the subsoils of cropland, grassland, and forestland stored 9, 30, and 125 Pg (Table 1) more than the topsoil, respectively. In addition, soil at depths of 20–100 cm beneath the surface contained on average 54% of the topsoil at 0–100 cm.

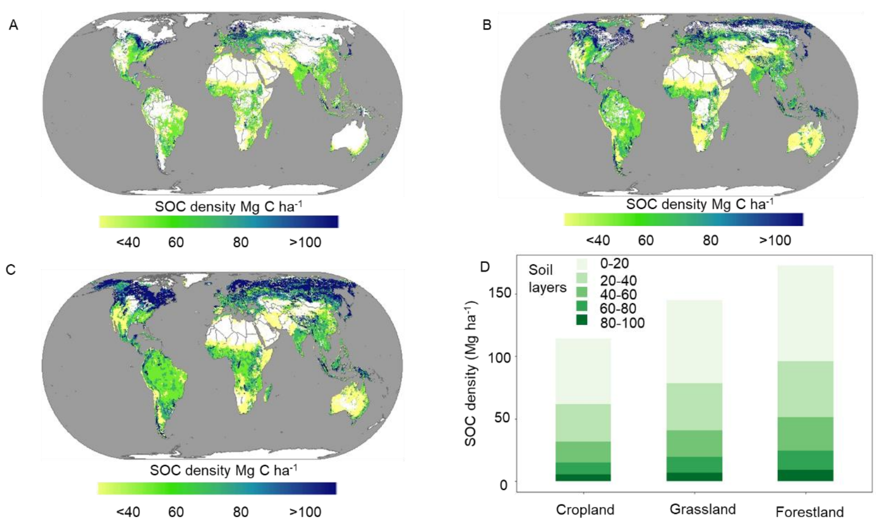

Figure 4. Grid-level maps showing the predicted global subsoil SOC density for the 20–100 cm soil layer. A–C represents cropland, grassland, and forestland, respectively. D shows the SOC density in soil profiles of cropland, grassland, and forestland.

4. Discussion

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

Open Access Earth System Science Data Discussions

4.1 Comparison of high-resolution SOC dynamics

Global SOC stock estimations reported in the literature vary considerably. For SOC stock, the estimated cropland, grassland and forestland (Table 1) were very close to the previous studies (Liu et al., 2021; Conant, 2010; Dixon et al., 1994). It indicated that our method is feasible and the estimation is relatively correct. The subsoil SOC stock of all land for the 0–100 cm soil layer (Table 1), which was slightly lower than the result of that (Sanderman et al., 2017) but higher compared to the commonly used range of 1462–1548 Pg C (Batjes, 1996) and other research results (Scharlemann et al., 2014; Roland Hiederer. and K öchy., 2011; Georgiou et al., 2022). The result of that (Sanderman et al., 2017) may be overestimated, mainly because of the training dataset used to build spatial predictions models was not ideal (R^2=0.54) for testing the hypotheses. Overall, we believe that our value is not an overestimate, as previous estimates (Batjes, 1996) used a database containing very few soil profiles from North America, Oceania, or the north temperate regions (Scharlemann et al., 2014)

We found that the subsoil contains an average of 54% of the top 0–100 cm soil's SOC stock, which is consistent with the percentages cited in previous works (47–55%) (Lal, 2018; Balesdent et al., 2018). Subsoil contains more SOC stock, which has greater potential for C sequestration. Our estimated SOC density (Table S1) for cropland was slightly higher than that reported in other study (Liu et al., 2021) , and lower than that of tropical cropland (Reichenbach et al., 2023). For forestland, it was 180.6 Mg ha^{-1} overall, consistent with that (Dixon et al., 1994) but much lower than that of mangroves and tropical forestland (Atwood et al., 2017; Reichenbach et al., 2023). For grassland, it was 153.7 Mg ha^{-1} overall, much higher than that of (Conant et al., 2017). Finally, globally, it was 150.9 Mg ha^{-1} overall, much higher than that of the research (Roland Hiederer. and K öchy., 2011)

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

Table 1. Comparisons of the estimated SOC density with other studies

	Global area (10^9 ha)	Topsoil (Pg) 0–30 (0–20) (cm)	Subsoil (Pg) 30–100 (20–100) (cm)	Total (Pg) 0–100 (cm)	References
Cropland		58	69	127	(Liu et al., 2021)
Cropland	1.20	58	67	125	This study
Forestland	4.1	359	787	1146	(Dixon et al., 1994)
Forestland	5.64	519	644	1164	This study
Grassland				343	(Conant, 2010)
Grassland	2.59	170	200	370	This study
All land		684–724	778–824	1462–1548	(Batjes, 1996)
All land		699	718	1417	(Roland Hiederer. and Köchy., 2011)
All land		699	716	1416	(Scharlemann et al., 2014)
All land		863	961	1824	(Sanderman et al., 2017)
All land		748	912	1659	This study

SOC: soil organic carbon.

4.2 Factors affecting soil β

Climatic factors and soil properties had significant effects on soil β values. MAT was significantly positively correlated with soil β; specifically, the higher the MAT, the faster the SOC density decreased with depth. In agreement with our result, SOC stocks declines strongly with MAT by analyzing >9,000 soil profiles (Hartley et al., 2021). The change in SOC stock was nonlinear and negative with respect to MAT, high rates of SOC decomposition occur with high temperatures when MAT exceeded 19 ℃ (Zhao et al., 2013). In the current study, MAP had a significant effect on the SOC density, with a threshold of 1,500 mm. Above the threshold, SOC may decompose; below the threshold, it tended to remain sequestered. In wetter climates where the precipitation exceeds evapotranspiration, there is a strong relationship between mineral-associated SOC concentration and persistence, due to the humid soil environments that favor greater root growth and abundance (Heckman et al., 2023).

Our results highlight the important role of edaphic properties in explaining variation in mean soil β values, as opposed to climate alone (Figure 2). When the C/N ratio is high, more SOC migrates downward; however, the SOC content decreases rapidly with depth. Under a soil C/N ratio > 15, warming significantly enhances the development of root biomass (Bai et al., 2023), this could induce a corresponding SOC accumulation, such that the soil β values would trend downward. Our results showed that for near-neutral pH soils, the β values did not significantly change; thus, in this case, there is a greater potential for soil C storage through increased microbial growth efficiency and greater channeling of substrates into biomass synthesis. By contrast, in acidic soils, microbial growth is a bigger constraint on the decomposition rate, leading to large losses of carbon (Malik et al., 2018). Soil pH had non-linear relationships with microorganisms, tends to be neutral, and the abundance of microorganisms is higher (Patoine et al., 2022). Microbial necromass was a major source for SOC formation in global ecosystems (Wang et al., 2021a).

The effects of MC, MN, and SOC on soil β values exhibited the same trend. MC had positive relationships with the SOC content across the large spatial scale, because of microbes should be considered not only as a controlling factor of the consumption of SOC, but also as an influencing factor of the production of SOC (Tao et al., 2023). In the current study, MC and MN concentrations were most closely linked to SOC, whereas climatic factors were most important for stoichiometry in microbial biomass ratios. Evidence from China shows that microbial residues contribute a larger proportion of SOC in subsoils than in topsoil (Wen et al., 2023). TN content, labile and recalcitrant C components, and soil water content contributed the most to SOC sequestration, which was attributed to differences in plant litter, root biomass input, and hydrological conditions (Xia et al., 2021)

4.3 Challenges and opportunities: Deep soil SOC sequestration

More and more studies have shown about the necessity to better understand subsoil SOC dynamics. Biotic controls on SOC cycling become weaker as mineral controls predominate with depth (Hicks Pries et al., 2023). The topsoil is rich in carbohydrates and lignin, while the subsoil is rich in protein and lipids, the decrease rate of the ratio of the microbially derived C to plant-derived C with SOM content was 23%–30% slower in the subsoil than in the topsoil (Huang et al., 2023). Warming stimulates microbes metabolic activities for structurally complex organic carbon, resulting Large loss of subsoil polymeric SOC than topsoil (Zosso et al., 2023). However, long-term experiments may not be long enough to quantify SOC dynamics in subsoil, large-

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

scale research methods and machine learning are particularly important and necessary. Based on measured soil profile data and environmental variables, Wang et al. combined with machine learning methods to assess SOC storage and spatial distribution of subsoil in frozen soil areas in the third pole region (Wang et al., 2021b). The process of studying deep soil organic carbon is complex, the experiments manipulate are difficult and time-consuming, which leads to a small amount of research data, which lead model-derived predictions contain large uncertainties. To avoid under- or overestimation of the SOC stocks of an ecosystem, it is important to consider the subsoil when formulating sequestration policies for the whole soil profile (Button et al., 2022), as the “4 per 1000” approach for the top 30 to 40 cm soil layer provides an incomplete representation of the soil profile (Rumpel et al., 2018). It may be essential to sample the soil deeper (e.g. 0–100cm) and incorporate deep soils into future manipulations, measurements and models.

In addition, researchers had quantified the contribution of optimizing crop redistribution and improved management, and topsoil carbon sequestration in offsetting anthropogenic GHG emissions and climate change (Wang et al., 2022b; Rodrigues et al., 2021; Yulong Yin et al., 2023), the ability and consequence of subsoil SOC sequestration of crop management remains to be further studied. Conducting global-scale subsoil SOC dynamics studies will fill the knowledge gap to develop appropriate soil C sequestration strategies and policies to help the world cope with climate change and food security (Amelung et al., 2020; Bossio et al., 2020). As such, it is crucial that future research efforts focus on SOC sequestration efficiency with climate change, considering the entire soil profile.

4.4 Strengths and limitations

Our research provides a scientific foundation for further study of SOC dynamics, sequestration, and emissions reduction across soil profiles, and have some implications for meeting Sustainable Development Goals (SDGs), especially SDG2 Zero hunger, SDG13 Climate action, and SDG15 Life on land (https://www.undp.org/sustainable-development-goals). To the best of our knowledge, this study presents the first global high-resolution maps of the spatial pattern of soil profile SOC density derived from soil β values driven by soil properties and climate. We found that there were great differences in the dynamics of SOC density among different land types, in which forestland showed the highest density followed by grassland and cropland. However, differences in SOC dynamics between the investigated soils was mainly due to the dominant biogeochemical properties of the soil, rather than land use (Reichenbach et al., 2023). Our study considered the effects of multiple environmental variables (climatic factors, soil physicochemical properties), and different ecosystems on subsoil SOC dynamics. The decline in SOC density across the profiles varies greatly with depth in most areas, suggesting that action should be taken to improve soil management in these areas. Our results emphasize the importance of implementing policies that improve the carbon sequestration potential of deep soil, as this may also lead to improved soil fertility and reduced greenhouse gas emissions. In the future, it is necessary to explore the carbon sequestration mechanism and carbon turnover time below the surface layer, so as to better understand and estimate deep SOC stocks.

Some important aspects of SOC stocks were not included in this study. For instance, microbial necromass is an essential factor in SOC accrual (Zhou et al.,2023), however, to date, although included to some extent in meta-analysis studies, reliable global-scale estimations are lacking. Due to difficulties in obtaining management data for grasslands and forestlands, we did not consider possible specific management factors on soil β value estimations. For example, N fertilizer application, irrigation amount, soil tillage practices, and organic carbon inputs (straw retuning, crop residues, and litterfall) may affect SOC vertical movement. Moreover, organic carbon inputs can modify SOC decomposition rates, particularly at deep soil depths (Cardinael et al., 2018). These shortcomings can only be overcome by obtaining and analyzing more detailed data on soil and climate characteristics, and developing more sophisticated modeling methods.

5. Data availability

The data of “global patterns of soil organic carbon dynamics in the 20–100 cm soil profile for different ecosystems: a global meta-analysis” are available at https://doi.org/10.5281/zenodo.10846543 (Wang et al., 2024). The file name is “GE_β.tif”, GE represents global ecosystems, which including cropland(CL), grassland(GL), and forestland(FL). “FL_β.tif” represents the spatial distribution of β

https://doi.org/10.5194/essd-2024-100
Preprint. Discussion started: 15 July 2024

for forestland at 20-100 cm depth. The file name is "GE_d_SOCD.tif", where SOCD represents soil organic carbon density, d represents soil depth, for example, "FL_20-100_SOCD.tif" represents the spatial distribution of SOCD for forestland at 20-100 cm depth.

6. Conclusion

Accurately quantifying the distribution of soil profile SOC stocks is crucial for C sequestration and mitigation. Herein, machine learning was applied to the β model to estimate SOC stocks in 20–100 cm depth soil profiles. The subsoil SOC density values of cropland, grassland, and forestland were estimated to be 63.8, 83.3, and 100.4 Mg ha^{-1}, respectively, and there was extensive geographic variability under different ecosystems. Moreover, the global subsoil SOC stocks of cropland, grassland, and forestland were 67, 200, and 644 Pg C. In summary, the dataset can be used to modify existing Earth system models and improve prediction accuracy, as well as also elucidate global SOC dynamics and variability in spatial patterns in whole soil profiles and provides a reference for decision makers to develop more effective carbon budget management strategies.

Author contributions

The study was completed with cooperation between all authors. ZC and YY conceived and designed the research. HW: conceptualization, investigation, methodology, data curation, visualization, conducted data analysis and wrote original draft. XT: methodology, data curation, visualization, TC: investigation, data curation, conceptualization, investigation. ZC, KH, ZW, HG, QM, YW, YC, MZ contributed to the scientific discussions. ZC and QZ: conceptualization, supervision, funding acquisition.

Competing interests. The authors declare that they have no conflict of interest

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Preprint. Discussion started: 15 July 2024

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