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

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Abstract

Determining the distribution of soil organic carbon (SOC) in subsoil (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 (the relative rate of decrease in the SOC density with soil depth), and SOC dynamics at high resolution for global ecosystems (cropland, grassland, and forestland). First, we quantified the spatial variability characteristics of soil β values, which indicated the rate at which SOC density decreases with soil depth, and driving factors by analyzing 17984 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 62 Mg ha^{-1} (95% CI: 52-73), 70 Mg ha^{-1} (95% CI: 57-83), and 97 Mg ha^{-1} (95% CI: 80-117), respectively. SOC density decreases with increasing depth, ranging from 30 Mg ha^{-1} (95% CI: 26-35) to 5 Mg ha^{-1} (95% CI: 4-7) (at depth intervals of 20-100 cm, in 20 cm increments) for cropland, from 32 Mg ha^{-1} (95% CI: 27-37) to 7 Mg ha^{-1} (95% CI: 5-9) for grassland, and from 40 Mg ha^{-1} (95% CI: 34-46) to 13 Mg ha^{-1} (95% CI: 9-17) for forestland. The global subsoil SOC stock was 803 Pg C (95% CI:661-962) (cropland, grassland, and forestland were 74 Pg C (95% CI:62-88), 181 Pg C (95% CI:148-215), and 547 Pg C (95% CI:451-660)), in which an average of 57% 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 across global ecosystems, 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.14787023 (Wang et al., 2025).

Keyword: Subsoil SOC distribution; Soil profiles; Random Forest; Driving factors; Global ecosystems

1. Introduction

Soil organic carbon (SOC) plays a pivotal role in global C cycling, climate change mitigation, reducing greenhouse gas (GHG) emissions, while simultaneously supporting ecosystem health (Bradford et al., 2016; Lal et al., 2021; Griscom et al., 2017). Subsoil, defined here as the soil layer below 20 cm, contains over half of the global SOC stock (Jobbágy & Jackson, 2000; Poffenbarger et al., 2020; Batjes, 1996). Worldwide, the extensive loss of SOC through agricultural practices such as crop production and grazing has substantially contributed to rising 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 better suited to long-term C sequestration than topsoil. The '4 per 1000' initiative aims to boost SOC storage in agricultural soils by 0.4% annually, offering a potential pathway for mitigate climate change and increase food security (Chabbi et al., 2017). Therefore, we think that soils could act as a large sink for fossil-fuel-derived carbon if subsoil carbon sequestration is promoted, particularly in agricultural and managed lands (Button et al., 2022). Despite the importance of subsoil organic carbon dynamics, we were still poorly understood, especially at large scale (Padarian et al., 2022). This is primarily due to the challenges associated with measuring SOC at greater depths, which is difficult, time-consuming and labor-intensive.

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 primary methods are commonly used to estimate large-scale SOC stocks: 1) area-weighted averaging based on vegetation inventories and soil survey data (Tang et al., 2018). 2) machine-learning based on remote-sensing, land-use, and edaphic data and climatic factors as covariates (Ding et al., 2016). 3) 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. Extrapolating surface SOC measurements from 0–40 cm or 0–50 cm to predict subsoil SOC at greater depths, such as 0–100 cm or 0–200 cm, introduces significant uncertainty, hindering precise estimation of the global subsoil SOC stock (Wang et al., 2023; Ding et al., 2016).

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 (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 17984 soil profiles (0–100 cm) of globally distributed observations from 14535 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 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 CN ratio, 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 soil organic matter (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 1,221 soil profiles were included in this dataset, including 758 for cropland, 219 for forestland, and 244 for grassland. Additionally, an expanded dataset was sourced from the WoSIS Soil Profile Database, contributing 7,636 profiles for cropland, 4,534 for forestland, and 4,593 for grassland. The spatial distribution of these profiles is shown in Figure 1. 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 Calculation of soil attributes from literature-derived database

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 (SOC, TN, Clay, MC, MN, etc.) measured over discrete, often discontinuous depth intervals. In some studies, bulk density data below the 20 cm soil layer were lacking. 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). To calculate SOC content, it is necessary to supplement SOC density with bulk density data. The equations used to calculate SOC at each research site was the following:

$$SOC\ density = SOC * BD * D * (1 - GC/100)/10 \quad [1]$$

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 density (Mg C ha^{-1}). GC (>2 mm) is the gravel content (%).

2.3 Calculation of soil β values from literature-derived database

To enhance the comparability of data from different studies, the corresponding soil β values were calculated using Equation 2, which follows the methodology adopted by Yang et al. (2011). The SOC density in the top 0-100 cm was calculated from the initial depth SOC density using Equation 3, which was developed by Jobbágy & Jackson (2000). The equations are as follows:

$$Y = 1 - \beta^{d} \quad [2]$$

$$X_{100} = \frac{1-\beta^{100}}{1-\beta^{d_0}} * X_{d0} \quad [3]$$

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; A lower β indicates a steeper decline with depth. X_{100} denotes the SOC density within the upper 100 cm; d_0 represents the depth of the 0-20 cm soil layer; (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 and gravel content 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 and gravel content (GC) datasets of the whole soil profile was acquired from Harmonized World Soils Database version 2.0 (HWSD v2.0) (https://gaez.fao.org/pages/hwsd), whose resolution is 1 km. The belowground net primary productivity (BNPP) data were sourced from Xiao et al. (2023). 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 spatial 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 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:

$$R^2 = 1 - \frac{\sum_{p=1}^{q}(y_p - \hat{y}_p)^2}{\sum_{p=1}^{q}(y_p - \bar{y})^2} \qquad [4]$$

$$RMSE = \sqrt{\frac{\sum_{p=1}^{q}(y_p - \hat{y}_p)^2}{q}} \qquad [5]$$

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 Estimating global SOC density and SOC stocks ecosystems across different ecosystems

To reveal the dynamics of SOC with depth, we used the globally predicted β values for cropland, grassland, and forestland ecosystems in Equation 3 to calculate cumulative SOC density at specific depths (e.g., 40, 60, 80, and 100 cm). Based on these cumulative values, the SOC density for each 20 cm interval as calculated by subtracting the cumulative SOC density of the shallower depth from the deeper depth. Subsequently, the total carbon stocks for different ecosystems worldwide were calculated by multiplying the SOC density by the corresponding land area (see Equation 6).

$$SOC\ stocks = SOC\ density * S_{ecosystem} \quad [6]$$

Where $S_{ecosystem}$ is the areas of cropland, grassland or forestland (ha), SOC stocks (Pg C).

2.7 Uncertainty analysis

A Monte Carlo simulation was used to estimate the overall uncertainty in the estimated spatial SOC density. The uncertainty mainly came from be soil β estimation-related parameters and the RF model. Input parameters in the RF model prediction followed independent normal distributions by assuming the grid value as the mean value and its 10 % as the standard deviation. Then, 1,000 random samplings were used to obtain the interval of each grid via Monte Carlo simulations. The sampling value was then used to run the RF model to predict the grid-level soil β with 100 bootstraps to run the RF model. Then we used predicted grid-level soil β to recalculated the distribution of SOC density (SOCD) across different ecosystem. Finally, we calculated the mean along with the 2.5% and 97.5% percentiles to establish the 95% confidence interval of SOC density and SOC stocks.

$$U_i = \frac{CI_i}{x_i} \quad [7]$$

Where x_i is the mean of prediction, CI_i is the confidence interval of x_i, U_i *is the* uncertainty

2.8 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). R software (ver. 3.5.1; R Development Core Team, Vienna, Austria) was 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

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

We analyzed 17,984 globally distributed soil profiles (0–100 cm) from 14,535 sites, including 5,931 cropland, 4,206 grassland, and 4,398 forestland sites (Figure 1) to estimate soil β values, which represent the relative rate of decrease in SOC density with soil depth. This included an additional 8,394 profiles for cropland, 4,753 for forestland, and 4,837 for grassland, obtained from the literature and the WoSIS Soil Profile Database. The average soil β values across all observations were 0.9731 for cropland, 0.9772 for grassland, and 0.9790 for forestland (Figure S1), with significant differences observed among the ecosystems.

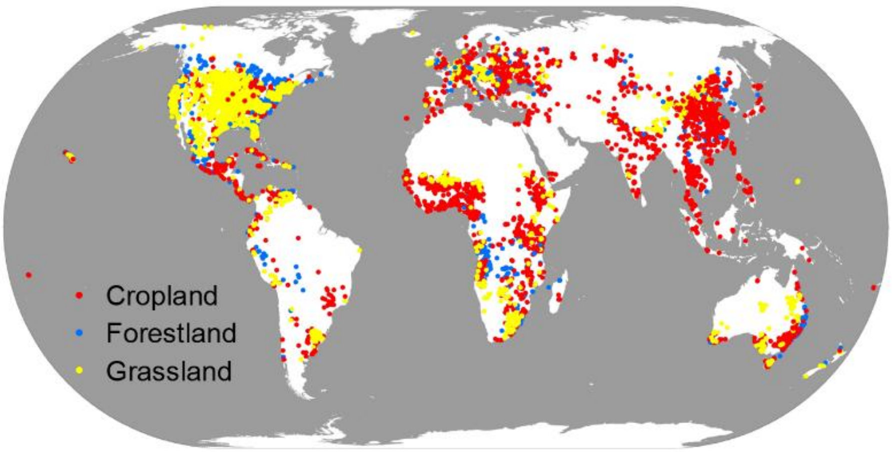

Figure 1. Geographic location of the study sites included in the meta-analysis of the 0–100 cm soil profiles. Red, yellow, and blue dots represent cropland, grassland, and forestland, respectively.

3.2 Impact of soil and climate variables on soil β values

The soil β value is significantly influenced by the combined effects of various climatic, biological, and soil factors. MAT, MAP and BNPP were the most influential driver of β values (Figure S2). Higher MAT promoted increases in soil β values and higher MAP promoted decreases; however, when the MAT was about 20°C and MAP was about

1000 mm, the soil β values growth and decline rate was substantially reduced (Figures 2A and B). BNPP demonstrated a nonlinear relationship: β values decreased with increasing BNPP levels, when BNPP was below 1.5 Mg ha^{-1} yr^{-1} and exceed 2 Mg ha^{-1} yr^{-1}, the soil β values decreased sharply (Figure 2C). The regression between CN, MC, MN, TN, pH and soil β values was parabolic. When CN >10, MC >100 mg/kg, MN >20 mg/kg, TN >3 g/kg and pH <6, the soil β value promoted decreased (Figures D, E, F, G and H). β values remained relatively stable across most clay percentages but showed a decrease when clay content exceeded 30% (Figure 2I). Through comparison and analysis, we ultimately selected 9 significant factors (BNPP, pH, Clay, MAT, MAP, TN, MN, MC, CN) for modeling based on their importance and explanatory power (Figure S2).

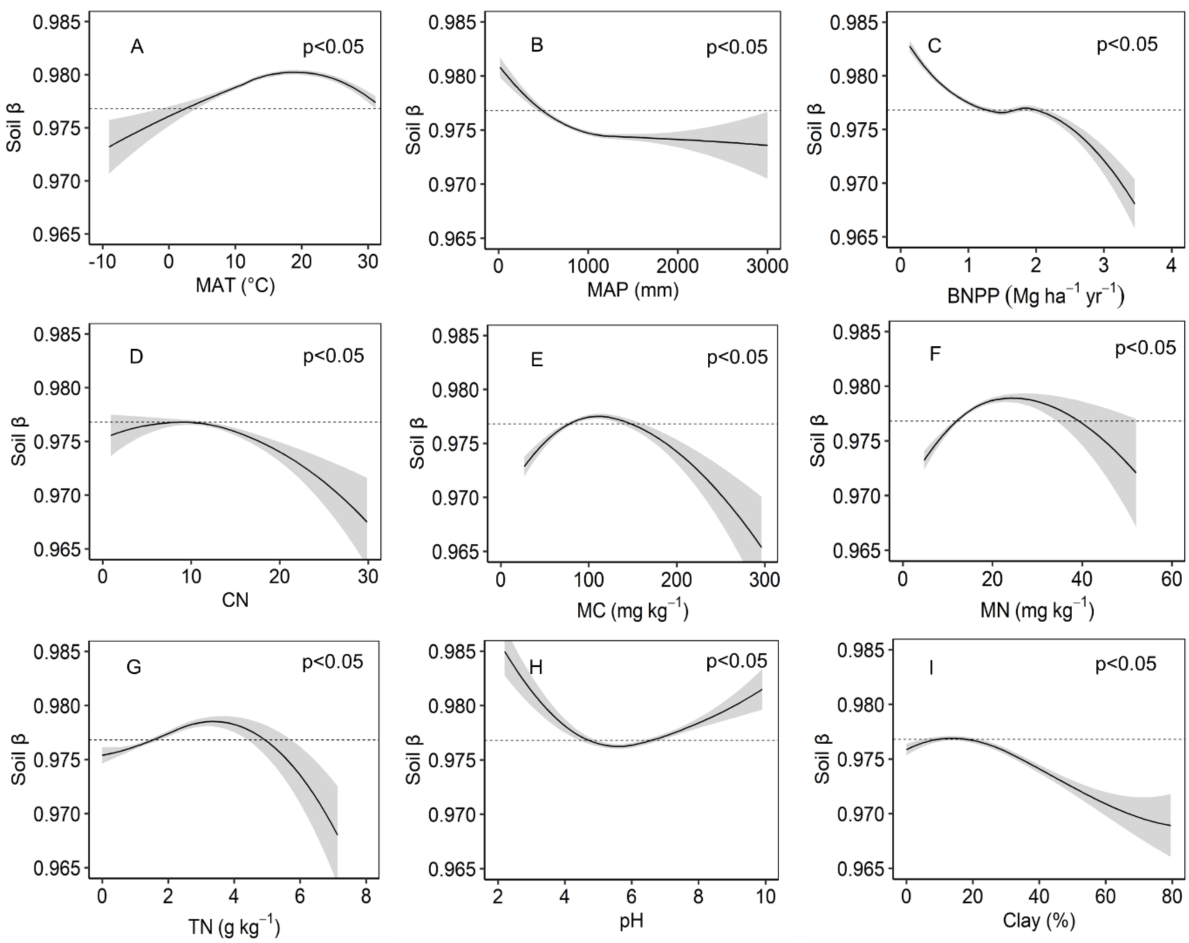

Figure 2. Plots A–I show the variables affecting soil β values. MAT, mean annual temperature; MAP, mean annual precipitation; BNPP, belowground net primary productivity; CN, the ratio of SOC to TN; MC, microbial biomass carbon; MN, microbial biomass nitrogen; TN, soil total nitrogen; pH, soil pH; Clay, clay content.

Shaded bands indicate 95% confidence intervals, and the dashed lines represent the average soil β values.

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 9 significant factors (BNPP, pH, Clay, MAT, MAP, TN, MN, MC, CN), as well as the corresponding high-spatial-resolution raster datasets (Figures S3–S5). The model performed well, with an adjusted coefficient of determination (R^2) of 0.85, 0.86, and 0.90 for cropland, grassland, and forestland, respectively, and the RMSE values are all less than 0.01 (Figure 3A, B and C). The predictions 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.

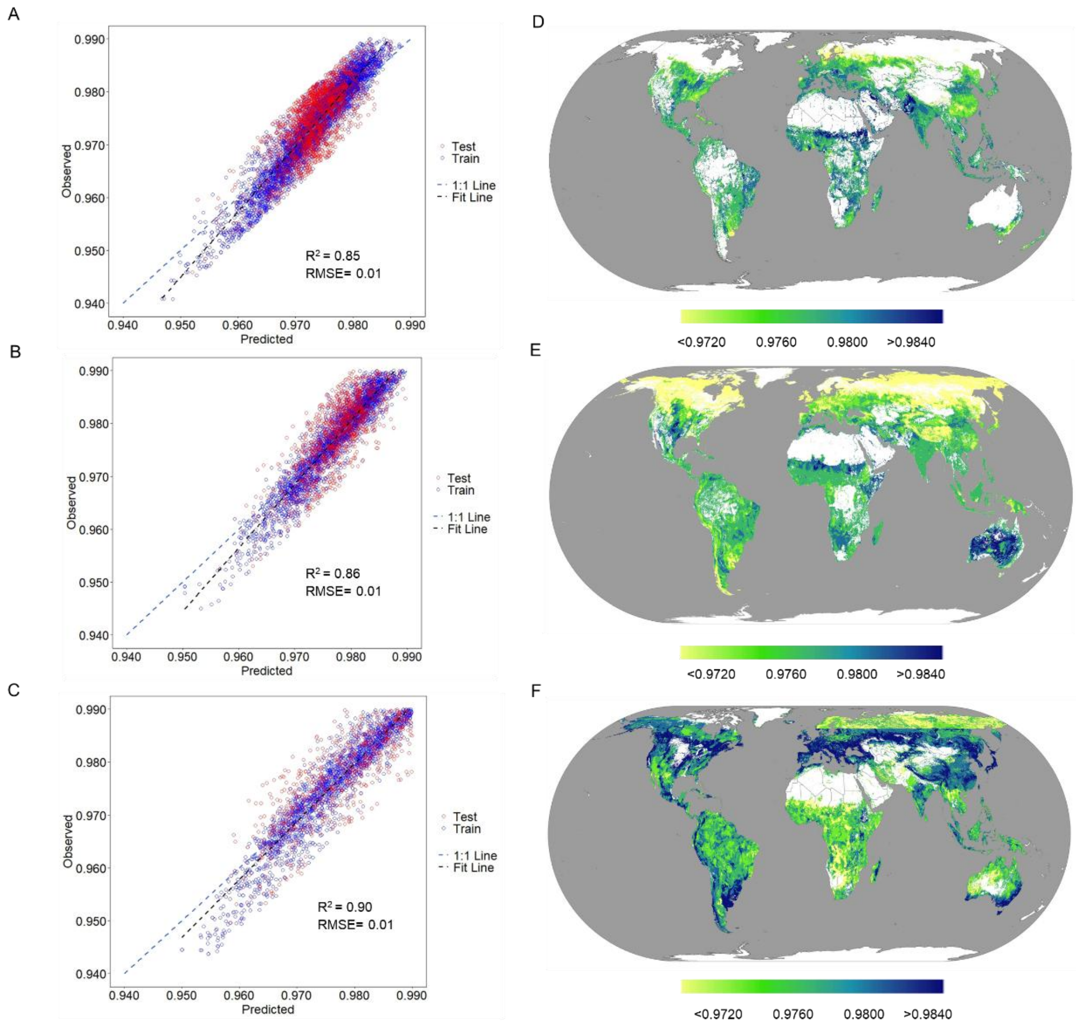

Figure 3. Grid-level maps showing the predicted global soil β values. Plots A–C reflect the performance of the random forest model as evaluated by the correlation between the observed and predicted responses of soil β values. Plots D–F illustrate the predicted spatial variability of predicted soil β 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 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 values were 0.9716 (95% CI: 0.9692-0.9738), 0.9762 (95% CI: 0.9656-0.9831), and 0.9792 (95% CI: 0.9687-0.9877) for cropland, grassland, and forestland, respectively, with CVs of 4.73%, 1.79%, and 1.94% (Figure 3D, E and F). The (β = 0.9786) reported by Jobbágy & Jackson (2000) falls within the 95% confidence intervals of grassland and forestland, but not cropland. The results of the predicted soil β indicate that the steeper decline in SOC stocks with increasing depth was greatest for cropland, followed by grassland and forestland.

The spatial distribution of soil β values across cropland, grassland, and forest ecosystems reveals both commonalities and notable differences. High β values are predominantly distributed in tropical and subtropical regions, including parts of South America, Oceania, and sub-Saharan Africa, whereas low β values are mainly concentrated in temperate regions, particularly in northern and western Europe and eastern and northern North America. Notably, the distribution of high β values varies across ecosystems. High β values are primarily observed in sub-Saharan Africa, central North America, and southern Oceania in cropland (Figure 3D). For grassland, mainly concentrated in southeastern South America, southern Africa, and Oceania (Figure 3E). Forestland exhibited the most extensive distribution of high β values, spanning southern South America, central and southern Africa, and Oceania (excluding the central region) (Figure 3F).

Low β values show slight variation: cropland exhibits a more confined range of low values, mainly in northwestern Europe, while grassland and forestland display broader areas of low values, particularly across eastern and northern North America. These patterns underscore the geographic variability of soil β values, reflecting the complex interplay between environmental and ecological factors shaping these spatial distributions.

3.5 Spatial variability of the SOC density in subsoil

The estimated values for the global average SOC density of cropland, grassland, and forestland 62 Mg ha^{-1} (95% CI:52-73), 70 Mg ha^{-1} (95% CI:57-83), and 97 Mg ha^{-1} (95% CI:80-117), 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 SOC 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.

For cropland, lower SOC density values were predominantly distributed in Eastern and Southwestern Asia, Sub-Saharan Africa, Southern Africa, Central North America, and Southern Oceania. In contrast, higher SOC density values were mainly concentrated in temperate regions, such as parts of Europe, Northern North America, and some regions in South America (Figure 4A). For grassland, SOC density showed significant spatial variation, with lower values primarily distributed in Eastern and Southwestern Asia, Eastern and Southern South America, and Oceania. In contrast, higher values were concentrated in temperate regions, such as Northern and Western Europe, Northern North America (Figure 4B). For forestland, SOC density displayed clear spatial heterogeneity. Lower values were primarily distributed in Northern South America, Central and Southern Africa, Northeastern Africa, and the Central region of Oceania, areas often characterized by tropical or subtropical climates with rapid organic matter decomposition rates (Figure 4C). In contrast, higher values were predominantly found in temperate and boreal forest regions, including northern and Western Europe, Northern North America, and parts of Eastern Asia. The spatial variation in SOC density at multiple depths (20–40, 40–60, 60–80, and 80–100 cm) was also estimated (Figures S6–S8), which exhibited a decreasing trend with increasing depth.

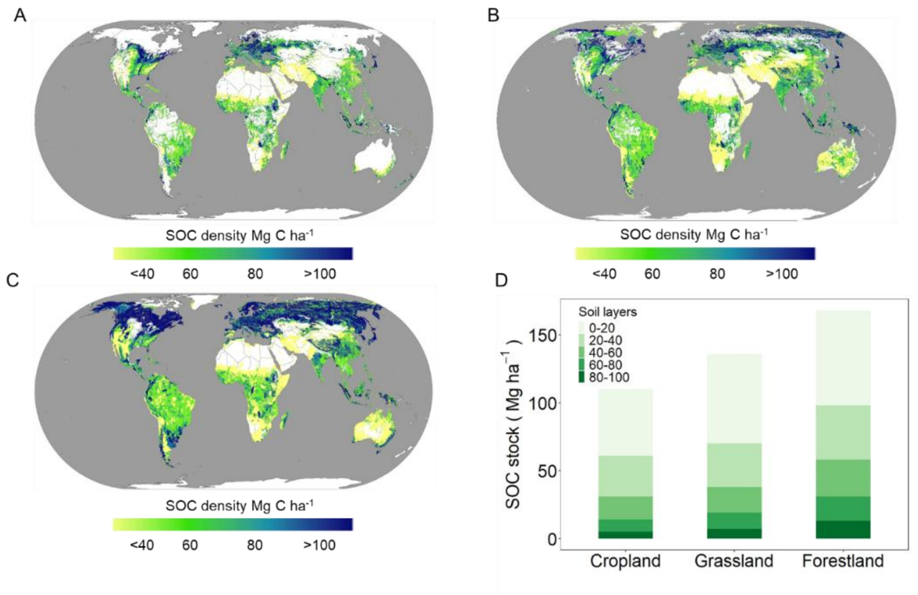

Figure 4. Grid-level maps showing the predicted global subsoil SOC density for the 20–100 cm soil layer. A–C represents cropland, grassland, and forestland, respectively. D shows the SOC density in soil profiles of cropland, grassland, and forestland.

3.6 Uncertainty analysis of subsoil SOC density across ecosystems

Overall, regions with high uncertainty are concentrated in tropical and subtropical areas, such as sub-Saharan Africa, Southeast Asia, the Amazon region of South America, and parts of Oceania. In contrast, regions with low uncertainty are primarily located in temperate and boreal areas, including northern Europe, Northern North America, and Northern Asia. Among them, forestland exhibits slightly higher SOC density prediction uncertainty (38%) compared to grassland (37%) and cropland (34%) (Figure 5).

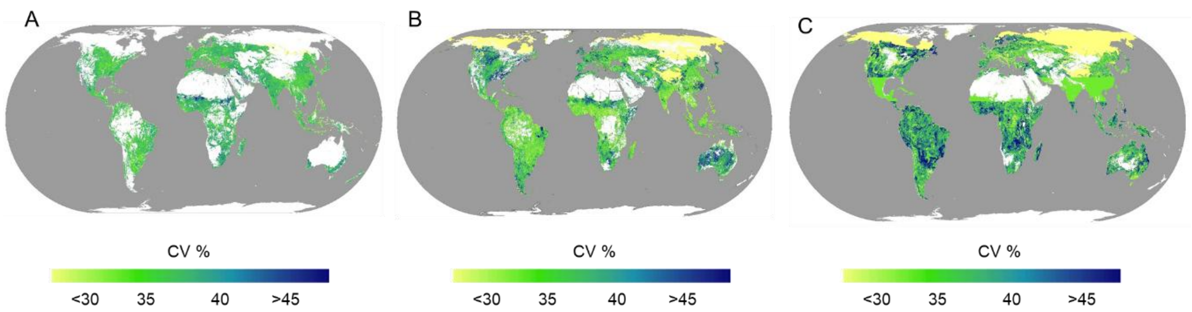

Figure 5. Grid-level maps illustrating the uncertainty of predicted global subsoil SOC density. A–C represents cropland, grassland, and forestland, respectively.

4. Discussion

4.1 Comparison of high-resolution SOC dynamics

Global estimations of SOC stock reported in the literature exhibit considerable variation. The estimated SOC stocks for cropland, grassland, and forestland (Table 1) in our study align closely with previous studies (Liu et al., 2021; Conant, 2010; Dixon et al., 1994). The SOC stock of all land in the 0–100 cm soil layer was 1418 Pg (95% CI:1276-1577), which was slightly lower than the estimate reported by Sanderman et al. (2017) and Batjes. (1996). However, we believe that our estimation was not underestimated. This discrepancy may be due to the overestimation in (Sanderman et al., 2017), which could be attributed to the suboptimal quality of the training dataset used in their spatial prediction models (R^2=0.54). Earlier assessments (Batjes, 1996) relied on databases that included very few soil profiles from regions such as North America, Oceania, or the northern temperate zones. The subsoil SOC stock of all land was 803 Pg (95% CI:661-962), which was consistent with other research results (Scharlemann et al., 2014; Roland Hiederer. and Köchy., 2011; Zhou et al, 2024). We found that the subsoil contains 57% of total SOC stock in the top 0-1 m soil layer, which is consistent with the percentages cited in previous works (47–55%) (Lal, 2018; Balesdent et al., 2018). Overall, this demonstrates the feasibility and accuracy of our methodology, with the estimations proving to be relatively accurate

Similar to the findings of Tao et al. (2023) our study reveals a global SOC density pattern with lower values at low latitudes and higher values at high latitudes. The vertical migration of organic matter is notably more pronounced in northern permafrost regions compared to other areas. For cropland, consistent with the estimates by Wu et al. (2024) the spatial variation in relative SOC density across China shows higher carbon densities in the Northeast Plain, the Yangtze River Basin, and the southeastern hills, while lower values are observed in the arid regions of Northwest China (e.g., the Taklamakan Desert) and the North China Plain. This pattern aligns well with the trends identified in our study. The FAO report "Global Assessment of Grassland Soil Carbon: Current Stocks and Sequestration Potential" aligns with our findings, highlighting high grassland carbon stocks in central China, Northern Russia, Northern Asia, Southeastern South America, and Central North America. However, our study also identifies Europe as having significant carbon stocks. This is mainly because temperate climate, particularly in Northern and Western Europe, is humid and mild, providing favorable conditions for the formation and accumulation of soil organic matter. Unlike croplands and grasslands, forestlands are long-lasting vegetation types, with SOC strongly shaped by local environmental conditions. Zhang et al. (2024) predicted forest SOC stocks across climatic zones and soil types, showing higher stocks in Europe, Russia, and Canada. Mediterranean and temperate regions also have higher SOC than tropical/subtropical regions, consistent with our findings, though their study only considers surface soil.

Additionally, we observed higher SOC density in boreal forests and tundra regions, showing spatial variability consistent with the spatial variation in carbon turnover times reported in other study (Li et al., 2023), particularly in northern high-latitude permafrost and tundra areas. This suggests that in low-temperature environments, longer soil carbon turnover times, and lower microbial activity reduce the decomposition rate of soil organic matter, allowing more SOC to accumulate. 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).

Our estimated SOC density at 111 Mg ha^{-1} (95% CI:101-122) for cropland (Table S1) was higher than that reported in other study (Liu et al., 2021), and lower than that of tropical cropland (Reichenbach et al., 2023). For forestland, the SOC stock was estimated at 177 Mg ha^{-1} (95% CI: 150–187) for the 0–100 cm soil layer (overall), consistent with the estimate reported by Dixon et al. (1994), but significantly lower than those observed in mangroves and tropical forestland (Atwood et al., 2017; Reichenbach et al., 2023). For grassland, it was 132 Mg ha^{-1} (95% CI:119-145) overall, much higher than that of (Conant et al., 2017). Finally, on a global scale, the SOC density of all land for the 0–100 cm soil layer was estimated at 136 Mg ha^{-1} (95% CI: 123–151), which is significantly higher than the estimate reported by Hiederer & Köchy (2011).

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

	Global area (10^9 ha)	Topsoil (Pg) 0–20/30 (cm)	Subsoil (Pg) 20/30–100 (cm)	Total (Pg) 0–100 (cm)	References
Cropland		58	69	127	Liu et al., 2021
Cropland	1.20	59	74 (95% CI:62-88)	133 (95% CI:121-146)	This study
Forestland	4.10	359	787	1146	Dixon et al., 1994
Forestland	5.64	395	547(95% CI:451-660)	942 (95% CI:846-1055)	This study
Grassland				343	Conant, 2010
Grassland	2.59	161	181 (95% CI:148-215)	342 (95% CI:308-376)	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				1360	Zhou et al, et al., 2024
All land		615	803 (95% CI:661-962)	1418 (95% CI:1276-1577)	This study

SOC: soil organic carbon, 95% CI: refers to the confidence interval

4.2 Factors affecting soil β values and spatial variation

MAT was the primary drivers of soil β values, exhibiting a significant positive correlation. Specifically, with the increase of MAT, the β value increases, and the decrease of SOC density with depth becomes smaller (Figure 2A). This shows that the higher the β value, the relatively lower the proportion of the SOC storage in the soil surface (consistent with previous research Hartley et al., 2021; Melillo et al., 2017). It is generally accepted that in cold and wet regions, low soil temperatures and/or anaerobic conditions promote the formation of thick organic horizons and peats, resulting in the storage of large amounts of SOC (Garcia-Palacios et al., 2021). Tropical soils have the lowest SOC persistence, while polar/tundra soils and soils dominated by amorphous minerals exhibit the highest SOC abundance and persistence (von Fromm et al., 2024). These differences indicate that soil β values are high in low-latitude regions, such as tropical rainforest areas, and low in high-latitude regions, such as the tundra, showing a spatial distribution pattern. Climate warming may lead to greater SOC losses in surface soils compared to deeper layers, especially in high-latitude SOC-rich systems (Wang et al., 2022). Experimental results of long-term warming show that soil respiration is sensitive to temperature rise (Xu et al., 2015). It could be driven by the changes in the temperature dependence for microbial process rates (Karhu et al., 2014). As field experiments have shown that warming can modify microbial physiology and resource availability (Poeplau et al., 2017).

We found a significant negative relationship between soil β values and MAP. This suggests that higher precipitation rates are associated with a steeper decrease in SOC density with increasing depth. This is primarily due to the pronounced positive correlation between MAP and the surface SOC density (Liu et al., 2023). 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). And, the higher the intensity of precipitation, the more susceptible deep soil carbon is to loss (Sun et al., 2024).

Additionally, BNPP plays a crucial role in the global land carbon cycle and carbon balance, as it is a major source of SOC. The increase in BNPP, along with greater root exudates and changes in microbial activity, may lead to new carbon accumulation (Zheng et al., 2024), which resulted in a decreasing trend of soil β values.

Our results highlight the important role of edaphic properties in explaining variation in soil β values, not just climate and biological factors (Figure S2). The soil CN ratio and soil clay content both exhibited a similar negative correlation with the β value. A higher soil CN ratio may decelerate the decomposition rate of organic matter, thereby facilitating an increase in SOC content in warm and arid regions (Spohn et al., 2023), such that the soil β values would trend downward. Under soil CN ratio > 15, warming significantly enhances the development of root biomass (Bai et al., 2023), this could induce a corresponding SOC accumulation. Clay fraction of the soil can absorb litter-derived C and microbial-derived C, promoting the accumulation of organic carbon (Hicks Pries et al., 2023).

Our results showed that for near-neutral pH soils, the β values tend to be stable. In acidic soils, significant losses of SOC occur because microbial growth is more severely constrained, leading to a reduced efficiency in the decomposition and utilization of organic matter by microorganisms (Malik et al., 2018). Salinization and alkalization impede plant growth, leading to reduced biomass and lower organic matter input into the soil, causing the soil organic carbon content and organic carbon pool to remain very low (Li et al., 2023). The harsh conditions of saline-alkaline soils hinder microbial survival and activity, reducing their efficiency in decomposing and utilizing organic matter. Soil pH had non-linear relationships with microorganisms, tends to be neutral, and the abundance of microorganisms is higher (Patoine et al., 2022). The combination of these factors explains the higher β values observed under extreme acidic or alkaline conditions. Thus, near-neutral pH soils, may enhance its carbon storage potential by improving microbial growth efficiency and facilitating the channeling of matrix components into biomass synthesis.

The effects of TN, MC, MN on soil β values exhibited the same trend, which initially increased and then decreased. The TN stock in the soil exhibits a significant positive correlation with the SOC stock (Feng et al.,2018), leading to a reduction in the β value in nitrogen-enriched soils. 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). Microbial necromass has been identified as a major contributor to SOC formation across global ecosystems (Wang et al., 2021a). Evidence from China shows that microbial residues contribute a larger proportion of SOC in subsoils than in topsoil (Wen et al., 2023). Therefore, in soil profiles with a high microbial carbon and nitrogen, the soil β value is smaller, indicating a steeper decrease in SOC density with increasing depth.

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 carbon to plant-derived carbon with SOM content was 23%–30% slower in the subsoil than in the topsoil (Huang et al., 2023). Warming stimulates microbial metabolic activity on structurally complex organic carbon, resulting in a larger loss of subsoil polymeric SOC compared to topsoil (Zosso et al., 2023). However, long-term experiments may not be long enough to quantify SOC dynamics in subsoil, large-scale research methods and machine learning are particularly important and necessary. Based on measured soil profile data and environmental variables, Wang et al.(2021b) employed machine learning methods to assess SOC stocks and spatial distribution of subsoil in frozen soil areas in the third pole region. The investigation of deep soil organic carbon is inherently complex and involves intricate and time-intensive methodologies. This complexity results in a paucity of research data, which consequently introduces considerable uncertainties into model-derived predictions. 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. 0–100 cm) 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; 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 establishes a scientific foundation for further study of SOC dynamics, sequestration, and emissions reduction across soil profiles, offering significant insights for achieving Sustainable Development Goals (SDGs), notably SDG2 (Zero Hunger), SDG13 (Climate Action), and SDG15 (Life on Land) (https://www.undp.org/sustainable-development-goals). To our knowledge, this is the first study to present global high-resolution maps illustrating the spatial distribution of SOC density within soil profiles, derived from soil β values informed by soil properties and climatic conditions. We observed pronounced variations in SOC density across ecosystems, with forestland demonstrating the highest densities, followed by grassland and cropland. However, the observed differences in SOC dynamics across these ecosystems were primarily attributed to the dominant biogeochemical properties of the soils (Reichenbach et al., 2023).

In our analysis, we incorporated a broad spectrum of environmental variables, including climatic factors and soil physicochemical properties, to examine subsoil SOC dynamics across different ecosystems. The variability in SOC density decline across soil profiles with depth in most areas underscores the imperative for refined soil management practices. Enhancing carbon sequestration in deeper soil horizons constitutes a promising avenue for future research. For example, increasing plant diversity and crop diversification has reinforced SOC stocks in subsoil, with this benefit amplifying over time (Lange et al., 2023, Xu et al., 2023). Current research has shed light on certain aspects of subsoil SOC sequestration mechanisms and turnover dynamics (Luo et al., 2019; Li et al., 2023). However, implementing targeted policies—such as incorporating organic materials and biochar—remains essential for augmenting the SOC sequestration potential of deeper soils (Button et al., 2022). These strategies could play a critical role in synergistically enhancing soil fertility and mitigating greenhouse gas emissions.

Some important aspects of SOC stocks were not included in this study. For instance, microbial necromass is a key contributor to SOC accumulation (Zhou et al., 2023). Due to difficulties in obtaining management data for grasslands and forestlands, we did not account for potential management-specific factors on soil β value estimations. For example, N fertilizer application, irrigation amount, soil tillage practices, and organic carbon inputs (straw return, crop residues, and litterfall) may influence the vertical movement of SOC. Moreover, organic carbon inputs can alter SOC decomposition rates, particularly in deeper soil layers (Cardinael et al., 2018).

We also acknowledge that soil layers may not always reach 1 meter, especially in mountainous areas. Due to the lack of global soil thickness data, this limitation may lead to overestimation or underestimation of soil carbon storage in some regions. Focusing on 1-meter profiles provides a reasonable approximation of SOC storage across different ecosystems. Although this approach may not fully capture the variation in soil thickness in high mountain areas, it enables us to gain valuable insights into SOC dynamics within the global carbon cycle. Future studies will incorporate more detailed soil thickness data to improve our understanding of SOC distribution.

5. Data availability

The data of "global patterns of soil organic carbon distribution in the 20–100 cm soil profile for different ecosystems: a global meta-analysis" are available at https://doi.org/10.5281/zenodo.14787023 (Wang et al., 2025). The file named "Rawdata.xlsx" contains data sourced from the literature. 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 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 soil profiles at depths of 20–100 cm. The subsoil SOC density values of cropland, grassland, and forestland were estimated to be 62 Mg ha^{-1} (95% CI:52-73), 70 Mg ha^{-1} (95% CI:57-83), and 97 Mg ha^{-1} (95% CI:80-117), respectively, with significant geographic variability across different ecosystems. Additionally, The global subsoil SOC stock was 803 Pg C (95% CI:661-962) (cropland, grassland, and forestland were 74 Pg C (95% CI:62-88), 181 Pg C (95% CI:148-215), and 547 Pg C (95% CI:451-660), in which an average of 57% resided in the top 0–100 cm of the soil profile. This dataset provides a valuable resource for refining existing Earth system models and enhancing prediction accuracy. Furthermore, it offers critical insights into global SOC dynamics and the spatial variability of SOC within entire soil profiles. Our findings also serve as a valuable reference for decision-makers in developing 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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