Global patterns and drivers of soil dissolved organic carbon concentrations

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Abstract

Dissolved organic carbon (DOC) constitutes~~is~~ the most active carbon pool in soils~~, which~~ and plays critical roles in soil carbon cycling, plant productivity, and global climate change. ~~An a~~Accuratel~~e~~y ~~assessment~~ assessing soil DOC ~~of the~~ quantity ~~of DOC in the soil~~ is essential to ~~for the detailed~~ elucidate~~ion of~~ ecosystem functions and services. However,~~Nevertheless~~, ~~the~~ global driving factors and the spatial distribution of soil DOC remain poorly ~~inadequately~~ quantified, largely due to limited~~the scarcity of~~ large-scale data. Here, we compile a comprehensive global database of ~~12807 soil DOC concentrations derived from 975 target papers in the literature was compiled.~~ soil DOC concentrations, encompassing 12,807 observations extracted from 975 scientific publications published between 1984 and 2020. We also record ~~D~~detailed geographic locations, climatic variables~~e~~, and soil properties ~~were also recorded~~ as predictors~~ of soil DOC~~. Machine learning techniques were employed, including 10-fold cross-validation and evaluating model performance by R-squared and root-mean-square error,~~were employed~~ to ~~assess~~ predict the relative importance of various predictors ~~in the determination of~~and the global distribution of soil DOC concentrations~~, which were subsequently extended for their prediction on a global scale~~. ~~The w~~Worldwide soil DOC concentrations ~~spanned a wide range (~~ranged from 0.04 to 7859 mg kg^{-1}~~)~~, averaging 222.78 mg kg^{-1}. The 12 selected predictors, ~~variables (~~including soil properties, month, climate, and ecosystem~~)~~, explained 65 percent~~%~~ of the variance in soil DOC concentrations. Among these predictors, ~~Elevation~~elevation, soil clay, and soil organic carbon were ~~three of~~ the most influential~~important predictors~~. Using these findings, a global map of predicted soil DOC concentrations was produced at a 0.05° by 0.05° resolution. Global soil DOC concentrations generally increased from the equator to the poles~~.~~, and ~~The soil DOC stocks in~~ the topsoil layer (0-30 cm) holded~~amounted to~~ 12.17 Pg of soil DOC, with substantial ~~significant~~ variations ~~observed~~ across ~~different~~ continents. These results ~~are instrumental for~~ inform~~ing~~ed ~~strategies on~~ soil management practices strategies, ecosystem services evaluations, and ~~the mitigation of~~ climate change mitigation efforts. Furthermore, ~~our~~ we envisioned integrating our database ~~can be combined~~ with other carbon pools to advance understanding of~~explore the~~ total soil carbon turnover and to refine ~~constrain~~ Earth system~~carbon~~ models. The dataset is publicly available at https://doi.org/10.6084/m9.figshare.26379898 (Ren and Cai, 2024).

1. **Introduction**

With global changes over the last few decades, terrestrial ecosystems, which serve as the fundamental safeguard for biodiversity and function as a carbon sink~~ on Earth~~, have become~~are becoming~~ increasingly vital in~~toward~~ mitigating global climate warming (Lee et al., 2023). Cumulatively, soil carbon pools constitute the largest carbon reservoirs ~~of~~ in terrestrial ecosystems, containing~~which are~~ three to four times more carbon~~greater~~ than ~~that of~~ the ambient atmospheric carbon pool (Lal, 2004; Zhou et al., 2024a). Even minor fluctuations in soil carbon can ~~have~~ significantly ~~impacts~~ affect on biogeochemical cycles and the global C balance. Dissolved organic carbon (DOC), ~~which~~ composed~~consists~~ of simple organic acids and complex macromolecular substances, is recognized as the most active carbon pool in ~~the~~ soil. Currently, the portion of organic carbon that is water-soluble and ~~can~~ able to pass ~~filter~~ through a 0.45 μm microporous filter membrane is referred to as DOC (Gmach et al., 2019; Guo et al., 2020). Although soil DOC typically accounts for ~~only <~~less than 2% of the soil carbon pool, it provides a substantial source of carbon and energy for soil microorganisms, while playing a key role in soil carbon sequestration, transport, and stabilization mechanisms (Nakhavali et al., 2021; Ren et al., 2024). The lateral transport of DOC is crucial for linking terrestrial and aquatic ecosystems and ~~plays a key role in the~~ for evaluating~~ion of~~ terrestrial carbon budgets (Fichot et al., 2023). Thus, an accurate assessment of soil DOC concentrations is vital, given~~ due to~~ its unique properties~~ and~~, roles, and~~given its~~ broad variability, which~~tions that~~ can span up to three orders of magnitude (Nakhavali et al., 2021; Ren et al., 2024). Despite ~~the~~ significant variations in soil DOC concentrations, their global distribution has not yet been systematically quantified. Bridging this knowledge gap is essential for more accurate~~ly~~ representations of~~depicting~~ the carbon cycle in Earth system models.

~~The s~~Soil DOC concentration depends on the dynamic balance between ~~its~~ sources (e.g., leachates from decomposing plant litter, ~~plant~~ root secretions, and microbial decomposition products) and losses (migration and microbial decomposition). ~~Therefore, a~~Any factor~~s~~ that alters~~affect~~ this ~~dynamic~~ balance ~~would~~ also influences~~ the~~ soil DOC concentrations. Extensive research has shown that ~~demonstrated that the~~ soil DOC concentration is affected by~~the outcome of~~ climate, vegetation type, ~~as well as~~and soil properties ~~(Fichot et al., 2023; Ren et al., 2024; Smreczak & Ukalska-Jaruga, 2021).~~ (Fichot et al., 2023; Ren et al., 2024; Smreczak and Ukalska-Jaruga, 2021), ~~Each~~ each ~~factor~~ playsing a distinct role in shaping ~~soil~~ DOC dynamics. For example, ~~the~~ climate, ~~which is~~often characterized by ~~the~~ annual mean temperature and precipitation, is ~~typically~~ recognized as a primary ~~driving~~ driver

~~factor that influences the~~of soil DOC concentrations (Lønborg et al., 2020). Temperature and precipitation directly influence soil DOC ~~concentrations~~ through effects on~~by affecting~~ microbial ~~activities~~activity, organic matter decomposition rates, ~~its~~ solubility, and mobility, and indirectly shape~~modulate~~ DOC dynamics by influencing~~manipulating~~ vegetation growth and soil structures (Ren et al., 2023). ~~The type of v~~Vegetation type affects~~impacts~~ soil DOC primarily by altering~~concentrations mainly by affecting~~ the ~~input~~ quantity and quality of organic matter inputs (Zhao et al., 2022). Together, climate and vegetation type~~s~~ profoundly affect~~have profound effects on~~ soil biological, chemical, and physical properties, all~~which are~~ closely ~~interconnected~~ with the ~~creation~~ formation and decomposition of soil DOC (Cotrufo and Lavallee, 2022). Some studies have reported large temporal variations in soil DOC concentrations at certain field sites (Ding et al., 2022; Zhao et al., 2022), with significantly higher DOC concentrations in summer and autumn than in winter and spring. Seasonal effects on soil DOC concentrations are closely associated with factors such as precipitation, soil moisture, and substrate availability (Ren et al., 2023). In warmer seasons, soil DOC production can increase due to active organic matter decomposition, driven by higher microbial activity, as well as greater DOC contributions from root exudation during periods of more active plant photosynthesis. Although~~The~~ relationships between soil DOC concentrations and environmental factors have been observed at~~revealed based on~~ local and regional scales~~. However, t~~, the relative importance of ~~environmental~~ these factors at the ~~that predict soil DOC concentrations on a~~ global scale remains unclear.~~is still lacking,~~ This lack of understanding hinders~~which impedes~~ the development of effective strategies for ~~the management of~~ soil carbon management and ~~mitigation of~~ climate change mitigation.

Accurate mapping of ~~the~~ soil DOC is essential for addressing pressing global challenges, including climate warming, food security, and eutrophication in aquatic systems (Guo et al., 2020; Langeveld et al., 2020). To the best of our knowledge, ~~there are~~ few global maps of the spatial distribution of soil DOC exist (Guo et al., 2020; Langeveld et al., 2020). However, these maps ~~have~~ are subject to considerable uncertainties due to ~~the~~ limited data ~~employed~~, restrictive factor selections, and ~~the~~ low interpretation rates. First~~ly~~, the global soil DOC maps produced by Guo et al. (2020) and Langeveld et al. (2020) rely on relatively few observational data points (2890 and 762 pairs, respectively). ~~there~~There is a lack of valid observational data for Africa, South America, Eastern Europe, and Central Asia. Second, when assessing the global distribution of soil DOC concentrations, Guo et al. (2020) and Langeveld et al. (2020) have not considered the impact of seasonal changes, even though soil DOC concentrations can vary substantially with shift of season. Third, topsoil DOC concentrations were treated as constant value by Guo et al. (2020) and Langeveld et al. (2020), overlooking the dynamic nature of soil DOC, which decrease with increasing depth. In reality, soil DOC concentrations are higher in surface soils (0-10 cm) and decline with depth, exhibiting a clear vertical gradient. ~~Secondly~~Finally, ~~Guo~~ Guo et al. (2020) and Langeveld et al. (2020) have explained only about one-third~~31%~~ of the variations in ~~the~~ soil DOC ~~using linear regression equations, while Langeveld Langeveld et al. (2020) explained only 36%~~ by using multivariate linear equations. Recent advancements in~~In contrast to linear regression,~~ machine learning has ~~been~~ enabled researchers to ~~extensively~~ apply~~ied~~ such techniques ~~in research due to~~because of their~~its~~ capacities to automate feature extraction, handle large datasets, and identify~~recognize~~ complex patterns, ultimately ~~which~~ offer~~ings~~ significant advantages in ~~terms of~~ predictive accuracy and adaptive learning.

To advance our knowledge of global soil DOC~~address these challenges~~, we developed a global~~comprehensive~~ database of ~~global~~ soil DOC concentrations, comprising 12,807 samples from 975 published studies. ~~Utilizing~~ Using Random Forest algorithms, we quantified the relative importance of environmental factors~~,~~ and ~~further,~~ predicted ~~the~~ soil DOC concentrations on a global scale. The ~~special~~ specific aims of this study were: (1) to determine~~What are the~~ global patterns of soil DOC concentrations~~?~~, (2) to identify~~What are~~ the primary factors ~~that~~ controlling soil DOC concentrations on a global scale~~? (3)~~, and to estmate ~~How large is~~ total global soil DOC storage~~?~~.

2. Material and method

2.1 Data sources and processing

We searched for publications up to December 2022~~Publication search for this study was performed~~ using Google Scholar (https://scholar.google.com), the Web of Science (http://apps.webofknowledge.com), and the China Knowledge Resource Integrated Database (http://www.cnki.net/) using the following search terms: (dissolved organic carbon OR dissolved organic matter OR "DOC" OR "DOM") ~~AND~~ and soil, up to December 2022. The ~~specific~~ data flow through the selection~~different~~ phases ~~for the selected papers~~ is shown in Fig. S1. To ensure a standardized and ~~bias-~~minimally biased~~ized~~ dataset, we applied the following inclusion criteria ~~were applied:~~. First, we ~~(1)~~ included only ~~D~~ data ~~must be~~ from terrestrial ecosystems ~~(,~~ excluding oceans and rivers) to maintain consistency in environmental factors and ecological interactions~~;~~. Second, we used ~~(2)~~ ~~O~~only ~~the~~ topsoil ~~layer~~ data (0-30 cm) ~~were used~~to ensure data representativeness and quantity. Third, we recorded~~; (3)~~ ~~D~~duplicate results from different articles ~~were recorded~~ only once to avoid overrepresentation of certain research groups or locations.~~;~~

Finally,~~ (4)~~ we included ~~Soils included~~ agricultural soils ~~that were~~ affected by human activities such as~~through~~ tilling and fertilization~~ etc.,~~ but excluded ~~did not cover~~ industrial and urban soils to avoid complexity introduced by industrial and urban settings. We extracted ~~D~~data presented solely in figures ~~were extracted~~ using the digitizer function of Origin 2019~~ software~~. Before extracting the target data, we employed the Isolation Forest method for anomaly detection. The algorithm constructs random binary trees, where anomalies are typically isolated more rapidly, while normal points require more splitting steps.

Based on these criteria, we compiled a total of 12,807 DOC observations ~~of soil DOC were compiled~~ from 975 publications. We also collected~~Additional~~ data on~~included specifics of the~~ experimental sites (longitude, latitude, and altitude), climat~~ic conditions~~e (mean annual temperature [MAT]~~(MAT)~~ and mean annual precipitation [MAP]~~(MAP)~~), biomes (~~e.g.,~~ wetland~~, —~~, forest~~, —~~, shrubland~~, —~~, tundra~~, —~~, grassland~~, —~~, and cropland) and soil ~~physical and chemical~~ properties (~~e.g.,~~ soil organic carbon, texture, and pH) (Table 1). These environmental factors are used as predictors. When ~~those~~ environmental factors were not reported in~~missing within the~~ original publication, the missing data were extracted from ~~the~~ grid datasets according to the geographic coordinates of each observed site (Table S1). We extracted elevation, MAT, and MAP data from WorldClim Version 2 (https://www.worldclim.com/), biome data from NASA's Socioeconomic Data and Applications Center (https://sedac.ciesin.columbia.edu), soil properties from OpenLandMap version 2.0.0 (https://openlandmap.org), and microbial biomass carbon data from the open database of figshare (https://doi.org/10.6084/m9.figshare.19556419). There is a significant linear relationship between the measured values and the corresponding extracted values (Fig. S2). Overall, ~~T~~our~~his~~ study sites spanned a wide range of latitudes (−~~-~~64.81° to 78.85°) and longitudes (−~~-~~159.66° to 175.95°) (Table 1~~).~~), ~~This database~~ encompass~~ed~~ing a large ~~gradient of~~ climate gradient~~regimes,~~ with MAT from −11.16 to 28.00℃ and MAP from 30 to 4200 mm.

2.2 Data standardization

~~In~~ For our database, the DOC concentrations were quantified using a mix of physical and chemical techniques. Physical methods included soil solution collection using lysimeters or ceramic suction. Chemical methods employed various solvents like distilled water, potassium chloride (KCl), or potassium sulfate (K_2SO_4) as described by Li et al. (2018)**.** Over 74.32% of the DOC was determined using chemical techniques, which highlighted their reliability. For consistency, the DOC values derived from physical approaches was converted to chemical method values using the following equation:

$$DOC_{soil} = (DOC_{solution} \times V \times 1000)/W \times [1/(V \times (1-W) \times BD \times 1000000)] \quad (1)$$

where, DOC_{soil} represents soil DOC concentration determined by chemical methods (mg g^{-1}); $DOC_{solution}$ is the concentration measured by physical methods (mg L^{-1}); W denotes the volumetric soil moisture (m^3 m^{-3}); V is the volume of the soil column for solution extraction (m^3); and BD is the soil bulk density (g cm^{-3}). The factor 1000 converts m^3 to L, and 1,000,000 converts m^3 to cm^3 following ~~the protocol~~ established by Guo (Guo, Z. et al., 2020). This standardization allowed for a consistent comparison and analysis of the DOC data across various studies.

2.3 Predictive modeling

The driving factors of soil DOC concentrations were divided into four categories~~ (~~: climate, ecosystem, soil properties, and temporal variation~~observation time)~~. ~~The s~~Soil properties included physical attributes (clay, sand, bulk density, and depth), chemical attributes (SOC, pH), and a biological attributes (microbial biomass carbon) attributes. ~~The~~ Temporal variation~~observation time~~ was represented by month. Climate ~~referred to~~comprised MAT, MAP, and elevation. Ecosystems encompassed wetland, forest, shrubland, tundra, grassland, and cropland. In our predictive models, correlated predictors ~~may~~ could substitute for each other, causing~~such that~~ their importance ~~will~~ to be shared~~,~~ and thus potentially underestimated~~which results in an estimated importance that is less than the true value~~. Consequently, we excluded~~the~~ soil total nitrogen, silt, and the aridity index because ~~were not included as~~ they were correlated with ~~the~~ soil organic carbon, sand, and MAP, respectively (Fig. ~~S2~~S3). Further, we did not include some variables because they were ~~not included due to~~ rarely report in the target papers.

To develop and optimize a predictive model for soil DOC, we employed an array of regression methods~~ was employed~~, which encompassed three linear and four nonlinear approaches (Table S2). The linear~~ regression~~ methods included a least absolute shrinkage and selection operator (LEAPS), elastic net (ENET), and standard linear modeling (LM) to identify the most important predictor variables~~ in a regression model~~, while minimizing ~~the risk of~~ overfitting. The nonlinear ~~regression~~ methods included the random forest (RF) algorithm, boosted tree (BOOSTED), bagged tree (Bagged), and cubist (CUBIST) models. Each model ~~was~~ had ~~equipped with~~ intrinsic feature selection processes, and we~~was~~ fine-tuned them to improve accuracy and control complexity. During ~~the~~ optimization phase, various actions were implemented~~;~~. LEAPS models were educated to accommodate the ~~highest~~ largest number~~count~~ of variables. We applied penalties~~To discipline the models, the penalty~~ for feature condensation (diminishing the role of less impactful variables in the resultant linear formula) ~~varied~~ between 0 and 0.1, incremented by 0.01, to discipline the models. RF ~~models'~~ growth was restricted~~capped~~ at a maximum of 1,000 trees~~,~~

and limited the number of~~model's~~ predictors ~~were restricted~~ to ~~a~~ one-third of the ~~possible~~ maximum possible, ensuring a balance between complexity and manageability. BOOSTED models underwent training with 10 to 100~~a~~ trees, ~~count ranging from ten to a hundred, where~~ each having between 1~~tree had a node range of one~~ to 7 nodes~~seven~~. We~~They~~ incorporated ~~a~~ shrinkage rates of ~~either~~ 0.01 or 0.1, with~~and~~ a maximum tree size of~~limit set to~~ ~~five~~ 5~~, optimizing the models' learning process~~. For CUBIST model, we explored ~~utilized a sequence of~~ neighboring values from 1 to 9 ~~with~~ in increments of 2 and varied~~, alongside~~ community sizes from~~spanning~~ 1 to 100, ~~to~~ refining~~e its~~ predictive accuracy. In every instance, the models were evaluated using Monte Carlo cross-validation~~, which involved~~ with 100 iterations, employing~~of data resampling with~~ ~~an~~a ~~80~~70/~~20~~ 15/15 split between training~~ and~~, validation, and testing sets~~datasets~~ (Fig. 2b and Fig. S6)~~, ensuring an accurate estimation of model uncertainty and safeguarding against over-fitting~~. The root mean square error and R^2 values were calculated to evaluate model accuracy and residual variance, which served as criteria for ranking model performance (Table S2). A 10-fold cross-validation method was used to evaluate model performance. A flowchart for model selection process was shown in Fig. S5.~~The relative RMSE, a measure of the estimation uncertainty for soil DOC, was determined by dividing the error's magnitude by the overall average soil DOC value. The nonlinear models (R^2 = 0.42-0.65; root mean square error (RMSE) = 250-332) outperformed the linear models (R^2 = 0.101-0.108; RMSE = 410-427) (Table S2). The RF model distinguished itself with the lowest RMSE within a standard deviation range, and the model was then selected for subsequent analyses focusing on variable importance (Fig. S3). Consequently, the relative importance of driving the soil DOC and the global map of soil DOC were the averaged values of the RF model results.~~

To evaluate the ~~impacts~~ effects of independent variables on ~~the~~ soil DOC, a variable importance analysis was conducted using permutation variable importance measurements~~ (Fig. 2)~~. This analysis was performed ~~utilizing~~ with the variable importance tool integrated into the R packages for the RF model that exhibited the highest ~~accuracy and~~ predictive quality. In essence, this method assessed prediction errors within the model by calculating mean square errors for each regression tree. The models’~~'~~ variable importance scores assessed the influence of predictor variables on the outcomes. For enhanced comparability of all model inputs, the independent environmental variables were scaled to a 0~~ to~~ –100% range to~~,~~ facilitate comparisons of~~reflecting~~ their proportional contribution to the model's predictions.

Partial dependence analyses were employed to examine~~test~~ the relationships between ~~the~~ predicted soil DOC and independent variables across their~~the~~ entire value ranges ~~spectrum of potential values considered~~ in the RF model ~~(Fig. 3)~~. These analyses allowed us to isolate the effects of specific independent variables by removing the influence of the others. Partial dependence plots offered insights into the average marginal effects of one or more independent variables on model predictions.~~In essence, this approach provided insights into the global relationships between the independent variables and predicted outcomes. The focus was set solely on the effects of the targeted independent variables by eliminating the influences of other independent variables. Partial dependence analyses, along with their graphical representations known as partial dependence plots, provided insight into the average marginal effect of one or more independent variables on a machine learning model's predictions within a defined value scope, offering a more nuanced view than assessing the overall relative importance of an independent variable.~~ For instance, ~~partial dependence~~ these plots ~~can~~ could reveal ~~expose~~ whether relationships were~~the connection between a predicted variable and an independent control is~~ linear, monotonic, or more complex. By examining~~The~~ curvature and inflection points, we could identify ~~of the partial dependence plot curve help us to decipher and pinpoint areas~~ where ~~an independent~~ variable ~~exerts~~ exerted ~~a notably~~ strong ~~and~~, immediate effects or where their influences were more subtle and possibly mediated by other variables~~on the forecasted outcome~~. ~~Additionally, it can indicate where the variable's influence is more subtle, potentially mediated through its effects on other independent variables. To facilitate the interpretation of the partial dependence plots,~~We reported the x-axis ~~for~~ as a~~the~~ standardized value, ~~was reported, which~~ ensuring~~ed~~ a clear progression from low to high values ~~in all curves~~. When we generated partial dependence with RF, several uncertainties arose. The high model complexity sometimes slowed predictions, especially with many trees. The limited interpretability of the RF models could complicate understanding partial dependence. Sensitivity to noise potentially led to overfitting and reduced accuracy. Variable importance measurements could also be biased by varying feature scales or categories, potentially skewing interpretations of feature-outcome relationships.

2.4 Global soil DOC mapping

The global distribution of ~~the~~ soil DOC and the relative uncertainties of our predictions were generated ~~(Figs. 4, S5). These maps were derived~~ by combining ~~utilizing~~ our DOC dataset ~~in conjunction~~ with the RF model, which incorporated ~~the~~ global climate, vegetation, and soil-rasterized datasets (Figs. 4, S5 and Table S1). We first produced~~generated~~ factor maps from the key input variables, focusing on the 12 distinct variables associated with each raster cell. Subsequently, the factor maps were employed to derive a spatially detailed global map of soil DOC. To achieve ~~For~~ global~~-~~scale mapping, we processed the driving factors ~~were initially processed~~ at a 0.05 °resolution to calculate ~~the~~ soil DOC values. Areas that did not meet the following criteria were excluded from our prediction: (1) absence of data for any essential predictors, (2) soil order and biomes not aligning with the previously discussed aggregated land use systems, or (3) locations in climate zones outside the scope of our model's focus. To evaluate ~~the~~ uncertainty ~~associated with map creation~~ due to data resampling and ~~any~~ unexplained variability not accounted~~unaccounted~~ for by the independent variables, we analyzed ~~finer~~ finer-resolution (5 km^2) grids ~~in regions~~ where driving factors were available~~accessible~~ at this detailed ~~level~~. This analysis clarified~~illuminated~~ the overall uncertainty inherent in our global soil DOC estimation. ~~A map representing the relative prediction uncertainty was crafted, showcasing the standard deviation in relation to the mean of the predictions. The standard deviation, indicative of the dispersion in potential predictions, was derived from the decision tree model's structure after 500 iterations of the model.~~

The corresponding map of relative uncertainty of prediction was built by displaying the standard deviation divided by the mean prediction, based on our final random forest RF model. The standard deviation reflected the range of possible predictions derived from the iterative build-up of decision trees after 500 model runs.

Soil DOC concentration varied significantly with temporal changes and soil depth (Fig. 2). Sampling time (month) was used to represent seasonal variations in soil DOC concentration. Soil DOC concentration decreased with soil depth and reached a turning point at approximately 10 cm (Fig. 2). Therefore, when extrapolating the RF model to the entire globe, we used a month range from 1 to 12 and depths of 5 (0–10 cm) and 20 (10–30 cm). From this, we generated a total of 24 maps of global soil DOC concentration. We combined these 24 maps into a single map representing the global distribution of soil DOC concentration based on soil depth. Finally, we calculated the global soil DOC stock using the following equation applied to the combined map of global soil DOC concentration:

$$SOC_s = \sum SOC_i \times BD_i \times (1 - f) \times T \times M_i \qquad (2)$$

where SOC_s is SOC stock and SOC_i is SOC concentration. The subscript i is the number of global grid. BD, f, and T are soil bulk density, the volumetric percentage of coarse fraction (>2 mm), and the depth of soil layer, respectively. M is the effective area of each grid.

3. Results

3.1 Soil DOC concentrations in different ecosystems globally

A total of 12,807 soil DOC observations were compiled from 975 publications that~~, which~~ spanned six continents, as well as major biomes and terrestrial ecosystems (Fig. 1~~), ~~). We found that~~and~~ the natural logarithm of soil DOC~~database~~ concentrations conformed to a normal distribution (Fig. 1b). ~~The g~~Global soil DOC concentrations ranged from~~varied between~~ 0.04 ~~and~~ to 7859 mg kg^{-1}. The global average, median, and standard deviation were 222.78, 101.01, and 445.78 mg kg^{-1}, respectively (Table 2). We observed that soil DOC ~~The~~ concentrations ~~of soil DOC~~ varied across ~~different~~ ecosystems. Tundra had the highest average and median soil DOC concentrations at 470.78 and 241.90 mg kg^{-1}, respectively.~~soil DOC concentration (470.78 mg kg^{-1}), while shrubland had the lowest (160.24 mg kg^{-1})~~. Grassland averaged 327.77 mg kg^{-1} with a median of 126.48 mg kg^{-1}, while forest averaged 256.18 mg kg^{-1} with a median of 115.51 mg kg^{-1}. Wetland averaged 218.53 mg kg^{-1} with a median of 107.11 mg kg^{-1}, cropland averaged 165.98 mg kg^{-1} with a median of 83.00 mg kg^{-1}, and shrubland averaged 160.24 mg kg^{-1} with a median of 127.84 mg kg^{-1} (Table 2).~~The average soil DOC concentrations for grassland, forest, wetland, and cropland were 327.77, 256.18, 218.53, and 165.98 mg kg^{-1}, respectively (Table 2).~~

3.2 Model performance and drivers of soil DOC concentrations

We estimated RMSE and R^2 for all tuned models and used these statistics to analyze residual variance and accuracy, as well as to rank model performance (Table S2). To facilitate interpretation of uncertainty, we also calculated relative RMSE by dividing the absolute error by the global mean soil DOC concentration. RF model resulted in the best performance within one standard error of the minimal RMSE and were thus used for further analyses of variable importance. The residual plot of train, validation, and test data for RF model were randomly distributed near zero (Fig. S7). Overall, nonlinear models (R^2= 0.42–0.65; RMSE = 250–332) outperformed linear models (R^2 = 0.101–0.108; RMSE = 410–427) (Table S2). The RF model yielded the lowest RMSE within one standard deviation range and was therefore selected for subsequent analyses of variable importance (Fig. S3). We based the relative importance of soil DOC drivers and the global map of soil DOC on averaged RF model results.

The RF~~Random forest~~ model explained~~accounted for~~ 65% of the variability in soil DOC concentrations across all sites and achieved ~~, with~~ the lowest RMSE compared with other models (Fig. 2, Table S2). Soil properties were the ~~The~~ most important predictor categories~~ of predictors for soil DOC concentrations were climate and soil properties~~, with elevation and ~~the~~ soil clay content exerting the greatest influence~~emerging as the most significant~~. Meantime, elevation and soil organic were the most sensitivity factors of RF model (Fig. S8). Although less influential, other predictors still contributed; among them,~~were nonetheless considered, with~~ soil organic carbon and soil pH ~~having the most~~were notable ~~effects (Fig. 2a)~~. Although ~~the~~ mean annual precipitation, and mean annual temperature, microbial biomass carbon, bulk density, sand, depth, month, and ecosystem also affected soil DOC ~~concentrations~~, their ~~relative~~ contributions were lower than those of the top ~~aforementioned~~ four predictors ~~(Fig. 2)~~. Elevation has strong interaction with soil pH, bulk density, and microbial biomass carbon (Fig. S9). Partial dependence analysis produced ~~showed similar~~ results (Fig. 3) similar to Pearson correlation ~~analysis~~ analyses (Fig. S4). ~~and~~ We found~~indicated that there was~~ a positive correlation between ~~the~~ soil DOC and both ~~the~~ elevation and soil organic carbon (Fig. 3g~~).~~), ~~Conversely,~~and a negative correlation between ~~the~~ soil DOC and both~~was negatively correlated with~~ mean annual temperature and soil pH (Fig. 3h).

3.3 Global soil DOC patterns

The RF model has the ability to predict soil DOC in wetland (R^2=0.87), forest (R^2=0.84), shruland (R^2=0.84), tundra (R^2=0.70), grassland (R^2=0.95), and cropland (R^2=0.90) ecosystems (Fig. S10). We observed ~~Our predicted global soil DOC mapping implied that there was a~~ significant spatial heterogeneity in predicted global~~of~~ soil DOC concentrations (Fig. 4a). ~~This revealed a latitudinal pattern that s~~Soil DOC concentrations increased from the equator toward the~~to~~ poles (Fig. 4b). High soil DOC concentrations were found in high-altitude plateaus and mountain ranges at low latitudes, including ~~(e.g.,~~ the Andes, African Highlands, and West Indies~~)~~ (Fig. 4a). The global average soil DOC concentration was 237.56 mg kg^{-1} (Table 3), and~~while~~ the topsoil (0-30 cm) DOC stock ~~in the topsoil (0-30 cm)~~ was 12.17 Pg.

Asia had the highest soil DOC concentration (274.43 mg kg^{-1}), followed by North America (263.63 mg kg^{-1})~~. Next were~~, Europe (227.34 mg kg^{-1}), and South America (~~227.34 and~~ 215.81 mg kg^{-1}~~, respectively~~)~~, with~~. Oceania and Africa ~~having~~ had the lowest soil DOC concentrations (198.13 and 186.35 mg kg^{-1}, respectively). For predicted soil DOC stocks, Asia and North America remained ranked~~in~~ first and second ~~place (~~at 4.8 and 2.45 Pg, respectively~~)~~. Despite its relatively low ~~the marginal~~ predicted soil DOC concentrations, ~~in~~ Africa~~, its predicted soil DOC stocks~~ ranked third in total DOC stock (2.07 Pg) because of ~~due to~~ its large land~~vast~~ area. South America followed at~~was in fourth place with a predicted soil DOC stock of~~ 1.37 Pg, while~~. Finally,~~ Europe and Oceania had~~showed~~ the lowest ~~predicted soil DOC~~ stocks at ~~(~~ 0.88 and 0.59 Pg, respectively~~)~~.

4 Discussions

4.1 Variations in soil DOC between ecosystems

Given the substantial number of measurements included in our study (12,807 observations), the range of topsoil (0–30 cm) DOC concentrations (0.04–~~-~~7859 mg kg^{-1}) was broader than previously ~~that~~ reported for a database of ~~by Guo (3,869~~2,890 observations~~)~~ (Guo et al., 2020). Our ~~reported~~ global ~~average~~ median soil DOC concentration was ~~222.78~~101.01 mg kg^{-1} (Table 2), in contast to a previously~~Guo's~~ reported average of only 77.39 mg kg^{-1}. For different ecosystems, the median soil DOC concentrations of wetlands, tundra, and shrublands in our study aligned with previously reported values~~those of previous research~~ (Guo et al., 2020), ~~which was~~ primarily due to the relatively ~~lower~~ small number of observations for these ecosystems~~ in comparison withothers~~, with tundra comprising only 1% of our database. However, significant differences emerged~~were found~~ in forests, grasslands, and croplands compared with previous~~Guo's~~ data. Tundra had the highest soil DOC concentration (Table 2). This can be attributed to low soil temperatures and limited microbial activity, which slow the decomposition of organic material and lead to higher soil DOC concentrations (Propster et al., 2023). In addition, prolonged soil freezing in tundra areas reduces evaporation and oxygen supply, further slowing organic decomposition. Soil DOC concentrations were also relatively high in grassland, forest, and shrub ecosystems because leaves, dead branches, and plant root exudates provide abundant organic C inputs (Cai et al., 2021). However, our results indicated that DOC concentrations in forest soils were consistently lower than in grasslands (Table 2). Grassland ecosystems often have higher plant diversity, including legumes and weeds, whose residue decomposition contributes to increased DOC concentrations (Perrot et al., 2023). In contrast, the cooler conditions in forest soils limit microbial activity and slow organic matter decomposition, reducing DOC consumption. Additionally, grassland soils tend to have better water conditions, promoting higher microbial activity and organic matter breakdown, thus increasing DOC concentrations (Deng et al., 2023). Differences in land use and management, forests being less disturbed while grasslands may be more frequently disturbed by grazing, can also influence soil organic matter decomposition and DOC levels. These combined factors of vegetation type, microbial activity, water conditions, and land use practices result in varying soil DOC concentrations between these two ecosystems. The lowest median soil DOC concentration appeared in cropland ecosystems, likely due to decreased soil organic matter inputs resulting from frequent tillage and harvesting, as well as accelerated DOC decomposition caused by tillage (Ren et al., 2024). ~~For instance~~ Meanwhile, our ~~average~~ median soil DOC concentration for croplands was ~~165.98~~83.00 mg kg^{-1}, whereas a previous value was ~~while Guo reported only~~ 60.58 mg kg^{-1} (Guo et al., 2020). This discrepancy ~~was~~ may be due to the previous~~Guo's~~ database having~~including~~ only 13% cropland observations, ~~whereas~~ while our cropland observations ~~are~~ were approximately ten times larger. ~~However, our results consistently indicated that DOC concentrations in forest soils were lower than in grasslands, with tundra showing the highest DOC levels (Table 2) (Z. Guo et al., 2020). This was due to the higher lignin content in forests, which reduces the quality of plant litter, hinders microbial decomposition, and releases less DOC (Wang et al., 2015). For tundra, besides low microbial activities in permafrost due to low temperatures, anaerobic conditions from soil oversaturation severely limit microbial activities and growth, reduce decomposition rates, and increase the DOC (Boddy et al., 2008; Petrone, 2005). Despite the frequent addition of nutrients in croplands, the DOC concentrations remained lower than expected. Intensive anthropogenic activities, such as management practices and frequent harvesting induced the significant loss of soil organic matter, which translated to reduced DOC (Z. Guo et al., 2020; Li et al., 2019; Ren et al., 2024).~~ In summary, our study builds~~t~~ on earlier~~preceding~~ work by incorporating a more extensive dataset that better ~~represented~~ represents ~~the~~ heterogeneous global conditions ~~found globally~~.

4.2 Effects of climate and controlled soil properties on soil DOC concentrations

The two most critical predictors of soil DOC concentrations were ~~climate and soil properties, with~~ elevation and soil clay content ~~being the two most significant factors~~ (Fig. ~~3~~2). In high-altitude regions, lower temperatures limit the metabolic activity of microorganisms, slowing the decomposition of soil DOC. Additionally, these regions typically receive more precipitation, which increases soil moisture and helps protect soil DOC from rapid breakdown. Soils with high clay content have a strong adsorption capacity that more effectively retains DOC and reduces its loss. Clay also provides a suitable habitat for microorganisms, affecting microbial communities' structure and activity and thus regulating the rate of soil DOC turnover. ~~As the elevation gradient increase, temperatures generally decrease, which can constrain microbial metabolic rates and reduce the decomposition of organic matter, which leads to additional organic carbon being retained in the soil as DOC (Li et al., 2023; Nottingham et al., 2019; Wei et al., 2024).~~ Typically, high-altitude regions host ~~specific~~ vegetation types characterized by ~~with~~ longer growth cycles and greater~~more~~ litterfall (Pesántez et al., 2018; Wei et al., 2024). Decomposing ~~These~~ plant residues contribute ~~decompose~~ to SOC, a portion of which is converted~~s~~ to DOC. Consequently, differences in ~~the~~ vegetation type and productivity also influence~~ the~~ soil DOC concentrations (Camino et al., 2014; Rahbek et al., 2019). We also found that forest and grassland sites above 2,000 m~~ (~~, which accounted for ~~constituted~~ 73% of the high DOC observations~~)~~ ~~were significant contributors~~. High-altitude regions often experience distinct precipitation patterns and soil moisture conditions compared with lower elevations (Li et al., 2023). Higher precipitation and lower evaporation rates may promote ~~result in the~~ greater dissolution and leaching of organic matter, thereby increasing soil DOC concentrations ~~in the soil~~ (He et al., 2021; Lu et al., 2019). Moreover, ~~H~~high-altitude areas are generally less disturbed~~frequented~~ by humans activities, which may help~~assist in the~~ preserv~~ation of~~e ~~the~~ soil DOC~~ in the soil through the prevention of disturbances and losses~~. Our results also indicated that soils in low-latitude plateaus and mountain ranges (e.g., Tibetan Plateau, Andes, African Highlands, and West Indies) exhibited higher DOC concentrations (Fig. 4a). The ~~impacts~~ effects of ~~the~~ soil clay content on DOC concentrations are complex, involving~~which occurred primarily through~~ adsorption, water retention, microbial activities, and organic matter protection mechanisms (Kaiser and Zech, 2000; Singh et al., 2017). Generally, ~~a~~ high clay content fosters DOC ~~tends to stimulate the~~ accumulation ~~of soil DOC~~ through the adsorption and stabilization of organic matter (Gmach et al., 2019; Kalbitz et al., 2000). Furthermore, the effects of SOC and soil pH on DOC should not be overlooked (Fig. 2a). SOC serves as the main source of DOC, ~~where~~ so higher SOC results in~~generally implies that~~ more DOC ~~can be~~ release~~d into the soil~~ through microbial metabolism (Kalbitz et al., 2000; Neff and Asner, 2001). Variations in ~~the~~ soil pH can ~~affect~~ alter the charge of soil colloids, influencing~~thereby altering their~~ adsorption-desorption mechanisms and thus affecting ~~for~~ DOC~~, which affects its~~ solubility ~~in the soil~~ (Andersson and Nilsson, 2001; Cheng et al., 2020; Kaiser et al., 2005). ~~In summary~~Overall, ~~the~~ soil DOC concentration arises from ~~is the result of~~ interactions ~~between~~ among~~the~~ soil and climate factors, as well as biological, chemical, physical~~ processes~~, and human influences at various spatial and temporal scales. Each~~, with each~~ factor plays~~ing~~ a distinct~~unique~~ role in shaping DOC dynamics.

4.3 Global patterns of soil DOC

Using our soil DOC concentration dataset, we quantified the soil DOC concentrations (0-30 cm) in terrestrial ecosystems, identified their key driving factors, and produced~~made~~ global predictions. Global DOC stocks in the topsoil are estimated at 12.17 Pg C, accounting for 0.775% of ~~the~~ global soil organic carbon, which is significantly higher than previous estimates (Guo et al., 2020). Our predictions indicated that soil DOC concentrations decreased markedly toward~~significantly with~~ lower latitudes, particularly in the Northern Hemisphere. Previous global maps of soil DOC concentrations failed to capture this latitudinal trend, ~~which was~~ likely due to ~~their~~ limited spatial coverage (Guo et al., 2020; Langeveld et al., 2020). Our predicted map shows that ~~the~~ soil DOC concentrations increase~~d~~ with latitude. In high-latitude regions, low temperatures limit microbial activity, which slows the decomposition of organic matter and leads to more organic carbon being retained in dissolved form (Patoine et al., 2022) , thereby increasing soil DOC concentrations. In addition, soils in high-latitude areas are often moist or frozen due to low temperatures, limiting oxygen supply and further inhibiting microbial decomposition (Zhou et al., 2024b). These moist or frozen conditions also help protect organic matter, reducing its decomposition and contributing to DOC accumulation. Thus, low temperatures and specific moisture conditions in high-latitude regions jointly result in relatively high soil DOC concentrations. ~~. This trend was attributed to lower temperatures, specific vegetation types, higher soil moisture, and reduced human activities at higher latitudes (Camino‐Serrano et al., 2014; Lapierre et al., 2015).~~ However, ~~there was~~ substantial heterogeneity exists at regional and local scales. For instance, despite their~~being at~~ similar latitudes, soil DOC concentrations in Northern Europe were significantly lower than in Siberia, ~~which we surmised was~~ primarily due to differences in climatic conditions~~between the maritime climate of Northern Europe and the cold subarctic climate of Siberia~~. Northern Europe's maritime climate, with mild temperatures and evenly distributed precipitation, promotes higher microbial activity and accelerates organic matter decomposition. In contrast, Siberia's cold subarctic climate results in lower soil temperatures that limit microbial activity and slow organic matter decomposition, leading to greater DOC retention~~.~~ (Jin and Ma, 2021). Furthermore, soils in Siberia are often frozen, restricting oxygen supply and further inhibiting decomposition, thereby contributing to DOC accumulation (Raudina et al., 2022). Climatic conditions thus play a key role in explaining the significant differences in soil DOC concentrations between these regions. Regional variations may also~~in soil DOC concentrations might~~ be related to topographic conditions. Higher soil DOC concentrations on the Tibetan Plateau compared ~~to~~ with Eastern China ~~might~~ may result from ~~the~~ high elevation and low MAT in the plateau (Fig. 4a). In contrast, other studies reported lower DOC levels in Arctic regions~~ was reported~~, which ~~might~~ may have been due to ~~their~~ omis~~sion~~tting ~~of~~ DOC concentration measurements in ~~the soil and~~ dry or frozen soils (Langeveld et al., 2020). ~~The~~ Our predictive model offered higher accuracy in estimating ~~the~~ global soil DOC storage ~~(Fig. 3).~~ because ~~This advantage stemmed from~~ our comprehensive dataset~~, which~~ included DOC concentrations in both dry soil and soil solutions, ~~which~~ provid~~ed~~ing a robust data foundation. In addition~~for global soil DOC predictions. Additionally~~, we

~~employed~~ used the optimal model ~~for predicting the global soil DOC~~ by comparing various linear and nonlinear models to predict global soil DOC~~non-linear models~~.

4.4 Implications for carbon cycling models

Carbon cycling models are key tools for predicting how soil organic carbon responds to future global changes. Considerable uncertainty exists in simulating and predicting soil organic carbon cycles in many current Earth system models, largely due to model structure, model parameters, and initial conditions (Luo et al., 2015). Regarding model structure, the soil carbon pools in models cannot be directly separated through experiments, which hamper the quantification of many parameters (Bailey et al., 2018). By integrating global soil DOC concentration data and coupling it with particulate organic carbon, mineral-associated organic carbon, and microbial biomass carbon pools, future models can establish a quantifiable structure based on measurable pools. Our study reveals key factors affecting soil DOC concentrations, such as elevation, soil clay content, and soil organic carbon, can be incorporated into carbon cycle models to improve their predictive capabilities. Moreover, this research provides a detailed global distribution map of soil DOC, which is essential for model parameterization and validation, particularly in regions where data are scarce.

4.~~4~~ 5 Limitations and predictive uncertainties

Although we compiled a comprehensive global soil DOC concentration dataset, identified key drivers, and made a global prediction, our study had certain limitations. First, certain ecosystems remained underrepresented; for instance, tundra accounted for only 1% of our database, while shrublands, grasslands, and wetlands collectively constituted only 21%. This underrepresentation may reduce the accuracy of predictions for different ecosystems. Second, although we considered the subsoil at the beginning of dataset, we did not explore this further due to the limited availability of data and considerations of predictive accuracy. We intend to continue expanding the subsoil DOC database in future work. Third, there was a deficiency in some predictive variables; although we had extracted missing data through gridded datasets, this inevitably introduced uncertainty in predictions, particularly for soil variables. Fourth, although data standardization enables consistent comparison and analysis of soil DOC across different measurement methods, there were potential issues such as the possible loss of original data characteristics, dependence on accurate parameters, overgeneralization, increasing the complexity of data interpretation, and introducing bias. Finally, despite employing advanced machine learning methods with multiple predictors to predict the global soil DOC, 35% of soil DOC concentration variability remains unexplained. However, these limitations also highlighted areas for future soil DOC research. Future research should enhance the collection of deep soil samples to address the current data scarcity and more accurately quantify the DOC reserves across the entire soil profile. There is a particular need to increase sample collection in key regions such as Siberia and Africa.

5 Data availability

The global soil DOC in this study and raw dataset of driving factors can be downloaded at https://doi.org/10.6084/m9.figshare.26379898 (Ren and Cai, 2024).

6 Conclusions

Through the development of a comprehensive soil DOC dataset, we quantified soil DOC concentrations in terrestrial ecosystems, identified their driving factors, and made global predictions. After~~Subsequent~~ to comparing multiple predictive models, we selected the Random Forest model as the best performer for mapping soil DOC concentrations. The results indicated that tundra exhibited the highest DOC concentrations, while shrubland and cropland soils had relatively lower concentrations. Climate factors (elevation) and soil properties (clay content, SOC, pH) jointly regulated ~~the~~ DOC variations. ~~The~~ We predicted that the soil DOC concentration increased significantly from the equator to the poles, and estimated that the DOC stocks in the topsoil of terrestrial ecosystems ~~was~~ were 12.17 Pg. The global soil DOC database we created ~~will~~ served as a critical resource for future research~~, while~~ and ~~enhancing~~ enhanced our understanding of the roles of soil in the global carbon cycle. This database ~~provides~~ provided valuable data support for climate change research, ecosystem management, agricultural sustainability, environmental policymaking, and the improvement of biogeochemical models. It aided~~This will aid~~ in addressing soil degradation, improving food security, and tackling global environmental challenges.

Author contributions

Andong Cai designed this study. Tianjing Ren collected the data. Tianjing Ren and Andong Cai discussed analyzing methods. Andong Cai conducted the analysis. Tianjing Ren drafted the manuscript. All authors discussed the results and contributed to the manuscript.

Competing interests

The contact author has declared that neither they have any competing interests.

Acknowledgements

We would like to thank Frank Boehm at NanoApps Consulting2341York Ave. Vancouver, BC, Canada for his assistance with English language and grammatical editing.

Financial support

This work was financially supported by the National Key Research and Development Program of China (2022YFD2300500).

References

Andersson, S., & Nilsson, S. I.: Influence of pH and temperature on microbial activity, substrate availability of soil-solution bacteria and leaching of dissolved organic carbon in a mor humus, Soil Biol. Biochem., 33, 1181-1191. https://doi.org/10.1016/S0038-0717(01)00022-0, 2001.

Bailey, V.L., Bond-Lamberty, B., DeAngelis, K., Grandy, A.S., Hawkes, C.V., Heckman, K., Lajtha, K., Phillips, R.P., Sulman, B.N., Todd-Brown, K.E.O., Wallenstein, M.D.: Soil carbon cycling proxies: Understanding their critical role in predicting climate change feedbacks, Glob. Chang. Biol., 24, 895-905, https://doi.org/10.1111/gcb.13926, 2018.

Cai, A., Liang, G., Yang, W., Zhu, J., Han, T., Zhang, W., Xu, M.: Patterns and driving factors of litter decomposition across Chinese terrestrial ecosystems, J. Clean. Prod. 278, 123964, https://doi.org/10.1016/j.jclepro.2020.123964, 2021.

Camino, M., Gielen, B., Luyssaert, S., Ciais, P., Vicca, S., Guenet, B., Vos, B.D., Cools, N., Ahrens, B., Altaf Arain, M., Borken, W., Clarke, N., Clarkson, B., Cummins, T., Don, A., Pannatier, E.G., Laudon, H., Moore, T., Nieminen, T.M., Nilsson, M.B., Peichl, M., Schwendenmann, L., Siemens, J., Janssens, I.: Linking variability in soil solution dissolved organic carbon to climate, soil type, and vegetation type, Global Biogeochem. Cy. 28, 497-509, https://doi.org/10.1002/2013gb004726, 2014.

Cheng, X., Hou, H., Li, R., Zheng, C., Liu, H.: Adsorption behavior of tetracycline on the soil and molecular insight into the effect of dissolved organic matter on the adsorption, J. Soil Sediment., 20, 1846-1857, https://doi.org/10.1007/s11368-019-02553-7, 2020.

Cotrufo, M.F., Lavallee, J.M.: Soil organic matter formation, persistence, and functioning: A synthesis of current understanding to inform its conservation and regeneration, Adv. Agron., 172, 1-66, https://doi.org/10.1016/bs.agron.2021.11.002, 2022.

Deng, M., Li, P., Liu, W., Chang, P., Yang, L., Wang, Z., Wang, J., Liu, L.: Deepened snow cover increases grassland soil carbon stocks by incorporating carbon inputs into deep soil layers, Glob. Chang. Biol., 29, 4686-4696, https://doi.org/10.1111/gcb.16798, 2023.

Ding, H., Hu, Q., Cai, M., Cao, C., Jiang, Y.: Effect of dissolved organic matter (DOM) on greenhouse gas emissions in rice varieties, Agr. Ecosyst. Environ., 330, 107870, https://doi.org/10.1016/j.agee.2022.107870, 2022.

Fichot, C.G., Tzortziou, M., Mannino, A.: Remote sensing of dissolved organic carbon (DOC) stocks, fluxes and transformations along the land-ocean aquatic continuum: Advances, challenges, and opportunities, Earth-sci. Rev., 242, 104446, https://doi.org/10.1016/j.earscirev.2023.104446, 2023.

Gmach, M.R., Cherubin, M.R., Kaiser, K., Cerri, C.E.: Processes that influence dissolved organic matter in the soil: a review, Sci. Agr., 77, 12-24, https://doi.org/10.1590/1678-992X-2018-0164, 2019.

Guo, B., Zheng, X., Yu, J., Ding, H., Pan, B., Luo, S., Zhang, Y.: Dissolved organic carbon enhances both soil N_2O production and uptake, Glob. Ecol. Conserv., 24, e01264, https://doi.org/10.1016/j.gecco.2020.e01264, 2020.

Guo, Z., Wang, Y., Wan, Z., Zuo, Y., He, L., Li, D., Yuan, F., Wang, N., Liu, J., Song, Y., Song, C., Xu, X., Hickler, T.: Soil dissolved organic carbon in terrestrial ecosystems: Global budget, spatial distribution and controls, Global Ecol. Biogeogr., 29, 2159-2175, https://doi.org/10.1111/geb.13186, 2020.

He, X., Augusto, L., Goll, D.S., Ringeval, B., Wang, Y., Helfenstein, J., Huang, Y., Yu, K., Wang, Z., Yang, Y., Hou, E.: Global patterns and drivers of soil total phosphorus concentration, Earth Syst. Sci. Data, 13, 5831-5846, https://doi.org/10.5194/essd-13-5831-2021, 2021.

Jin, H., Ma, Q.: Impacts of permafrost degradation on carbon stocks and emissions under a warming climate: a review, Atmosphere-Basel, 12, 1425-1436, https://doi.org/10.3390/atmos12111425, 2021.

Kaiser, K., Guggenberger, G., Haumaier, L., Zech, W.: Dissolved organic matter sorption on sub soils and minerals studied by ^{13}C-NMR and DRIFT spectroscopy, Eur. J. Soil Sci., 48, 301-310, https://doi.org/10.1111/j.1365-2389.1997.tb00550.x, 2005.

Kaiser, K., Zech, W.: Dissolved organic matter sorption by mineral constituents of subsoil clay fractions, J. Plant Nutr. Soil Sc., 163, 531-535, https://doi.org/10.1002/1522-2624(200010)163:5%3C531::AID-JPLN531%3E3.0.CO;2-N, 2000.

Kalbitz, K., Solinger, S., Park, J.-H., Michalzik, B., Matzner, E.: Controls on the dynamics of dissolved organic matter in soils: a review, Soil Sci., 165, 277-304, https://doi.org/10.1097/00010694-200004000-00001, 2000.

Lønborg, C., Carreira, C., Jickells, T., Álvarez-Salgado, X.A.: Impacts of global change on ocean dissolved organic carbon (DOC) cycling, Front. Mar. Sci., 7, 466. ,https://doi.org/10.3389/fmars.2020.00466, 2020.

Lal, R.: Soil carbon sequestration impacts on global climate change and food security, Science, 304, 1623-1627, https://doi.org/10.1126/science.1097396, 2004.

Langeveld, J., Bouwman, A.F., van Hoek, W.J., Vilmin, L., Beusen, A.H.W., Mogollón, J.M., Middelburg, J.J.: Estimating dissolved carbon concentrations in global soils: a global database and model, SN. Applied Sciences, 2, 110-121, https://doi.org/10.1007/s42452-020-03290-0, 2020.

Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., Trisos, C., Romero, J., Aldunce, P., Barret, K.: IPCC, 2023: Climate change 2023: synthesis report, summary for policymakers. Contribution of working groups I, II and III to the sixth assessment report of the intergovernmental panel on climate change [Core Writing Team, H. Lee and J. Romero (eds.)], IPCC, Geneva, Switzerland, https://doi.org/10.59327/IPCC/AR6-9789291691647, 2023.

Li, J., Wu, B., Zhang, D., Cheng, X.: Elevational variation in soil phosphorus pools and controlling factors in alpine areas of Southwest China, Geoderma, 431, 235-246, https://doi.org/10.1016/j.geoderma.2023.116361, 2023.

Li, S., Zheng, X., Liu, C., Yao, Z., Zhang, W., Han, S.: Influences of observation method, season, soil depth, land use and management practice on soil dissolvable organic carbon concentrations: A meta-analysis, Sci. Total. Environ., 631-632, 105-114, https://doi.org/10.1016/j.scitotenv.2018.02.238, 2018.

Lu, S., Xu, Y., Fu, X., Xiao, H., Ding, W., Zhang, Y.: Patterns and drivers of soil respiration and vegetation at different altitudes in Southern China, Appl. Ecol. Env. Res., 17, 118-126, https://doi.org/10.15666/aeer/1702_30973106, 2019.

Luo, Y., Keenan, T.F., Smith, M.: Predictability of the terrestrial carbon cycle, Glob. Chang. Biol., 21, 1737-1751, https://doi.org/10.1111/gcb.12766, 2015.

Nakhavali, M., Lauerwald, R., Regnier, P., Guenet, B., Chadburn, S., Friedlingstein, P.: Leaching of dissolved organic carbon from mineral soils plays a significant role in the terrestrial carbon balance, Glob. Chang. Biol., 27, 1083-1096, https://doi.org/10.1111/gcb.15460, 2021.

Neff, J.C., Asner, G.P.: Dissolved organic carbon in terrestrial ecosystems: synthesis and a model, Ecosystems, 4, 29-48, https://doi.org/10.1007/s100210000058, 2001.

Patoine, G., Eisenhauer, N., Cesarz, S., Phillips, H.R.P., Xu, X., Zhang, L., Guerra, C.A.: Drivers and trends of global soil microbial carbon over two decades, Nat. Commun., 13, 4195, https://doi.org/10.1038/s41467-022-31833-z, 2022.

Perrot, T., Rusch, A., Gaba, S., Bretagnolle, V.: Both long-term grasslands and crop diversity are needed to limit pest and weed infestations in agricultural landscapes, P. Natl. Acad. Sci., 120, e2300861120, https://doi.org/10.1073/pnas.230086112, 2023.

Pesántez, J., Mosquera, G.M., Crespo, P., Breuer, L., Windhorst, D.: Effect of land cover and hydro-meteorological controls on soil water DOC concentrations in a high-elevation tropical environment, Hydrol. Process., 32, 2624-2635, https://doi.org/10.1002/hyp.13224, 2018.

Propster, J.R., Schwartz, E., Hayer, M., Miller, S., Monsaint-Queeney, V., Koch, B.J., Morrissey, E.M., Mack, M.C., Hungate, B.A.: Distinct growth responses of tundra soil bacteria to short-term and long-term warming, Appl. Environ. Microb., 89, e01543-01522, https://doi.org/10.1128/aem.01543-22, 2023.

Rahbek, C., Borregaard, M.K., Colwell, R.K., Dalsgaard, B., Holt, B.G., Morueta-Holme, N., Nogues-Bravo, D., Whittaker, R.J., Fjeldså, J.: Humboldt's enigma: What causes global patterns of mountain biodiversity?, Science, 365, 1108-1113, https://www.science.org/doi/10.1126/science.aax0149, 2019.

Raudina, T.V., Smirnov, S.V., Lushchaeva, I.V., Istigechev, G.I., Kulizhskiy, S.P., Golovatskaya, E.A., Shirokova, L.S., Pokrovsky, O.S.: Seasonal and spatial variations of dissolved organic matter biodegradation along the aquatic continuum in the Southern Taiga bog complex, Western Siberia, Water, 14, 3969, https://doi.org/10.3390/w14233969, 2022.

Ren, T., Tang, S., Han, T., Wang, B., Zhou, Z., Liang, G., Li, Y.e., Cai, A.: Positive rhizospheric effects on soil carbon are primarily controlled by abiotic rather than biotic factors across global agroecosystems, Geoderma, 430, 116337, https://doi.org/10.1016/j.geoderma.2023.116337, 2023.

Ren, T., Ukalska-Jaruga, A., Smreczak, B., Cai, A.: Dissolved organic carbon in cropland soils: A global meta-analysis of management effects, Agr. Ecosyst. Environ., 371, 109080, https://doi.org/10.1016/j.agee.2024.109080, 2024.

Singh, M., Sarkar, B., Hussain, S., Ok, Y.S., Bolan, N.S., Churchman, G.J.: Influence of physico-chemical properties of soil clay fractions on the retention of dissolved organic carbon, Environ. Geochem. Hlth., 39, 1335-1350, https://doi.org/10.1007/s10653-017-9939-0, 2017.

Smreczak, B., Ukalska-Jaruga, A.: Dissolved organic matter in agricultural soils, Soil Sci. Annu., 72, 132234, https://doi.org/10.37501/soilsa/132234, 2021.

Wei, D., Tao, J., Wang, Z., Zhao, H., Zhao, W., Wang, X.: Elevation-dependent pattern of net CO_2 uptake across China, Nat. Commun., 15, 2489, https://doi.org/10.1038/s41467-024-46930-4, 2024.

Zhao, X., Tian, P., Sun, Z., Liu, S., Wang, Q., Zeng, Z.: Rhizosphere effects on soil organic carbon processes in terrestrial ecosystems: A meta-analysis, Geoderma, 412, 115739, https://doi.org/10.1016/j.geoderma.2022.115739, 2022.

Zhou, Z., Ren, C., Wang, C., Delgado-Baquerizo, M., Luo, Y., Luo, Z., Du, Z., Zhu, B., Yang, Y., Jiao, S., Zhao, F., Cai, A., Yang, G., Wei, G.: Global turnover of soil mineral-associated and particulate organic carbon, Nat. Commun., 15, 5329, https://doi.org/10.1038/s41467-024-49743-7, 2024a.

Zhou, Z., Wang, C., Cha, X., Zhou, T., Pang, X., Zhao, F., Han, X., Yang, G., Wei, G., Ren, C.: The biogeography of soil microbiome potential growth rates, Nat. Commun., 15, 9472, https://doi.org/10.1038/s41467-024-53753-w, 2024b.