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RESEARCH ARTICLE

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Younger carbon dominates global soil carbon efflux

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1 | INTRODUCTION

Abstract

Soil carbon (C) is comprised of a continuum of organic compounds with distinct ages (i.e., the time a C atom has experienced in soil since the C atom entered soil). The contribution of different age groups to soil C efflux is critical for understanding soil C stability and persistence, but is poorly understood due to the complexity of soil C pool age structure and potential distinct turnover behaviors of age groups. Here, we build upon the quantification of soil C transit times to infer the age of C atoms in soil C efflux (a_{efflux}) from seven sequential soil layer depths down to 2 m at a global scale, and compare this age with radiocarbon-inferred ages of C retained in corresponding soil layers (a_{soil}). In the whole 0–2 m soil profile, the mean a_{efflux} is 194¹⁰²¹ (mean with 5%–95% quantiles) year and is just about one-eighth of a_{soil} (1476 $^{2547}_{717}$ year), demonstrating that younger C dominates soil C efflux. With increasing soil depth, both a_{efflux} and $a_{\rm soil}$ are increased, but their disparities are markedly narrowed. That is, the proportional contribution of relatively younger soil C to efflux is decreased in deeper layers, demonstrating that C inputs (new and young) stay longer in deeper layers. Across the globe, we find large spatial variability of the contribution of soil C age groups to C efflux. Especially, in deep soil layers of cold regions (e.g., boreal forests and tundra), a_{efflux} may be older than a_{soil}, suggesting that older C dominates C efflux only under a limited range of conditions. These results imply that most C inputs may not contribute to longterm soil C storage, particularly in upper layers that hold the majority of new C inputs.

KEYWORDS

carbon age, carbon input, carbon sequestration, deep soil, radiocarbon, soil organic carbon, transit time

the consequence of input changes on long-term soil C balance is difficult to be predicted and widely debated (Song et al., 2019; Terrer et al., 2021). A fundamental cause is that C inputs may stay for short or long timescales in soil depending on climatic and

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Managing C inputs to soil has been recommended to sequester C in order to mitigate climate change (Lal, 2004). However,

soil physiochemical conditions (Crowther et al., 2016; Jackson et al., 2017; Terrer et al., 2019), reflected by distinct C turnover behaviors and persistence among soils. Such turnover behaviors and persistence can be described by soil C transit times. Transit time is defined as the time elapsed since a C atom entered soil until it exits via any efflux pathways (Sierra et al., 2017, 2018). At steady state, soil C efflux is equal to influx, thus transit time can be calculated as the ratio of soil C stock to C output or input (Fan et al., 2020; Luo et al., 2019), representing the mean age of C atom in the efflux (Metzler & Sierra, 2018); hereafter, we call it a_{efflux} . Relying on depth-resolved output or input (e.g., belowground net primary production [BNPP]), we can estimate mean transit times in different soil depths, which is a key step toward reliable prediction of whole-soil C dynamics and long-term soil C sequestration under changing C inputs induced by climate change and land management.

By comparing a_{efflux} with the mean age of C in the soil (a_{soil} , i.e., the mean time a C atom has experienced since the C atom entered soil), another dimension of information on the contribution of soil C age groups to effluxes can be obtained. This contribution is important for understanding the persistence of soil C pools in different ages, which may range from days to millennia. Soil radiocarbon measurements combined with C models have been widely employed to infer a_{soil} (Balesdent et al., 2018; He et al., 2016; Shi et al., 2020). Three categories regarding the relations between a_{efflux} and a_{soil} exist, and each has its own valuable meaning for interpreting soil C dynamics (Bolin & Rodhe, 1973; Sierra et al., 2018). If $a_{efflux} = a_{soil}$ (type I relation), released C is at the same age as retained soil C. It implies that all soil C compounds regardless of chemical structure and physical accessibility have the same probability of being released. If $a_{\text{efflux}} < a_{\text{soil}}$ (type II relation), released C is younger than existing soil C. In this type of soil, most C atoms enter and leave soil in a relatively short time, but those atoms that remain in the soil stay there for a long time. If $a_{efflux} > a_{soil}$ (type III relation), released C on average is older than retained soil C. That is, new entering C atoms stay for a long period before exiting. This may occur when C is only released after sequential transport from one physical or chemical state to another (Sierra et al., 2018). For example, big molecules of plant materials may have to be fragmented into small molecules via any physical or chemical pathways before being released. Above all, the relation between a_{efflux} and a_{soil} is indicative of transformation and stabilization processes of soil C. Process-based soil C models usually predict type II relation (Sierra et al., 2018). A number of studies have also separately quantified a_{efflux} (Carvalhais et al., 2014; Luo et al., 2019) or a_{soil} (Balesdent et al., 2018; Braakhekke et al., 2014; He et al., 2016; Shi et al., 2020). However, there is a lack of a comprehensive quantification of $a_{\rm efflux}$, $a_{\rm soil}$, and their relations at the global scale using consistent data and methods, particularly at fine spatial resolutions. Particularly, to our knowledge, no previous studies have addressed the relation between a_{efflux} and a_{soil} across soil depths. This information is vital for understanding soil C stability and persistence and predicting soil C dynamics under climate and land use changes.

In this study, we build upon global datasets of BNPP and root biomass depth distribution to develop machine learning-based predictive models. Then, the models are used to digitally map depthresolved soil C inputs represented by BNPP and interlayer transport of soil C. Combined with a global mapping product of soil C stocks— WISE30sec (Batjes, 2016), a_{efflux} is estimated by dividing soil C stock over inputs in the 0–2 m soil profile as well as in seven sequential soil layer depths down to 2 m (0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, 0.8–1.0, 1.0–1.5, and 1.5–2.0 m) across the globe at the resolution of 0.0083° (which is equal to 1 km² at the equator). At last, we conduct a pixelto-pixel comparison of a_{efflux} to a_{soil} inferred from a one-pool radiocarbon model constrained by a global dataset of soil radiocarbon measurements. Ultimately, we are aiming to quantify the spatial pattern of a_{efflux} and a_{soil} and their relation across biomes and through soil depths, and investigate underlying environmental drivers.

2 | MATERIALS AND METHODS

2.1 | The relation between soil carbon transit times and ages

Transit time is the time elapsed since C atoms entered soil until they leave via output flux. At steady state, it can be estimated by dividing soil C stock over C output. However, it is a big challenge to measure C output flux in situ, especially its depth origin. Under the assumption of steady state, C output is equal to input, and transit time can be estimated by dividing soil C stock (SOC_s) over input, representing the mean age of C atoms in efflux (a_{efflux}):

$$a_{\rm efflux} = \frac{\rm SOC_s}{\rm Input} \tag{1}$$

Soil C age is defined as the time a C atom has experienced since it entered soil (a_{soil}). It is thus straightforward that we can calculate the ratio of a_{efflux} to a_{soil} (r_a) as:

$$r_{\rm a} = \frac{a_{\rm efflux}}{a_{\rm soil}} \tag{2}$$

Figure S1 shows the data, method, and procedure used to estimate a_{efflux} , a_{soil} , and their relation. Detailed steps are described in following sections.

It should be noted that, in order to calculate a_{efflux} , a_{soil} , and therefore r_a using our data-driven approach at the global scale, steady state must be assumed, which is a common practice in large-scale assessments of soil C turnover and persistence (Balesdent et al., 2018; Carvalhais et al., 2014; He et al., 2016; Shi et al., 2020). The main reason is that non-steady-state calculations need long-term temporal measurements of carbon input and output fluxes at the site level in order to quantify temporal dynamics of a_{efflux} and a_{soil} . We admit that soil C may not be at the strict steady state because of natural and anthropogenic disturbances (e.g., fire and land use change) and climate variability, but temporal monitoring of carbon inputs and outputs presents a significant measurement challenge, making it difficult, if not impossible, to estimate time-dependent soil carbon ages. Nevertheless, a global-scale quantification of the relation between $a_{\rm efflux}$ and $a_{\rm soil}$ through soil profiles will be informative to understand the spatial variability of soil carbon turnover and persistence, providing a reference and benchmark for assessing whether, how, where, and to what extent the soil carbon turnover in different soil depths may respond to climate and management changes.

2.2 | Estimation of carbon input

To estimate a_{efflux} across the globe, we need carbon inputs to soil which mainly include BNPP and aboveground NPP (ANPP) transported down the profile (Clark et al., 2001). We first mapped the depth allocation of BNPP in seven soil layer depths (0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1.0, 1.0-1.5, and 1.5-2.0 m) down to 2 m to represent C inputs. Global maps of BNPP and its depth allocation at the resolution of 0.0083° (i.e., ~1 km at the equator) were produced using machine learning-based predictive models driven by in situ measurements of NPP including its belowground and aboveground fractions in 725 soil locations across the globe (Figure S2). A detailed description of the datasets and models for digital mapping of BNPP can be found in Xiao et al. (2022). In essence, the allocation of BNPP to the seven sequential soil layers was estimated according to root biomass depth distribution (Figure S2) by assuming that BNPP depth allocation is proportional to root biomass distribution in the soil profile. To our knowledge, this is the most comprehensive, spatially explicit, and depth-resolved estimation of BNPP at a global scale. In this study, we further updated the predictive model for mapping BNPP across the globe by including MODIS NPP (Zhao et al., 2005) as a predictor. By including MODIS NPP, the predictive model could explain 63%-additional 8% improvement compared with Xiao et al. (2022)—of the variance in observed BNPP (Figure S3a).

Vertical C transport along the soil profile (e.g., via leaching and/ or bioturbation) would contribute to C inputs to a typical layer. Thus, input represented by BNPP alone would be a biased estimation of C input. We used a partial differential equation to model vertical C transport through soil profile (Koven et al., 2013):

$$V = \frac{\partial}{\partial z} \left(D \times \frac{\partial \text{ SOC}_{s}}{\partial z} \right), \tag{3}$$

where V, SOC_s , and z are the amount of transported soil C (kg m⁻² year⁻¹), total soil C stock (kg m⁻²), and soil depth (m), respectively; D is the diffusion coefficient constant which is assigned to be 1.0×10^{-4} m² year⁻¹ in accordance with a vertically resolved soil C model (Koven et al., 2013). In a typical layer, thus C input was estimated as the sum of BNPP and V in that layer. In the first 0–0.2 m layer, soil C inputs may include additional amounts of C from soil surface (Kaiser & Kalbitz, 2012). Specifically, we assumed that 10% of ANPP ends up in the topsoil. That is, $Input_{0-0.2} = BNPP_{0-0.2}+V_{0-0.2}+0.1\times ANPP$. A global map of ANPP at the resolution of 1 km was produced using the same machine learning-based approach to predict BNPP. The random forest (RF) Global Change Biology –WILEY

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predictive model for ANPP could explain 74% of the variance in observed ANPP (Figure S3b).

2.3 | Calculation of a_{efflux} and its uncertainty

We calculated layer-specific a_{efflux} as:

$$a_{\text{efflux},i} = \frac{\text{SOC}_{\text{s},i}}{\text{Input}_i} = \frac{\text{SOC}_{\text{s},i}}{\text{BNPP}_i + V_i}$$
(4)

where $SOC_{s,i}$ and $BNPP_i$ are the soil organic C stock and BNPP in the *i*th soil layer, respectively. For SOC_s , we used the WISE30sec database, which is a mapping product of global soil C stocks at the same seven soil layers and 1 km resolution across global soils (Batjes, 2016). Then, in each 1 km pixel across global uplands, a_{efflux} was calculated based on the WISE30sec database and the mapping products of BNPP_i and V_i .

Prediction uncertainty in Input was brought into the estimation of a_{efflux} to quantify the uncertainty in a_{efflux} using a Monte Carlo approach by randomly drawing 500 trees with replacement from the predictive model (i.e., the RF model) to generate 500 estimates of C input (Xiao et al., 2022). The 500 estimates enabled us to obtain 500 estimates of a_{efflux} for each 1 km pixel. The prediction uncertainty of a_{efflux} was estimated as the coefficient of variation (CV) of the 500 estimates (i.e., dividing their standard deviation by their mean).

In addition, we assessed the sensitivity of a_{efflux} to vertical C transport by excluding V from the calculation (i.e., treating BNPP as the only soil C input). In each of the seven soil layers, as such, we obtained two sets of a_{efflux} estimates, enabling us to obtain insights into the likely a_{efflux} ranges induced by uncertainty in C input estimations with and without considering vertical C transport.

2.4 | Estimation of *a*_{soil} for each depth interval

A global dataset of $\Delta^{14}C_{data}$ was obtained up to July 7, 2020 (Lawrence et al., 2020). It is an open-source database for the synthesis of soil radiocarbon data using "ISRaD.getdata" function in R package "ISRaD" (Lawrence et al., 2020). From this dataset, the column "lyr_14c_fill_extra" was used because it merges radiocarbon measurements reported as either Δ^{14} C or "fraction of modern" which was subsequently converted to Δ^{14} C (personal communication with Dr. Corey Lawrence). We focused on Δ^{14} C in mineral soils from 0 to 2 m soil depth with clear records of observation year and soil layer depths. In total, we used 3128 unique measurements of Δ^{14} C from 750 profiles (Figure S2).

We first derived a_{soil} combining the radiocarbon measurements with a radiocarbon model, then developed predictive models for a_{soil} , and at last extrapolated the model to predict a_{soil} in the same soil layer depths to a_{efflux} across the globe to assist comparison. The soil radiocarbon model (Cherkinsky & Brovkin, 1993; Trumbore, 2000; Vaughn & Torn, 2018) was written as:

 $F_{\text{soil }t} \cdot C_t = F_{lt} \cdot I_t - F_{\text{soil }t-1} \cdot C_{t-1} \cdot (1-k-\gamma),$

(5)

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where $F_{\text{soil},t}$ and $F_{l,t}$ represent the fraction of ¹⁴C in measured soil C and C input to soil at time *t*, respectively; C_t and I_t are the amounts of soil C stock and C input to soil at time *t*; *k* is the decay rate of soil C; and γ is the β -decay rate of ¹⁴C and equal to 1/8267 per year. At steady state, both I_t and C_t are constant. That is, $C_t = C_{t-1} = I_t/k$, so Equation (5) reduces to:

$$F_{\text{soil},t} = F_{l,t} \cdot k - F_{\text{soil},t-1} \cdot (1 - k - \gamma).$$
(6)

In the $\Delta^{14}C_{data}$ dataset, however, radiocarbon data were reported as $\Delta^{14}C$ —the per mille (‰) deviation from a standard of fixed isotopic composition, and were transferred to *F* using following equation:

$$F = \frac{\Delta^{14} C}{1000} + 1.$$
 (7)

For Δ^{14} C in C input, it was assumed to be equal to that in the atmosphere at time t. Atmospheric Δ^{14} C during the period 1950–2010 was extracted from Hua et al. (2013) for the northern and southern hemispheres, separately (Figure S4). To utilize soil Δ^{14} C measurements in more recent years, the atmospheric Δ^{14} C data during the period 2011–2019 were extrapolated from the data in the period 1970–2010 using an exponential decreasing model (Figure S4). These data were used to calculate *F* for both soil and C input using Equation (7). Using the derived *F* values of C input during the period, then, *k* was iteratively solved. Two possible *k* solutions could be obtained for several positive large Δ^{14} C values due to the ascending and then descending of atmospheric Δ^{14} C during and after the bomb test. The small one was used (Shi et al., 2020). Once *k* was obtained, the reciprocal of the decay rate *k* defines a_{soil} :

$$a_{\rm soil} = \frac{1}{k}.$$
 (8)

Finally, a total of 3128 estimates of $a_{\rm soil}$ in different soil layer depths across 750 soil Δ^{14} C profiles were obtained. Here, we note that the modeling assumes that the lag time induced by the residence of assimilated C (including ¹⁴C) in living plant material before entering soil C pool has negligible effect on the estimation of $a_{\rm soil}$ (Trumbore, 2000) and not been modeled.

2.5 | Digital global mapping of a_{soil}

In order to conduct pixel-to-pixel comparisons with a_{efflux} , we derived maps of a_{soil} at the same resolution of a_{efflux} . Using the geographical coordinates of Δ^{14} C locations, we retrieved more than 20 environmental covariates (Table S1) with a variance inflation factor value less than 10 as independent predictors to fit a RF model to predict a_{soil} . There were 11 soil physiochemical properties obtained from ISRIC-WISE database (Batjes, 2016) with a resolution of 1 km, and nineteen climatic variables obtained from WorldClim (Fick & Hijmans, 2017) with the same resolution as the WISE database. In addition, a spatial layer of biome type by aggregating two land cover maps [i.e., the MODIS land cover map (Channan et al., 2014) and the

Terrestrial Ecoregions of the World (Olson et al., 2001)] was generated to represent nine biome types including tropical/subtropical forests, tropical/subtropical grasslands/savannas, temperate forests, temperate grasslands, Mediterranean/montane shrublands, boreal forests, tundra, deserts, and croplands. We also retrieved soil order from the Global Soil Regions Map database (https://www.nrcs.usda. gov/wps/portal/nrcs/detail/soils/use/?cid=nrcs142p2_054013).

Before fitting the RF algorithm, we first converted categorical variables (e.g., biome type) to dummy variables, and a_{soil} was natural log-transformed. Then, the functions "findCorrelation" and "findLinearCombo" in R package "caret" were used to exclude those predictors with high multicollinearities. The remaining predictors were used to fit an RF model using fivefold cross-validation repeated 10 times in order to target the model with the highest predictive power. That is, 80% (randomly selected) of the 750 a_{soil} profiles were used for calibration and the remaining 20% profiles for validation. The best model hyperparameters were targeted by running the model under a series of parameter combinations, the model performance was assessed by the rooted mean squared error and determination coefficient (R^2). Combing with the spatial layers of predictors, the RF model was used to predict a_{soil} across the globe at the resolution of 1 km (most data layers are already at the 1 km resolution as abovementioned, for those layers that are not at the target resolution, they were resampled to the 1 km resolution). In each 1 km pixel, prediction uncertainty was also quantified as $a_{\rm efflux}$ (i.e., using estimates of randomly drawn 500 trees of the fitted RF model to calculate SD and mean and thus CV).

2.6 | The ratio of a_{efflux} to a_{soil} (r_a) and its drivers

To obtain insights into the spatial pattern of the relation between a_{efflux} and a_{soil} , we conducted a pixel-to-pixel comparison between a_{efflux} and a_{soil} by calculating the ratio of a_{efflux} to a_{soil} (r_a) in each 1 km pixel. Using the 500 estimates of a_{efflux} and a_{soil} in each pixel, we obtained 500 estimates of r_a which enable us to calculate the SD and mean and thus CV (i.e., *SD/mean*). To determine if r_a is significantly smaller or larger than 1, we calculated the 95% confidence interval (CI) of r_a as: $mean \pm 1.96 \times SD$. If CI does not overlap with 1, r_a is significantly different from 1 (type II relation if mean <1, and type III relation if mean >1); otherwise, r_a is not significantly different from 1 (i.e., type I relation). Based on the maps of a_{efflux} and a_{soil} , we also randomly sampled 10,000 pixels to assess the relationship between a_{efflux} and a_{soil} grouped by biome types using a linear regression. This enabled us to test how a_{efflux} correlates to a_{soil} and how this correlation varies among biome types.

Focusing on pixel-level mean r_a , we further assessed the direct and indirect effects of a number of environmental variables on r_a using a path model (i.e., structural equation model). Four latent variables were considered in the path model including climate, soil, C input, and topography. To simplify the model and ease interpretation, indicators for latent variable "climate" were selected to be mean annual temperature (MAT) and precipitation (MAP), for "soil" were SOC_s and soil order, for "topography" were landform and elevation. MODIS NPP was selected as an indicator for "C input." We considered the following potential paths in a hypothesis-oriented path model. First, we hypothesized that all the four latent variables have direct effect on r_a , a_{efflux} , and a_{soil} ; and a_{efflux} and a_{soil} also have direct effect on r_a . Second, topography indirectly affects r_a through its effect on climate, C input, soil, a_{efflux} , and a_{soil} . Third, climate indirectly affects r_a through its effect on soil, C input, soil, a_{efflux} , and a_{soil} . Fourth, soil indirectly affects r_a through its effect on C input, a_{efflux} , and a_{soil} . At last, C input indirectly affects r_a through its effect on a_{efflux} and a_{soil} . The model was fitted to the data from 10,000 pixels randomly selected across the globe. The partial least squares approach was used to fit the path model, and all indicators were standardized. The path analyses were performed using the package *plspm* in R 4.1.1 (R Core Team, 2021).

3 | RESULTS

3.1 | Global pattern and depth distribution of a_{efflux} and a_{soil}

Across the globe, a_{efflux} in the whole 0–2 m soil profile ranges from 21 (5% quantile) to 1020 year (95% quantile) with a median and an average of 45 and 194 year, respectively, presenting a right-skewed distribution (Figure 1a). a_{efflux} is oldest in northern high latitudes (Figure 1a) with relatively cold climatic condition. Biome-specific assessment also indicates that a_{efflux} is oldest in two coldest biomes (Figure 1b), that is, boreal forests $[603_{52}^{2387}$ year (mean, 5% and 95% quantiles)] and tundra (342¹⁴³¹₅₇ year). However, the accuracy of a_{efflux} estimation in these cold regions is relatively low (Figure 2). For the depth distribution of a_{efflux} , global average a_{efflux} is estimated to be $54_{11}^{196},\;136_{15}^{505},\;431_{25}^{1693},\;686_{36}^{3522},\;1280_{39}^{7347},\;1798_{88}^{9912},\;\text{and}\;4180_{95}^{26,720}$ year in the 0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1.0, 1.0-1.5, and 1.5-2.0 m soil depths, respectively, increasing exponentially with soil depth (Figure S5). The accuracy of a_{efflux} estimation is reduced with increasing soil depth (Figure S6a), suggesting that the quantity and quality of deep soil C input will be vital for accurate estimation of a_{efflux} . In all seven soil depths, similar spatial pattern of a_{efflux} exists as that of the whole 2 m soil profile (Figure S7), and boreal forests and tundra consistently have the oldest a_{efflux} (Figure S7; Table S2). If vertical C transport is not considered, these estimates are nearly doubled (Figure S5; Table S2). Vertical transport redistributes C pools with distinct functional properties, which may shape the turnover behavior of soil C in a particular layer after receiving C from neighboring layers.

Global average a_{soil} in the 2 m soil profile is 1476_{717}^{2547} year (Figure 1c) and much older than a_{efflux} . Unlike a_{efflux} , large a_{soil} (i.e., soil C is old) is not only present in cold regions but also in relatively dry areas such as deserts and temperate grasslands (Figure 1d). In addition, the global average CV of a_{soil} is 0.25 in the 2 m soil profile, the CV of a_{soil} in seven layers did not show an apparent spatial pattern like a_{efflux} (Figure 2) and is generally smaller than 0.3

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in most areas (Figure 2b). The depth distribution of $a_{\rm soil}$ does not follow the same pattern as $a_{\rm efflux}$ and shows a linear increase with soil depth (Figure 3a). Averaging across the globe, $a_{\rm soil}$ is estimated to be 474_{131}^{1015} , 950_{413}^{1838} , 1835_{750}^{3290} , 2831_{1130}^{5187} , 3792_{1373}^{7039} , 5029_{1886}^{8906} , and $6614_{2126}^{14,071}$ year in the seven soil layers, respectively (Figure S8). In all layer depths, $a_{\rm soil}$ is markedly older than $a_{\rm efflux}$; but this disparity is narrowed with increasing soil depth (Figure 3a). In upper layers, oldest $a_{\rm soil}$ occurs in northern cold regions; but in deeper layers, $a_{\rm soil}$ is also old in relatively dry areas. For example, soil C in tundra is oldest in the top 0.2 m soil, but in the 1.5–2.0 m layer, soil C is oldest in temperate grasslands (Figure S8). With increasing soil depth, unlike $a_{\rm efflux}$, the accuracy of $a_{\rm soil}$ estimation does not become poor (Figure S7). On the contrary, $a_{\rm soil}$ in the upper 0–0.2 m soil shows the largest uncertainty.

3.2 | Relations between a_{efflux} and a_{soil}

Type II (i.e., r_a is significantly smaller than 1), I (r_a is not significantly different from 1), and III (r_a is significantly greater than 1) relations occur in 96.4%, 0.4%, and 3.2% of global land areas, respectively (Figure 1e). In type I soils, the average r_a is $0.08^{0.72}_{0.02}$. Across the globe, r_a ranges from 0.02 (5% quantile) to 0.72 (95% quantile) with a median and an average of 0.04 and 0.14, respectively, in the whole 0-2 m soil profile (Figure 1f). These results suggest that, in most soils, released C is much younger than retained soil C. In terms of the accuracy of estimated r_a , the CV is relatively large compared with the CV of a_{efflux} and a_{soil} (Figure 2c), because the uncertainty in both a_{efflux} and a_{soil} is propagated into the estimation of r_a . In general, the spatial pattern of the CV of r_a follows that of a_{efflux} (Figure 2c).

Biomes show significant differences in r_a (Figure 1f). Boreal forests and tundra present the largest r_a with an average of $0.4^{1.82}_{0.03}$ and 0.16^{0.66}_{0.03}, respectively; while deserts present the smallest r_a (0.02^{0.04}_{0.01}) (Figure 1f). After deserts, the following smallest r_a occurs in temperate grasslands ($0.041_{0.013}^{0.065}$) and tropical/subtropical grasslands/savannas $(0.042_{0.012}^{0.066}, Figure 1f)$. These results suggest that more relatively old soil C contributes to C efflux in cold biomes than in dry biomes. In the seven soil depths, global average r_a increases exponentially with soil depth, and is estimated to be $0.12_{0.02}^{0.36}, 0.13_{0.02}^{0.52}, 0.19_{0.02}^{0.98}, 0.18_{0.01}^{0.86}$ $0.30_{0.01}^{1.93}$, $0.31_{0.02}^{1.58}$ and $0.78_{0.01}^{2.00}$, respectively (Figure 3a; Figure S8). This global average exponential increase of r_a with soil depth is mainly attributed to the depth distribution of $r_{\rm a}$ in temperate forests, boreal forests, and tundra ecosystems (Figure 3b) as r₂ in other biomes generally does not show this exponential decreasing pattern (Figure 3b). Consistently, boreal forest and tundra soils have the highest r_{a} in all soil layers. In deeper layers, r, in a large fraction of boreal forest and tundra areas is greater than 1 (Figure S9).

In the whole 0–2 m soil profile, the relationship between a_{efflux} and a_{soil} shows large variability, albeit a_{efflux} is consistently smaller than a_{soil} except in some soils in boreal forests and tundra systems (Figure 4). Across the globe, a_{efflux} is positively related to a_{soil} (p < .01) with 1 year of increase of a_{efflux} per 10 years of increase of a_{soil} (i.e., the regression slope between a_{efflux} and a_{soil} is 0.1; Figure 4).



FIGURE 1 Soil carbon transit times (a_{efflux}), ages (a_{soil}), and their ratios (a_{efflux} : a_{soil}) in the 0–2 m soil profile across the globe. Left panels (a, c, e), global pattern at the resolution of 0.0083°; right panels (b, d, f), the corresponding aggregated values in nine biomes. Violin plots in (b, d, f) show the distribution, and boxplots show the median and interquartile range with whiskers extending to 1.5 times of the interquartile range. Red dots show biome-specific and global averages. Significant differences of a_{efflux} among biomes are denoted by different letters above the boxes (p < .05). See Figures S7–S9 for soil layer-specific estimation of a_{efflux} , a_{soil} , and a_{efflux} : a_{soil} , respectively. [Colour figure can be viewed at wileyonlinelibrary.com]

Among biomes, however, the relationship between a_{efflux} and a_{soil} changes substantially (Figure 4). In boreal forests, a_{efflux} increases by 5 years per 10 years increase of a_{soil} , while it shows insignificant relationships with a_{soil} in Mediterranean/montane shrublands and croplands. Through the soil profile, the relationship between a_{efflux} and a_{soil} is layer-specific (Figure S10). In line with the global spatial pattern presented in Figure S8, more a_{efflux} is exceeding a_{soil} with increasing soil depth. In deeper layers, a_{efflux} is even negatively related to a_{soil} in some biomes (Figure S11).

3.3 | Drivers of a_{efflux} , a_{soil} , and r_a

The path model considering direct and indirect effects of climate-, topography-, and soil-related variables and NPP on $r_{\rm a}$ can explain 38%, 66%, and 92% of the variance of $a_{\rm efflux}$, $a_{\rm soil}$, and $r_{\rm a}$ in the 0–2 m soil profile, respectively (Figure 5). Overall, the path model can explain 54% of the variance of the data (i.e., $R^2 = .54$). For a_{efflux} , soil indicated by soil organic carbon stock and soil order presents the strongest effect (the path coefficient ρ reaches to 0.80). The effects of other variables (e.g., climate and NPP) are significant but weak ($\rho < 0.1$; Figure 5). For a_{soil} , NPP shows the strongest effect ($\rho = -0.44$), followed by climate ($\rho = -0.22$). The importance of climate for a_{soil} is further amplified by its indirect effect on $a_{\rm soil}$ via its strong direct effect on NPP ($\rho = 0.80$; Figure 5). The ratio of a_{efflux} to a_{soil} (a_{efflux} : a_{soil}) is strongly directly influenced by $a_{\rm efflux}$ (ho = 0.66), soil (ho = 0.35), and a_{soil} ($\rho = -0.14$; Figure 5). In addition, soil also exerts an indirect effect on a_{efflux} : a_{soil} via its strong direct effect on a_{efflux} as described above. In different soil layer depths, $a_{\rm efflux}$ and soil consistently have the strongest effects on $a_{\rm efflux}$: $a_{\rm soil}$ (Figure S11). These results reveal distinct controls over $a_{\rm soil}$ and $a_{\rm efflux}$. That is, soil properties are predominant determinants for a_{efflux} , while climate and NPP for a_{soil} . This phenomenon is general in different depths through the soil profile although the variation of the magnitudes of the effects (Figure S11).

FIGURE 2 Uncertainties in estimated soil carbon transit times $[a_{efflux}, (a)]$, ages $[a_{soil}, (b)]$, and their ratios $[a_{efflux};a_{soil}, (c)]$ in the 0–2 m soil profile across the globe. The uncertainty is quantified as the coefficient of variance (CV) of 500 estimates (i.e., 500 trees in the random forest models for predicting a_{efflux} and a_{soil}) in each pixel. [Colour figure can be viewed at wileyonlinelibrary.com]



4 | DISCUSSION

4.1 | Fast transit of carbon inputs

Across the globe, our results quantitatively demonstrate that retained soil C on average is nearly eight times older than released soil C. This result indicates that most new C inputs leave soil in relatively short time (i.e., fast transit), and only a small fraction contributes to long-term soil C storage. This may be due to the fact that new C substrates entering soil are usually energy-rich and less protected by physical stabilization processes (e.g., binding with soil minerals), thereby preferentially utilized by and readily accessible to soil microorganisms (Dungait et al., 2012; Fontaine et al., 2007; Kleber et al., 2015). In the rhizosphere, for example, the majority of new and thus young C inputs derived from root exudates may be respired as CO_2 by microbes (Finzi et al., 2015) instead of contributing to long-term soil C storage. Soil fauna also feeds on new C inputs as well as microbes whose growth mainly attribute to utilization of new C (Osler & Sommerkorn, 2007; van den Hoogen et al., 2019). In addition, younger C substrates are more vulnerable to loss via physical transportation processes such as leaching due to their relatively large size (small specific surface area) thereby weak bonding with soil minerals (Hedges & Keil, 1999). As soil C efflux is dominated by relatively younger C, the observed changes in soil C efflux under changing climatic conditions (e.g., warming) would be mainly attributed to young C, masking the response of old C. We need innovative approaches to explicitly separate the responses of C pools with different ages (e.g., C isotope tracing) in order to reliably predict longterm soil C dynamics in response to carbon input changes.

4.2 | Limited contribution of additional carbon inputs to long-term soil carbon storage

The relatively faster transit times compared with the age of C retained in soil may help explain why additional C inputs do not always benefit soil C accumulation observed in a number of field experiments (Jiang et al., 2020; Kuzyakov et al., 2019). Under



FIGURE 3 Depth distribution of soil carbon transit times (a_{efflux}), ages (a_{soil}), and their ratios (a_{efflux} : a_{soil}). (a) Depth pattern of global average a_{efflux} : a_{soil} , and a_{efflux} : a_{soil} (inset); (b) depth pattern of average a_{efflux} : a_{soil} (r_a) among biome types. Lines are regression lines. [Colour figure can be viewed at wileyonlinelibrary.com]



FIGURE 4 The relationship between soil carbon transit times (a_{efflux}) and ages (a_{soil}) in the 0–2 m soil profile in randomly sampled 10,000 pixels across the globe. Colored lines show the regression line for nine biome types, and the black line shows the regression line for all data points. Dashed line shows the 1:1 line. Values in the parentheses of figure legend are the regression slope with **p <.01. See Figure S10 for soil layer-specific results. [Colour figure can be viewed at wileyonlinelibrary.com]



FIGURE 5 Drivers of soil carbon transit times (a_{efflux}), ages (a_{soil}), and their ratios (a_{efflux} : a_{soil}) in the 0–2 m soil profile. Numbers show the path coefficients (ρ) of a path analysis to detect direct and indirect effects of the variables. Arrows indicate effect direction, while red and blue paths indicate the effect is negative and positive, respectively. Insignificant paths are not shown. Indicators of the relevant latent variable (i.e., landform and elevation for topography, mean annual temperature and precipitation for climate, soil organic carbon stock and order for soil) are shown in the same box as blue color text. NPP, net primary productivity. R^2 in the box shows the determinant coefficient for the corresponding variable in the same box, while R^2 outside the circle panel shows the determinant coefficient for the whole path model. See Figure S10 for soil layer-specific results. [Colour figure can be viewed at wileyonlinelibrary.com]

elevated atmospheric CO₂, field manipulation experiments have found enhanced photosynthetic C assimilation and thus stimulated C inputs to soil, but soil C stock shows no or marginal response to such enhanced belowground C inputs and remains relatively stable (Jiang et al., 2020, Kuzyakov et al., 2019). The reason for this imbalance is widely debated. One explanation proposed is that microbial decomposition is accelerated as microbes mine nutrients from soil organic matter in order to utilize the enhanced input of newly assimilated C, particularly in nutrient-poor environments. But this cannot explain that plants also need additional nutrients to support their stimulated growth if plants do not significant increase nutrient use efficiency (Terrer et al., 2019). Our results shed light on another mechanism, that is, only a small fraction of additional C inputs contribute to long-term soil C storage and the remaining majority has left the system in a relatively short time via rapid loss pathways such as rhizosphere microbial respiration (Haichar et al., 2014) and leaching (Nakhavali et al., 2021). Consistent with this mechanism, a recent study of a mature forest under elevated CO₂ indeed found that half of the extra C fixed under elevated CO₂ was quickly released through soil respiration and another fraction was transported out via leaching, resulting in neutral soil C accumulation (Jiang et al., 2020). Our results indicate that it may be general across the globe that rapid cycling of new C

inputs weakens the efficiency of additional C inputs for long-term soil C storage.

4.3 | Controls over whole-profile soil carbon turnover and persistence

Our results reveal that the ratio of released to retained soil C ages (i.e., r) shows significant difference among biome types. Particularly, in colder biomes (e.g., boreal forests and tundra), more old soil C contributes to soil C efflux (i.e., $r_a > 1$), particularly in deeper soil layers. A series of processes may result in such protection of young soil C such as permafrost, lower oxygen availability, and stronger organo-mineral interactions in deeper soil depths (Dungait et al., 2012; Fontaine et al., 2007; Kleber et al., 2015). This may have significant implications for soil C balance changes in cold biomes under climate change. In these systems, there are more C in deeper layers, this may further amplify the response of soil C in these colder systems to global warming. Field warming experiments conducted in tundra systems have found that old C in deep layers is also sensitive to warming (Pries et al., 2016; Schuur et al., 2009; Sistla et al., 2013), which may due to that thermal limitation of soil C decomposition in deep soils is important for long-term soil C persistence in permafrost regions.

It is intriguing to note that a_{soil} is strongly negatively associated with climate (which is represented by MAT and MAP) and NPP (which is also strongly affected by climate), but the association of a_{efflux} with these factors is much weaker. On the contrary, soil (which is represented by SOC_c and soil order) has strong effect on a_{efflux} , but its effect on a_{soil} is much weaker. This phenomenon is general in all soil layer depths. These results provide insights into mechanisms underpinning different soil C turnover processes. That is, the importance of climate may mainly attribute to its direct and indirect effects on soil C persistence reflected by a_{soil}, while soil properties on soil C decomposition reflected by a_{efflux} . Shi et al. (2020) had also found that climate is the major control of soil Δ^{14} C thereby soil carbon age. Another study focusing on soil carbon turnover time (which is equivalent to a_{efflux} in this study) in the 0.3–1 m soil found that soil properties are more important than climate (Luo et al., 2019). It is likely that final soil C storage is the combined and integrated consequences of the two processes. Indeed, a previous study has demonstrated that climatic and soil properties show similar importance for controlling the global spatial pattern of soil C storage (Luo et al., 2021). In terms of global spatial pattern of a_{efflux} and a_{soil} , we also found that higher a_{efflux} mainly occurs in northern high latitudes (Figure 1a), but large a_{soil} values gather not only in cold regions but also in relatively dry areas such as deserts and temperate grasslands (Figure 1d). These results further indicate a distinct role of thermal and moisture regimes in influencing a_{efflux} and a_{soil} , which may have significant consequences on long-term soil C dynamics in response to climate change.

4.4 | Limitations and future research

To quantify the relation between a_{efflux} and a_{soil} across the globe and through soil profile at different depths using our data-driven approach, soil carbon had to be assumed to be at the steady state (i.e., input = output). A key reason is the lack of relevant temporal data at the point level. Field carbon outfluxes derived from new carbon inputs are difficult to be separated from total soil carbon outfluxes, which are a mix of autotrophic and heterotrophic respiration with different depth origin. Especially, partitioning outfluxes to different soil depths where CO₂ is produced is a grand challenge. Within a modeling context (e.g., using an Earth system model), non-steadystate simulations could be conducted using carbon inputs and outputs for the entire simulation period to account for climate and land use changes, but the model would have to make some extra strong assumptions on a series of land surface processes (e.g., land use history, plant growth and carbon partitioning, and heterogeneous soil biogeochemical processes). Despite this limitation, considering the large difference between $a_{\rm soil}$ and $a_{\rm efflux}$ (Figure 1c,d), a little bias in a_{efflux} and/or a_{soil} estimation induced by the steady-state assumption would not invalidate the general relation of $a_{soil} > a_{efflux}$ found here. Indeed, a modeling study using the Earth system model-ORCHIDEE, which explicitly takes into account climate and land use changes in the period 1860-2010 (process-based models would be the only approach available for such purpose), had demonstrated that steady-state assumption only results in a subtle change of global average soil C turnover time (i.e., a_{efflux} in our study) of 9 years (Wu et al., 2020). Similarly, Lu et al. (2018) found that the steady-state assumption leads to overestimations of a_{efflux} of about 3 years in the model CABLE. Together, these modeling studies suggest that the range of uncertainty due to the assumption of steady state in our quantification of a_{efflux} and a_{soil} may be relatively low.

Earth system models usually have a litter or labile C pool with relatively fast decay rates (Metzler & Sierra, 2018), which to some extent captures the rapid C losses of new entering C. However, the size and decay rate of this pool have been rarely explicitly tested or verified. The spatially explicit maps for a_{efflux} and a_{soil} provide benchmark global layers to force and verify these models and explore the relevant implications for long-term C dynamics. The result of most soils with a a_{efflux} -:a_{soil} not being equal to 1 demonstrates the need of partitioning soil carbon into different fractions with distinct turnover behaviors and persistence [e.g., particulate organic matter and mineral-associated organic matter as suggested by Lavallee et al. (2020)] when modeling soil C dynamics using models based on first-order kinetics. That is, the composition of soil carbon is generally heterogeneous and different fractions of soil C can decay with distinct rates. In this study, however, we only estimated mean transit time and age of soil C. If the age structure or distribution underpinning such mean values could be specified, it will be especially useful for initializing and parameterizing the sizes and decay rates of C pools in pool-based models. In addition, it should be highlighted that both a_{efflux} and a_{soil} exhibit particular vertical gradients. The underlying processes and controls of these gradients should be further studied, which are probably much more complex than the temperature and moisture modifiers included in most models.

We noticed that the uncertainty of a_{efflux} estimation (which is quantified as the CV of estimates of 500 RF trees in each 0.0083° grid) in cold regions is relatively large (Figure 2). This may be largely due to cryoturbation-induced redistribution of soil C in permafrostaffected regions (Mishra et al., 2021), which might not be well represented by the process of vertical transport considered in this study. Soil profile C redistribution may play an important role in regulating $a_{\rm efflux}$ (Luo et al., 2020). Indeed, our sensitivity analysis suggests that global average $a_{\rm efflux}$ is increased by 72% (from 194 to 334 year) if vertical transport is not considered (Figure S5). Vertical transport of soil C through soil profile has been recognized as a critical process regulating whole-profile C dynamics (Bruun et al., 2007; Guidi et al., 2022; Kaiser & Kalbitz, 2012; Rumpel & Kögel-Knabner, 2010). Yet, few studies have explored the detailed role of vertically transported soil C in controlling whole-profile soil C dynamics, especially across large extents (Luo et al., 2020). Our results imply that vertical transport of soil C would be generally important in controlling whole-profile SOC dynamics, and should be explicitly considered.

5 | CONCLUSIONS

Using a data-driven approach combining global observational datasets, we have quantified the relation between soil carbon

transit times (a_{efflux}) and ages (a_{soil}) across soil depths at a global scale. To our knowledge, we are the first to do so. The results verify that, in most soils across the globe, a_{efflux} is much smaller than a_{soil} as predicted by soil C models (Manzoni et al., 2009; Sierra et al., 2018). That is, most new C inputs transit fast and ORCID leave soil in relatively short time, suggesting that only a very small fraction of C inputs contributes to long-term soil C storage. Our results provide additional insights into the vertical gradient of the relation between a_{efflux} and a_{soil} . The significant increase of *a*_{efflux} with soil depth suggests that increasing C inputs to deeper soil layers would be more efficient for long-term C sequestration. While, in upper layers, practices that promote the REFERENCES stabilization of new C inputs would be preferred. For example, there is evidence that the application of biochar enhances soil C accumulation as biochar can stabilize new entering C by formatting microaggregates via organo-mineral interactions (Weng et al., 2017). In addition, we have noticed that the role of the vertical C transport has been rarely tested, albeit it has been acknowledged in some modeling frameworks (Koven et al., 2013; Luo et al., 2020). This knowledge gap may be a key uncertainty source in predictions of whole-soil C dynamics. Overall, we suggest that relatively rapid release of young C in upper soil layers that hold most soil C stocks must be properly considered for reliable soil C predictions and land management to simulate long-

AUTHOR CONTRIBUTIONS

term C sequestration.

Zhongkui Luo conceived the study; Guocheng Wang, Liujun Xiao, Zhongkui Luo compiled the data; Liujun Xiao and Zhongkui Luo led the data assessment with the contributions of Carlos A. Sierra and Mingming Wang; Zhongkui Luo interpreted the results with the contribution of Carlos A. Sierra, Shuai Zhang, and Mingming Wang; Zhongkui Luo led manuscript writing with substantial contributions of all authors.

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CONFLICTS OF INTEREST

The authors declare no competing interests.

DATA AVAILABILITY STATEMENT

Data used in this study are available at: https://figshare.com/artic les/dataset/Datasets_of_NPP_soil_radiocarbon_and_root_bioma ss/12840050. Digital global maps of big size can be requested from the corresponding author (luozk@zju.edu.cn).

CODE AVAILABILITY STATEMENT

R scripts used to analyze the data and generate the results are available at https://github.com/LegendXiao/The-ratio-of-aefflux-to-asoil.

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- Balesdent, J., Basile-Doelsch, I., Chadoeuf, J., Cornu, S., Derrien, D., Fekiacova, Z., & Hatté, C. (2018). Atmosphere-soil carbon transfer as a function of soil depth. Nature, 559, 599-602.
- Batjes, N. H. (2016). Harmonized soil property values for broad-scale modelling (WISE30sec) with estimates of global soil carbon stocks. Geoderma, 269, 61-68.
- Bolin, B., & Rodhe, H. (1973). A note on the concepts of age distribution and transit time in natural reservoirs. Tellus, 25, 58-62.
- Braakhekke, M. C., Beer, C., Schrumpf, M., Ekici, A., Ahrens, B., Hoosbeek, M. R., Kruijt, B., Kabat, P., & Reichstein, M. (2014). The use of radiocarbon to constrain current and future soil organic matter turnover and transport in a temperate forest. Journal of Geophysical Research-Biogeosciences, 119, 372-391.
- Bruun, S., Christensen, B. T., Thomsen, I. K., Jensen, E. S., & Jensen, L. S. (2007). Modeling vertical movement of organic matter in a soil incubated for 41 years with 14C labeled straw. Soil Biology and Biochemistry, 39, 368-371.
- Carvalhais, N., Forkel, M., Khomik, M., Bellarby, J., Jung, M., Migliavacca, M., Mu, M., Saatchi, S., Santoro, M., Thurner, M., Weber, U., Ahrens, B., Beer, C., Cescatti, A., Randerson, J. T., & Reichstein, M. (2014). Global covariation of carbon turnover times with climate in terrestrial ecosystems. Nature, 514, 213-217.
- Channan, S., Collins, K., & Emanuel, W. (2014). Global mosaics of the standard MODIS land cover type data. University of Maryland and the Pacific Northwest National Laboratory.
- Cherkinsky, A., & Brovkin, V. (1993). Dynamics of radiocarbon in soils. Radiocarbon, 35, 363-367.
- Clark, D. A., Brown, S., Kicklighter, D. W., Chambers, J. Q., Thomlinson, J. R., & Ni, J. (2001). Measuring net primary production in forests: Concepts and field methods. Ecological Applications, 11, 356–370.
- Crowther, T. W., Todd-Brown, K. E. O., Rowe, C. W., Wieder, W. R., Carey, J. C., Machmuller, M. B., Snoek, B. L., Fang, S., Zhou, G., Allison, S. D., Blair, J. M., Bridgham, S. D., Burton, A. J., Carrillo, Y., Reich, P. B., Clark, J. S., Classen, A. T., Dijkstra, F. A., Elberling, B., ... Bradford, M. A. (2016). Quantifying global soil carbon losses in response to warming. Nature, 540, 104-108.
- Dungait, J. A., Hopkins, D. W., Gregory, A. S., & Whitmore, A. P. (2012). Soil organic matter turnover is governed by accessibility not recalcitrance. Global Change Biology, 18, 1781-1796.
- Fan, N., Koirala, S., Reichstein, M., Thurner, M., Avitabile, V., Santoro, M., Ahrens, B., Weber, U., & Carvalhais, N. (2020). Apparent ecosystem carbon turnover time: Uncertainties and robust features. Earth System Science Data Discussions, 2020, 1–25.
- Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. International Journal of Climatology., 37, 4302-4315.
- Finzi, A. C., Abramoff, R. Z., Spiller, K. S., Brzostek, E. R., Darby, B. A., Kramer, M. A., & Phillips, R. P. (2015). Rhizosphere processes are quantitatively important components of terrestrial carbon and nutrient cycles. Global Change Biology, 21, 2082-2094.

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- Fontaine, S., Barot, S., Barré, P., Bdioui, N., Mary, B., & Rumpel, C. (2007). Stability of organic carbon in deep soil layers controlled by fresh carbon supply. *Nature*, 450, 277–280.
- Guidi, C., Frey, B., Brunner, I., Meusburger, K., Vogel, M. E., Chen, X., Stucky, T., Gwiazdowicz, D. J., Skubala, P., Bose, A. K., Schaub, M., Rigling, A., & Hagedorn, F. (2022). Soil fauna drives vertical redistribution of soil organic carbon in a long-term irrigated dry pine forest. *Global Change Biology*, 28, 2169–2182.
- Haichar, F. E., Santaella, C., Heulin, T., & Achouak, W. (2014). Root exudates mediated interactions belowground. *Soil Biology & Biochemistry*, 77, 69–80.
- He, Y., Trumbore, S. E., Torn, M. S., Harden, J. W., Vaughn, L. J. S., Allison, S. D., & Randerson, J. T. (2016). Radiocarbon constraints imply reduced carbon uptake by soils during the 21st century. *Science*, 353, 1419–1424.
- Hedges, J. I., & Keil, R. G. (1999). Organic geochemical perspectives on estuarine processes: Sorption reactions and consequences. *Marine Chemistry*, 65, 55–65.
- Hua, Q., Barbetti, M., & Rakowski, A. Z. (2013). Atmospheric radiocarbon for the period 1950–2010. *Radiocarbon*, *55*, 2059–2072.
- Jackson, R. B., Lajtha, K., Crow, S. E., Hugelius, G., Kramer, M. G., & Pineiro, G. (2017). The ecology of soil carbon: Pools, vulnerabilities, and biotic and abiotic controls. *Annual Review of Ecology, Evolution,* and Systematics, 48, 419–445.
- Jiang, M., Medlyn, B. E., Drake, J. E., Duursma, R. A., Anderson, I. C., Barton, C. V. M., Boer, M. M., Carrillo, Y., Castañeda-Gómez, L., Collins, L., Crous, K. Y., De Kauwe, M. G., dos Santos, B. M., Emmerson, K. M., Facey, S. L., Gherlenda, A. N., Gimeno, T. E., Hasegawa, S., Johnson, S. N., ... Ellsworth, D. S. (2020). The fate of carbon in a mature forest under carbon dioxide enrichment. *Nature*, 580, 227–231.
- Kaiser, K., & Kalbitz, K. (2012). Cycling downwards Dissolved organic matter in soils. Soil Biology & Biochemistry, 52, 29–32.
- Kleber, M., Eusterhues, K., Keiluweit, M., Mikutta, C., Mikutta, R., & Nico, P. S. (2015). Mineral-organic associations: Formation, properties, and relevance in soil environments. *Advances in Agronomy*, 130, 1–140.
- Koven, C., Riley, W., Subin, Z., Tang, J., Torn, M., Collins, W., Bonan, G., Lawrence, D., & Swenson, S. (2013). The effect of vertically resolved soil biogeochemistry and alternate soil C and N models on C dynamics of CLM4. *Biogeosciences*, 10, 7109–7131.
- Kuzyakov, Y., Horwath, W. R., Dorodnikov, M., & Blagodatskaya, E. (2019). Review and synthesis of the effects of elevated atmospheric CO₂ on soil processes: No changes in pools, but increased fluxes and accelerated cycles. *Soil Biology and Biochemistry*, 128, s66–s78.
- Lal, R. (2004). Soil carbon sequestration to mitigate climate change. *Geoderma*, 123, 1-22.
- Lavallee, J. M., Soong, J. L., & Cotrufo, M. F. (2020). Conceptualizing soil organic matter into particulate and mineral-associated forms to address global change in the 21st century. *Global Change Biology*, 26, 261–273.
- Lawrence, C. R., Beem-Miller, J., Hoyt, A. M., Monroe, G., Sierra, C. A., Stoner, S., Heckman, K., Blankinship, J. C., Crow, S. E., McNicol, G., Trumbore, S., Levine, P. A., Vindušková, O., Todd-Brown, K., Rasmussen, C., Hicks Pries, C. E., Schädel, C., McFarlane, K., Doetterl, S., ... Wagai, R. (2020). An open-source database for the synthesis of soil radiocarbon data: International soil radiocarbon database (ISRaD) version 1.0. *Earth System Science Data*, 12, 61–76.
- Lu, X., Wang, Y. P., Luo, Y., & Jiang, L. (2018). Ecosystem carbon transit versus turnover times in response to climate warming and rising atmospheric CO₂ concentration. *Biogeosciences*, 15, 6559–6572.
- Luo, Z., Luo, Y., Wang, G., Xia, J., & Peng, C. (2020). Warming-induced global soil carbon loss attenuated by downward carbon movement. *Global Change Biology*, 26, 7242–7254.

- Luo, Z., Viscarra-Rossel, R. A., & Qian, T. (2021). Similar importance of edaphic and climatic factors for controlling soil organic carbon stocks of the world. *Biogeosciences*, 18, 2063–2073.
- Luo, Z., Wang, G., & Wang, E. (2019). Global subsoil organic carbon turnover times dominantly controlled by soil properties rather than climate. *Nature Communications*, 10, 3688.
- Manzoni, S., Katul, G. G., & Porporato, A. (2009). Analysis of soil carbon transit times and age distributions using network theories. *Journal* of *Geophysical Research: Biogeosciences*, 114, G04025.
- Metzler, H., & Sierra, C. A. (2018). Linear autonomous compartmental models as continuous-time Markov chains: Transit-time and age distributions. *Mathematical Geosciences*, *50*, 1–34.
- Mishra, U., Hugelius, G., Shelef, E., Yang, Y., Strauss, J., Lupachev, A., Harden, J. W., Jastrow, J. D., Ping, C.-L., & Riley, W. J. (2021). Spatial heterogeneity and environmental predictors of permafrost region soil organic carbon stocks. *Science Advances*, *7*, eaaz5236.
- Nakhavali, M., Lauerwald, R., Regnier, P., Guenet, B., Chadburn, S., & Friedlingstein, P. (2021). Leaching of dissolved organic carbon from mineral soils plays a significant role in the terrestrial carbon balance. *Global Change Biology*, *27*, 1083–1096.
- Olson, D. M., Dinerstein, E., Wikramanayake, E. D., Burgess, N. D., Powell, G. V., Underwood, E. C., D'amico, J. A., Itoua, I., Strand, H. E., & Morrison, J. C. (2001). Terrestrial ecoregions of the world: A new map of life on earth: A new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. *Bioscience*, 51, 933–938.
- Osler, G. H. R., & Sommerkorn, M. (2007). Toward a complete soil C and N cycle: Incorporating the soil fauna. *Ecology*, *88*, 1611–1621.
- Pries, C. E. H., Schuur, E. A., Natali, S. M., & Crummer, K. G. (2016). Old soil carbon losses increase with ecosystem respiration in experimentally thawed tundra. *Nature Climate Change*, 6, 214–218.
- R Development Core Team. (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing.
- Rumpel, C., & Kögel-Knabner, I. (2010). Deep soil organic matter—A key but poorly understood component of terrestrial C cycle. *Plant and Soil*, 338, 143–158.
- Schuur, E. A., Vogel, J. G., Crummer, K. G., Lee, H., Sickman, J. O., & Osterkamp, T. (2009). The effect of permafrost thaw on old carbon release and net carbon exchange from tundra. *Nature*, 459, 556–559.
- Shi, Z., Allison, S. D., He, Y., Levine, P. A., Hoyt, A. M., Beem-Miller, J., Zhu, Q., Wieder, W. R., Trumbore, S., & Randerson, J. T. (2020). The age distribution of global soil carbon inferred from radiocarbon measurements. *Nature Geoscience*, 13, 555–559.
- Sierra, C. A., Hoyt, A. M., He, Y., & Trumbore, S. E. (2018). Soil organic matter persistence as a stochastic process: Age and transit time distributions of carbon in soils. *Global Biogeochemical Cycles*, 32, 1574–1588.
- Sierra, C. A., Müller, M., Metzler, H., Manzoni, S., & Trumbore, S. E. (2017). The muddle of ages, turnover, transit, and residence times in the carbon cycle. *Global Change Biology*, 23, 1763–1773.
- Sistla, S. A., Moore, J. C., Simpson, R. T., Gough, L., Shaver, G. R., & Schimel, J. P. (2013). Long-term warming restructures Arctic tundra without changing net soil carbon storage. *Nature*, 497, 615–618.
- Song, J., Wan, S., Piao, S., Knapp, A. K., Classen, A. T., Vicca, S., Ciais, P., Hovenden, M. J., Leuzinger, S., & Beier, C. (2019). A metaanalysis of 1,119 manipulative experiments on terrestrial carboncycling responses to global change. *Nature Ecology & Evolution*, 3, 1309–1320.
- Terrer, C., Jackson, R. B., Prentice, I. C., Keenan, T. F., Kaiser, C., Vicca, S., Fisher, J. B., Reich, P. B., Stocker, B. D., Hungate, B. A., Peñuelas, J., McCallum, I., Soudzilovskaia, N. A., Cernusak, L. A., Talhelm, A. F., Van Sundert, K., Piao, S., Newton, P. C. D., Hovenden, M. J., ... Franklin, O. (2019). Nitrogen and phosphorus constrain the CO₂ fertilization of global plant biomass. *Nature Climate Change*, *9*, 684–689.

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- Terrer, C., Phillips, R. P., Hungate, B. A., Rosende, J., Pett-Ridge, J., Craig, M. E., van Groenigen, K., Keenan, T. F., Sulman, B. N., & Stocker, B. (2021). A trade-off between plant and soil carbon storage under elevated CO₂. *Nature*, *591*, 599–603.
- Trumbore, S. (2000). Age of soil organic matter and soil respiration: Radiocarbon constraints on belowground C dynamics. *Ecological Applications*, 10, 399–411.
- van den Hoogen, J., Geisen, S., Routh, D., Ferris, H., Traunspurger, W., Wardle, D. A., de Goede, R. G. M., Adams, B. J., Ahmad, W., Andriuzzi, W. S., Bardgett, R. D., Bonkowski, M., Campos-Herrera, R., Cares, J. E., Caruso, T., Caixeta, L. D., Chen, X. Y., Costa, S. R., Creamer, R., ... Crowther, T. W. (2019). Soil nematode abundance and functional group composition at a global scale. *Nature*, *572*, 194–198.
- Vaughn, L. J., & Torn, M. S. (2018). Radiocarbon measurements of ecosystem respiration and soil pore-space CO₂ in Utqiagvik (Barrow), Alaska. Earth System Science Data, 10, 1943–1957.
- Weng, Z., Van Zwieten, L., Singh, B. P., Tavakkoli, E., Joseph, S., Macdonald, L. M., Rose, T. J., Rose, M. T., Kimber, S. W. L., Morris, S., Cozzolino, D., Araujo, J. R., Archanjo, B. S., & Cowie, A. (2017). Biochar built soil carbon over a decade by stabilizing rhizodeposits. *Nature Climate Change*, 7, 371–376.
- Wu, D., Piao, S., Zhu, D., Wang, X., Ciais, P., Bastos, A., Xu, X., & Xu, W. (2020). Accelerated terrestrial ecosystem carbon turnover and its drivers. *Global Change Biology*, 20, 5052–5062.

- Xiao, L., Wang, G., Chang, J., Chen, Y., Guo, X., Mao, X., Wang, M., Zhang, S., Shi, Z., Luo, Y., Cheng, L., Yu, K., Mo, F., & Luo, Z. (2022). Depth distribution of belowground net primary production across global biomes. *Research Square*. https://doi.org/10.21203/ rs.3.rs-65178/v3
- Zhao, M., Heinsch, F. A., Nemani, R. R., & Running, S. W. (2005). Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sensing of Environment*, 95, 164-176.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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