Biogeosciences Discuss., https://doi.org/10.5194/bg-2018-342
Manuscript under review for journal Biogeosciences
Discussion started: 15 August 2018

Evaluating the simulated mean soil carbon transit times by Earth system models using observations

Jing Wang[1], Jianyang Xia[1*], Xuhui Zhou[1], Kun Huang[1], Jian Zhou[1], Yuanyuan Huang[2], Lifen Jiang[3], Xia Xu[4], Junyi Liang[5], Ying-Ping Wang[6], Xiaoli Cheng[7], Yiqi Luo[3,8]

[1]Tiantong National Forest Ecosystem Observation and Research Station & Research Center for Global Change and Ecological Forecasting, School of Ecological and Environmental Sciences, East China Normal University, Shanghai 200062, China

[2]Laboratoire des Sciences du Climat et de l'Environnement, 91191 Gif-sur-Yvette, France

[3]Center for ecosystem science and society, Northern Arizona University, Arizona, Flagstaff, AZ 86011, USA

[4]College of Biology and the Environment, Nanjing Forestry University, Nanjing 210037, China

[5]Environmental Sciences Division & Climate Change Science Institute, Oak Ridge National Laboratory, Oak Ridge, Tennessee 37830, USA

[6]CSIRO Ocean and Atmosphere, PMB #1, Aspendale, Victoria 3195, Australia

[7]Wuhan Botanical Garden, Chinese Academy of Sciences, Wuhan 430074, Hubei Province, China

[8] Department of Earth System Science, Tsinghua University, Beijing 100084, China

Correspondence to: Jianyang Xia (jyxia@des.ecnu.edu.cn)

Abstract. One known bias in current Earth system models (ESMs) is the underestimation of global mean soil carbon (C) transit time (τ_{soil}), which quantifies the mean age of the C atoms at the time they leave the soil. However, it remains unclear where such underestimations are located globally. Here, we constructed a global database of measured τ_{soil} across 187 sites to evaluated results from twelve ESMs. The observations showed that the estimated τ_{soi} was dramatically shorter from the soil incubations studies in the laboratory environment (median as 4 with the interquartile range of 1-25 years) than that derived from field *in-situ* measurements (31 with 5-84 years) with the shifts of stable isotopic C (^{13}C) or the *stock-over-flux* approach. In comparison with the field observations, the multi-model ensemble simulated a shorter median (19 years) and a smaller spatial variation (interquartile range of 6-28 years) of τ_{soil} across the same site locations. We then found a significant and negative linear correlation between the *in-situ* measured τ_{soil} and mean annual air temperature, and the underestimations of modeled τ_{soil} are mainly located in cold and dry biomes especially tundra and desert. Furthermore, we showed that one ESM (i.e., CESM) has improved its τ_{soil} estimate by incorporation of the soil vertical profile. These findings indicate that the spatial variation of τ_{soil} is a useful benchmark for ESMs, and we recommend more observation and modeling efforts on soil C dynamics in hydrothermal limited regions.

1 Introduction

Carbon (C) cycle feedback to climate change is highly uncertain in current Earth system models (ESMs) (Friendlingsterin et al., 2006, Bernstein et al., 2008, Ciais et al., 2013, Bradford et al., 2016), which largely stems from their diverse simulations of C exchanges among the atmosphere, vegetation, and soil (Luo et al., 2016, Smith et al., 2016, Mishra et al., 2017). Soil organic carbon (SOC) represents the largest terrestrial carbon pool, which stores at least three times as much as the atmospheric and vegetation C reservoirs (Parry et al., 2007, Bloom et al., 2016). However, a five- to six-fold difference in soil C stocks among ESMs or offline global land surface model has been found (Todd-Brown et al., 2013, Luo et al., 2016). This large uncertainty is difficult to be reduced or even diagnosed because many processes collectively affect the time of C atoms transit the soil system (i.e., transit time; τ_{soil}) (Sierra et al., 2016, Spohn and Sierra, 2018,). Some recent attempts at evaluating and diagnosing the modeled SOC in ESMs have shown significant simulation uncertainties in the τ_{soil} (Todd-Brown et al., 2013, Carvalhais et al., 2014, He et al., 2016, Koven et al., 2017). For example, there is a fourfold difference in the simulated τ_{soil} among the ESMs from the 5th phase of Coupled Model Intercomparison Project (CMIP5) (Todd-Brown et al., 2013). A recent data-driven analysis has suggested that the current ESMs have substantially underestimated the τ_{soil} by 16-17 times at the global scale (He et al., 2016). Therefore, identifying the locations of such underestimations is critical to improve the predictive ability of ESMs on terrestrial C cycle, and the construction of a benchmarking database based on available observations becomes urgently needed (Koven et al., 2017).

The terms of transit time, turnover time and age of soil C have been muddled in diagnosing the models (Sierra et al. 2016). These diagnostic times (Sierra et al., 2016) are based on the different assumptions and mainly derived from four approaches. The first approach calculates τ_{soil} as the division of SOC stock over flux such as net primary productivity (NPP) or heterotrophic respiration (R_h). It assumes the soil system as a time-invariant linear system in a steady state (Bolin et al., 1973, Sanderman et al., 2003, Six and Jastrow, 2012). The second approach is based on the shifts in stable isotopic C (^{13}C) after successive changes in C_3–C_4 vegetation, together with additional information from the disturbed and undisturbed soils (Balesdent et al., 1987; Zhang et al., 2015). The third approach is based on simulating soil C dynamics with linear models by assimilating the observational data from laboratory incubations of soil samples (Xu et al., 2016). The last approach derives the weighted inverse of the first-order cycling rate by fitting a one- or multiple-pool linear model to field observations of radiocarbon (^{14}C) (Trumbore et al., 1993, Fröberg et al., 2011). The former three approaches indicate the transit time which is the mean age of C leaved the system at the certain time. However, although radiocarbon has been widely used to quantify the age or transit time of soil C, its validity has been challenged by some recent theoretical analyses (Sierra et al., 2016, Metzler et al., 2018). Also, the methodological uncertainty is large especially when these approaches are applied to estimate the τ_{soil} of different soil fractions (Feng et al., 2016). Thus, this study mainly collects the τ_{soil} from the approaches of *stock-over-flux*, ^{13}C changes and lab incubations in the further analyses.

In this study, we first construct a database from the literatures which reported the τ_{soil} (Figure 1a, Supplementary materials on Text S1). Then, the database is used to evaluate the simulated τ_{soil} by the ESMs in the CMIP5. Many ESMs, e.g., CESM, have released new versions in the recent years, so we also evaluate whether the simulated τ_{soil} has been improved. In the case of CESM, one of its major developments on the soil C cycling is the vertically resolved soil biogeochemical scheme (Koven et al., 2013). Thus, we employ a matrix approach developed by Huang et al., (2017) to examine the impact of the vertically resolved soil biogeochemical scheme on the simulated τ_{soil} by CESM.

Biogeosciences Discuss., https://doi.org/10.5194/bg-2018-342
Manuscript under review for journal Biogeosciences
Discussion started: 15 August 2018

2 Materials and Methods

2.1 A global database of site-level τ_{soil}

We collected the literatures that reported the τ_{soil} based on measurements (Supplementary Materials on Text1): (1) $\delta^{13}C$ shifts after successive changes in C_3−C_4 vegetation, (2) measurements of CO_2 production in laboratory SOC incubation over at least seven months, and (3) simultaneously measurements of SOC stock and heterotrophic respiration. A database containing the measured τ_{soil} from 187 sites across the globe was constructed (Figure.1). The information of climate (e.g., mean annual temperature and precipitation) was also collected from the literatures or extracted from the WorldClim database version 1.4 (http://worldclim.org/) if they were not available. The WorldClim dataset provided a set of free global climate data for ecological modelling and Geographic Information System (GIS) analyzing with a spatial resolution of 0.86 km^2 (Hutchinson et al., 2004). We calculated the mean temperature and precipitation by averaging the monthly climate data over 1990−2000 for those observational sites with missing climate information. The classes of biomes were processed to match the seven biomes classification adopted by the MODIS land cover product MCD12C1 (NASA LP DAAC 2008, Friedl et al., 2010) and Todd-Brown et al. (2013) (Figure S4): (1) tropical forest including evergreen broadleaf forest between 25° N and 25° S; (2) temperate forest including deciduous broadleaf, evergreen broadleaf outside of 25° N and 25° S and mixed forest south of 50° N; (3) boreal forest including evergreen needleleaf forest, deciduous needleleaf forest, mixed forest north of 50° N; (4) grassland and shrubland including woody savanna south of 50° N, savanna and grasslands south of 55° N; (5) deserts and savanna including barren or sparsely vegetated, open shrubland south of 55° N, and closed shrubland south of 50° N; (6) Tundra; and (7) Croplands. Other land cover types like permanent wetland, urban, and bare land were not included in this study.

2.2 Outputs of Earth system models from CMIP5.

The *historical* simulation outputs of 12 ESMs participating CMIP5 (https://esgf-data.dkrz.de/search/cmip5-dkrz/) were analyzed in this study (Table S3). For each model, the SOC, litter C, NPP, and Rh were extracted from the outputs in historical simulations (*cSoil, cLitter, npp*, and *rh*, respectively, from the CMIP5 variable list). The litter and soil carbon were summed as the bulk soil carbon stock. Among the 12 models, only the inmcm4 model did not output NPP, so we calculated it as gross primary production minus autotrophic respiration. Due to the diverse spatial resolutions among the models, we aggregated the results of different models to 1°×1° with the nearest interpolation method (Fig.S1). The τ_{soil} of SOC was calculated as the ratio of carbon stock over flux (NPP or Rh):

$$\tau = \frac{\text{SOC}}{\text{flux}} \tag{1}$$

2.3 Global τ_{soil} based on HWSD SOC and MODIS NPP.

Based on the equation (1), we also calculated the τ_{soil} in each grid with the satellite-based NPP and the empirical SOC dataset (τ_{soil} = SOC_{HWSD}/NPP_{MODIS}). Satellite-based NPP was obtained from the MODIS through the aboard NASA's

Biogeosciences Discuss., https://doi.org/10.5194/bg-2018-342
Manuscript under review for journal Biogeosciences
Discussion started: 15 August 2018

Terra satellite (http://modis.gsfc.nasa.gov), with a spatial resolution of 0.8×0.8 m^2 for every 8-day interval over the period 2000–2010 (LP DAAC 2008). The MODIS NPP was calculated by subtracting autotrophic respiration from GPP. In this study, we aggregated the MODIS NPP to 1°×1°resolution with the nearest interpolation method. The empirical SOC estimate at the global scale was provided by the Harmonized World Soil Database (HWSD), which is attached to the Food and Agriculture Organization of the United Nations (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012). The vertical profile of SOC was divided into two layers (0−30cm and 30−100cm) in HWSD. In each layer, the database reports layer depth, soil texture, bulk density and organic content. For total organic carbon of HWSD, we estimate the SOC with bulk density, organic content, and layer thickness (Batjes et al., 1996) for 1 m at a 1°×1° resolution with the equation (2). Because the large fraction of global soil exists at high latitudes, we also used the Northern Circumpolar Soil Carbon Database (NCSCD) (Tarnocai et al., 2009) to validated HWDS SOC estimation. In equation 2, for an individual soil profile with n layers, SOC is the total amount of organic carbon (kg C m^{-2}) over depth d, BD is the bulk density (kg m^{-3}), d_i is the thickness of this layer (m), P_i is the proportion of organic carbon (g C g^{-1}), and S_i is the volume of the fraction of fragments (vol%).

$$SOC=\sum_{i=1}^{n} BD \times (1\text{-}Si) \times di \times Pi \qquad (2)$$

2.4 Matrix approach through CLM4.5 and CLM4.5_noV.

The Community Land Model Version 4.5 (CLM4.5) is the terrestrial component of Community Earth System Model (CESM). This version mainly consists of exchanges among different carbon and nitrogen pools and other biogeochemical cycles, as well as includes a vertical dimension of soil carbon and nitrogen transformations (Koven et al., 2013). The matrix approach was applied to extract the soil module from original CLM4.5 which could evaluate which processes influence τ_{soil} in the model (Huang et al., 2017). Once get the total C pool and R_h in each pool, we can calculate the τ_{soil} with the equation (1). We represented the structure of SOC as 7 carbon pools as *i)* one coarse woody debris (CWD) pool, *ii)* three litter pools (litter1, litter2 and litter3) and *iii)* three soil carbon pools (soil1, soil2, and soil3). In this matrix, C is transferred from three litter pools and CWD to three soil pools with different transfer rates. In each layer, these transfer rates are regulated by the transfer coefficients and fractions. C inputs from litterfall were allocated into different C compartments by modifications by soil environmental factors (temperature, moisture, nitrogen and soil oxygen) and vertical transfer process. To understand whether the incorporation of soil vertical profile affect the simulation of τ_{soil}, we compared the results based on matrix approach with (i.e., CLM4.5) or without (i.e., CLM4.5_noV) the soil vertical transfer process.

In the CLM4.5, soil C dynamics was simulated with 10 soil layers, and the same organic matter pools among different vertical soil layers are allowed to mix mainly through diffusion and advection. The matrix approach determinates the soil dynamic of each SOC pool by simulating the first-order kinetics as equation (3):

$$\frac{dC(t)}{dt}=B(t)I(t)\text{-}A\xi(t)KC(t)\text{-}V(t)C(t) \qquad (3)$$

where the $C_{(t)}$ is the organic C pool size at time *t*. $I_{(t)}$ is the total organic C inputs while $B_{(t)}$ is the vector of partitioning coefficients. *K* is a diagonal matrix which representing the intrinsic decomposition rate of each C pool. The decomposition rate in the matrix approach is modified by the transfer matrix (A) and environmental scalars (ξ). The

Biogeosciences Discuss., https://doi.org/10.5194/bg-2018-342
Manuscript under review for journal Biogeosciences
Discussion started: 15 August 2018

scalar matrix (ξ) shown in equation (4) is the environmental factor to modify the SOC intrinsic decomposition rate. Each scalar matrix combines temperature (ξ_T), water (ξ_W), oxygen (ξ_O), depth (ξ_D) and nitrogen (ξ_N) controlled scalar on SOC decay.

$$\xi' = \xi_T \xi_W \xi_O \xi_D \xi_N \quad (4)$$

A is the horizontal C transfer matrix which quantifies C movement among different C pools shown as matrix (5). The non-diagonal entries a_{ij} shown in matrix (5) represent the fraction of C moves from the jth to the ith pool. In CLM4.5 and CLM4.5_noV, transfer coefficients are the same in each soil layer.

$$A = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & A44 & 0 & 0 & 0 \\ 0 & A52 & A53 & 0 & A55 & A56 & A57 \\ 0 & 0 & 0 & A64 & A65 & A66 & 0 \\ 0 & 0 & 0 & 0 & A75 & A76 & A77 \end{pmatrix} \quad (5)$$

V(t) is the vertical C transfer coefficient matrix among different soil layers, each of the diagonal blocks is a tridiagonal matrix that describes transfers coefficient with $V_{ij(t)}$ In this section, CLM4.5_noV assumes no vertical transfers in all pools. Therefore, *V*(t) for CLM4.5_noV is a blank matrix in the simulation. In the contrast, CLM4.5 was assigned by a matrix with vertical transfers in each C pool. As the vertical transfer rates among different C pool categories in CLM4.5, the matrix shown as matrix (6).

$$V(t) = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & V22(t) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & V33(t) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & V44(t) & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & V55(t) & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & V66(t) & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & V77(t) \end{pmatrix} \quad (6)$$

2.4 Statistical analyses.

The median and interquartile were used for the quantification of both observational and modelling results due to the probability distribution of τ_{soil} is not normal. To test the difference in τ_{soil} among three approaches, we first normalized the data with the log-transformation and then applied the one-way ANOVA with multi-comparison technique (Fig. 1b insert). The linear regression and correlation analyses were applied with the *R language* (3.2.1; *R* development Core team).

3 Results and discussion

3.1 Estimated τ_{soil} and its spatial variation by different approaches

The one-way ANOVA with multi-comparison analysis showed no significant difference in the log-transformed τ_{soil} between the methods of ^{13}C (60 with the interquartile range of 8−29 years) and *stock-over-flux* (16 with the

Biogeosciences Discuss., https://doi.org/10.5194/bg-2018-342
Manuscript under review for journal Biogeosciences
Discussion started: 15 August 2018

interquartile range of 3−156 years, Figure 1b). The range of these field *in-situ* measurements (median as 31 with interquartile range of 5-84 years) is comparable to a former estimate of mean SOC turnover time (48 with 24−107 years) across twenty long-term experiments in temperate ecosystems using the ^{13}C labelling approach (Schmidt et al., 2011). However, the estimates of τ_{soil} from laboratory studies (4 with 1−15 year) was significantly shorter than the other two methods (Figure 1b). It suggests that the τ_{soil} could be underestimated by the measurements from the laboratory incubations studies. Thus, the τ_{soil} from the laboratory incubation studies were excluded in the following analyses.

We then integrated the estimates of τ_{soil} based on the ^{13}C, and *stock-over-flux* approaches to examine the inter-biome difference. As shown by Fig. 2b, the longest τ_{soil} was found in desert and shrubland (170 with 58-508) and tundra (159 with 39-649 years). Boreal forest (58 with 25-170 years) has longer τ_{soil} than the temperate (44 with 13−89 years) and tropical forests (15 with 9-130 years). Grassland and savanna had short (35 with 21-57 years) and croplands had moderate (62 with 21-120 years) τ_{soil} in comparison with other biomes (Figure 2).

3.2 Modelled τ_{soil} and its estimation biases

The longest ensemble mean τ_{soil} of multiple models were found in dry and cold regions (Figure 2). In comparison with the integrated observations from ^{13}C and stock over flux, the modelled τ_{soil} were significantly shorter across all biomes (Figure 2b insert). The negative bias was larger in dry (desert, grassland, and savanna) and cold (tundra and boreal forest) regions than tropical and temperate forests. The longest modelled τ_{soil} appeared in the desert and shrubland ecosystem with the median of 37 years (interquartile range of 14−88 years). The modelled median τ_{soil} were also shorter than observations in tropical forest (8 years), temperate forests (29 years), boreal forest (27 years), grassland/savanna (24 years), tundra (21 years) and croplands (28 years) (Figure 2, Table S1). In comparison with the observations, the models obviously underestimated the τ_{soil} in the cold and dry biomes (Table S1; Figure 2b). A recent global data-model comparison study at the 0.5°×0.5° resolution has also detected a similar spatial pattern of underestimation bias in ecosystem C turnover time (Carvalhais et al., 2014), but its magnitudes of bias in the cold regions are much smaller than that found in this study.

By grouping the τ_{soil} into different climatic categories, we found that the observed τ_{soil} was significantly covaried with MAT (y = -5.28x+156.04, r^2 = 0.48, P <0.01) but not MAP (Figure 3). These results support the previous findings of negative covariations between τ_{soil} and temperature at both the site and global levels (Trumbore *et al.* 1996). Although there is no significant correlation between τ_{soil} and MAP in the observations, the models produced negative correlations of τ_{soil} with MAT (r^2 = 0.24, P < 0.05) and MAP (r^2 = 0.44, P < 0.05) (Figure 3).

We further evaluated the global distribution of the modelled τ_{soil} against the results calculated from HWSD SOC over MODIS NPP. The CMIP5 models underestimated the SOC stock in tundra (~1.8 times) and desert (~1.3 times) but overestimated the NPP in tundra and desert by 4 and 5 times, respectively (Figure 3c and Figure S3), resulting in the larger underestimation biases of τ_{soil} in tundra and desert than in other ecosystems. We further replaced the MODIS NPP with the ensemble mean NPP of 10 TRENDY models in the calculation, and found that the underestimations of τ_{soil} are still clearly in tundra and desert (Figure S5).

Biogeosciences Discuss., https://doi.org/10.5194/bg-2018-342
Manuscript under review for journal Biogeosciences
Discussion started: 15 August 2018

Improved modeling of τ_{soil} with vertically resolved SOC dynamics

Given that many ESMs have further developed their representations of the soil biogeochemistry in recent years, we also examined whether the τ_{soil} estimates have been improved by one of the CMIP5 models (i.e., CESM). It is encouraging that the biases of τ_{soil} in dry and cold regions have been substantially reduced in the new land version of CESM (i.e., version 4.5 of the Community Land Model; CLM4.5). One major improvement in CLM4.5 is the vertically resolved SOC dynamics (Koven et al., 2013). By turning off the vertical C movements with a matrix approach (Huang et al., 2017), we show a similar pattern of underestimation on τ_{soil} by the CLM4.5 (i.e., CLM4.5_noV in Fig. 4). This result suggests that the vertically resolved soil biogeochemistry is promising in improving the τ_{soil} estimates by ESMs. However, it should be noted that the spatial variation of τ_{soil} was still largely underestimated by the CLM4.5 (Fig. 4b insert).

The higher NPP simulated by ESMs in the cold and dry regions have been reported by previous studies (Shao et al., 2013, Smith et al., 2016, Xia et al., 2017). The models produce high NPP in cold regions largely because they overestimate the efficiency of plant transferring assimilated C to growth (Xia et al., 2017). The CMIP5 models overestimate the precipitation and underestimate the dryland expansion by 4 folds during 1996-2005 (Ji et al., 2015), which could lead to high NPP and fast SOC turnover rates as found in this study (Figure. 3c). These results suggest that once the NPP simulation is improved without the correction of the τ_{soil} underestimation, the models will produce smaller SOC stock in the cold and dry ecosystems.

This study shows that adding the vertical resolved biogeochemistry is a promising approach to correct the bias of τ_{soil} in current models. However, other processes, such as the microbial dynamics, SOC stabilization and nutrient cycles, which also have not been fully considered by the CMIP5 models but could affect the estimation of τ_{soil} (Luo et al., 2016). For example, adding soil microbial dynamics could increase τ_{soil} in cold regions by lowering the transfer proportion of decomposed SOC to the atmosphere (Wieder et al., 2013). By contrast, the incorporation of nitrogen cycles might shorten τ_{soil} by increasing plant C transfers to short-lived litter pools (e.g., O-CN and CABLE model) (Gerber et al., 2010) or reducing litter C transfers to the slow soil C pools (e.g., LM3V model) (Xia et al., 2013).

Large challenges still exist in using observations derived from different methods to constrain the modelled τ_{soil}. Laboratory incubation studies report much shorter τ_{soil} than other methods, mainly due to the optimized soil moisture and/or temperature during the soil incubation (Stewart et al., 2008; Feng et al., 2016). It suggests that the ESM models will largely underestimate τ_{soil} if its turnover parameters are derived from laboratory incubation studies. It should be noted that the observations from the ^{13}C and the stock-over-flux approaches in this study are derived for the bulk soil. However, SOC is commonly represented as multiple pools with different cycling rates in most of the CMIP5 models (Luo et al., 2016, Sierra et al., 2016, 2018, Metzler and Sierra, 2018). As synthesized by Sierra et al. (2016), the observations of τ_{soil} are useful for a specific model once its pool structure is identified. Model database, such as the bgc-md (https://github.com/MPIBGC-TEE/bgc-md), could be a useful tool to improve the integration of observations and soil C models. Thus, an enhanced transparency of C-cycle model structure in ESMs is highly recommended, especially when they participate in the future model intercomparison projects such as the CMIP6 (Jones et al., 2016).

4 Conclusions

This study detected large underestimation biases of τ_{soil} in ESMs in cold and dry biomes, especially the tundra and desert. Improving the modelling of SOC dynamics in these regions is important because the cold ecosystems (e.g., the permafrost regions) are critical for global C feedback to future climate change (Schuur et al., 2015) and the dry regions strongly regulate the interannual variability of land CO_2 sink (Poulter et al., 2014, Ahlström et al., 2015). The current generation of ESMs represents the soil C processes with a similar model formulation as first-order C transfers among multiple pools (Sierra et al., 2015, Luo et al., 2016, Metzler and Sierra, 2018). Thus, tremendous research efforts are still required to attribute the underestimation biases of τ_{soil} in current ESMs to their sources, such as the model structure, parameterization, and climate forcing. Reducing these biases would largely improve the accuracy of ESMs in the projection of future terrestrial C cycle and its feedback to climate change. Recent modelling activities aiming to increase the soil heterogeneity, e.g., soil vertical profile (Koven et al., 2013, 2017) and microbial dynamics (Allison et al., 2010, Wieder et al., 2013), are promising. Overall, this study shows the great spatial variation of τ_{soil} in the natural ecosystems, and we recommend more research efforts to improve its representation by ESMs in the future.

5 Acknowledgments

We appreciated Dr. Todd-Brown for her supports of the soil data in CMIP5 and in HWSD, and Dr. Deli Zhai for the valuable comments. The model simulations analyzed in this study were obtained from the Earth System Grid Federation CMIP5 online portal hosted by the Program for Climate Model Diagnosis and Intercomparison at Lawrence Livermore National Laboratory (https://pcmdi.llnl.gov/projects/esgf-llnl/). This work was financially supported by the National Key R&D Program of China (2017YFA0604600), the National Natural Science Foundation (31430015, 41630528), and the National 1000 Young Talents Program of China.

6 Author information and contributions

The authors declare no competing financial interests. Correspondence should be addressed to J. Xia (jyxia@des.ecnu.edu.cn). J.X designed the study. J.W collected and organized the data. L. J provided the CMIP5 and HWSD data. X. X provided the laboratory incubation data. Y. Huang provides the CLM4.5 matrix module. J.W and J.X wrote the first draft, and all other authors contributed to the revision and discussions on the results.

References

Ahlström, A., Raupach, M. R., Schurgers, G., Smith, B., Arneth, A., Jung, M., Reichstein, M., Canadell, J. G., Friedlingstein, P., Jain, A. K. and Kato, E.: The dominant role of semi-arid ecosystems in the trend and variability of the land CO2 sink. Science, 348(6237), 895-899. https://doi: 10.1126/science.aaa1668, 2015.

Allison, S.D., Matthew, D. W. and Mark, A. B.: Soil-carbon response to warming dependent on microbial physiology. Nat. Geosci. 3(5), 336-340, doi: 10.1038/ngeo846,2010

Balesdent, J., Mariotti, A., and Guillet, B.: Natural ^{13}C abundance as a tracer for studies of soil organic matter dynamics.

Soil Biol.Biochem., 19(1), 25-30. https://doi: 10.1016/0038-0717(87)90120-9, 1987.

Batjes, N. H.: Total carbon and nitrogen in the soils of the world. Euro.J. soil science 47(2), 151-163, https://doi: 10.1111/j.1365-2389.1996.tb01386.x, 1996

Bernstein, L., Bosch, P., Canziani, O., Chen, Z., Christ, R., and Riahi, K.: IPCC, 2007: Climate Change 2007: Synthesis Report, 2008.

Bloom, A. A., Exbrayat, J. F., van der Velde, I. R., Feng, L., and Williams, M.: The decadal state of the terrestrial carbon cycle: Global retrievals of terrestrial carbon allocation, pools, and residence times. P. Natl. Acad. Sci. USA, 113(5): 1285-1290, https://doi: 10.1073/pnas.1515160113, 2016.

Bolin, B., and Henning, R.: A note on the concepts of age distribution and transit time in natural reservoirs. Tellus, 25, 58-62, https://doi: 10.1111/j.2153-3490.1973.tb01594.x, 1973

Bradford, M.A., Wieder, W.R., Bonan, G.B., Fierer, N., Raymond, P.A. and Crowther, T.W.: Managing uncertainty in soil carbon feedbacks to climate change. Nat.Clim.Change, 6(8), 751-758, https://doi: 10.1038/nclimate3071, 2016.

Carvalhais, N., Forkel, M., Khomik, M., Bellarby, J., Jung, M., Migliavacca, M., Mu, M., Saatchi, S., Santoro, M., Thurner, M. and Weber, U.: Global covariation of carbon turnover times with climate in terrestrial ecosystems. Nature 514, 213-217, https://doi: 10.1038/nature13731, 2014.

Ciais, P., Sabine, C., Bala, G., Bopp, L., Brovkin, J., and Thornton, P.: Climate Change 2013: the physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. (eds Stocker, T. F. et al.) Cambridge Univ. Press, 465-570, 2013.

FAO/IIASA/ISRIC/ISSCAS/JRC, Harmonized World Soil Database (version 1.10), FAO, Rome, Italy and IIASA, Laxenburg, Austria, 2012.

Feng, W., Shi, Z., Jiang, J., Xia, J., Liang, J., Zhou, J. and Luo, Y.: Methodological uncertainty in estimating carbon turnover times of soil fractions. Soil Biol. Biochem. 100, 118-124, https://doi: 10.1016/j.soilbio.2016.06.003, 2016.

Friedl, M. A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., and Huang, X.: MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. Remote sen. Environ., 114, 168-182, https://doi: 10.1016/j.rse.2009.08.016, 2010.

Friedlingstein, P., Cox, P., Betts, R., Bopp, L., von Bloh, W., Brovkin, V., Cadule, P., Doney, S., Eby, M., Fung, I. and Bala, G.: Climate-carbon cycle feedback analysis: Results from the C4MIP model intercomparison. J. Clim. 19(14), 3337–3353, https://doi: 10.1175/JCLI3800.1, 2006.

Fröberg, M., Tipping, E., Stendahl, J., Clarke, N., and Bryant, C.: Mean residence time of O horizon carbon along a climatic gradient in Scandinavia estimated by ^{14}C measurements of archived soils. Biogeochemistry, 104, 227-236, https://doi: 10.1007/s10533-010-9497-3, 2011

Gerber, S., Hedin, L. O., Oppenheimer, M., Pacala, S. W., and Shevliakova, E.: Nitrogen cycling and feedbacks in a global dynamic land model. Global Biogeochem. Cy. 24(1), https://doi: 1029/2008GB003336, 2010.

He, Y., Trumbore, S. E., Torn, M. S., Harden, J. W., Vaughn, L. J., Allison, S. D., and Randerson, J. T.: Radiocarbon constraints imply reduced carbon uptake by soils during the 21st century. Science 353 (6306), 1419-1424, https://doi: 10.1126/science.aad4273, 2016.

Huang, Y., Lu, X., Shi, Z., Lawrence, D., Koven, C.D., Xia, J., Du, Z., Kluzek, E. and Luo, Y.: Matrix approach to

Biogeosciences Discuss., https://doi.org/10.5194/bg-2018-342
Manuscript under review for journal Biogeosciences
Discussion started: 15 August 2018

land carbon cycle modeling: A case study with Community Land Model. Glob.Change Biol., https://doi: 10.1111/gcb.13948,2017.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., and Jarvis, A.: Very high resolution interpolated climate surfaces for global land areas. International Journal of Clim. 25(15), 1965-1978, https://doi: 10.1002/joc.1276, 2005.

Hutchinson, M. F., and T. Xu.: Anusplin version 4.2 user guide. Centre for Resource and Environmental Studies, The Australian National University, Canberra, 54, 2004

Ji, M., Huang, J., Xie, Y. and Liu, J.: Comparison of dryland climate change in observations and CMIP5 simulations. Adv. in Atmo. Sciences, 32(11), 1565-1574, https://doi:10.1007/s00376-015-4267-8, 2015.

Jones C., Jasmin G. J., and Randerson, J.T.: C4MIP-The Coupled Climate-Carbon Cycle Model Intercomparison Project: experimental protocol for CMIP6. Geosci. Model Dev. 8, 2853, https://doi: 10.5194/gmd-9-2853-2016, 2016.

Koven, C. D., Hugelius, G., Lawrence, D. M., and Wieder, W. R.: Higher climatological temperature sensitivity of soil carbon in cold than warm climates. Nat. Clim. Change 7(11), 817–822, https://doi: 10.1038/nclimate3421, 2017.

Koven, C.D., Riley, W.J., Subin, Z.M., Tang, J.Y., Torn, M.S., Collins, W.D., Bonan, G.B., Lawrence, D.M. and Swenson, S.C.: The effect of vertically resolved soil biogeochemistry and alternate soil C and N models on C dynamics of CLM4. Biogeosciences, 10(11), 7109, https://doi: 10.5194/bg-10-7109-2013, 2013.

Luo, Y., Ahlström, A., Allison, S.D., Batjes, N.H., Brovkin, V., Carvalhais, N., Chappell, A., Ciais, P., Davidson, E.A., Finzi, A. and Georgiou, K.: Toward more realistic projections of soil carbon dynamics by Earth system models. Glob. Biogeochem. Cycles, 30(1), 40-56, https://doi: 10.1002/2015GB005239, 2016.

Metzler H., Müller M., and Sierra C.A.: Transit-time and age distributions for nonlinear time-dependent compartmental systems. P. Natl. Acad. Sci. USA, 22:201705296. https://doi: 10.1073/pnas.1705296115, 2018.

Metzler H., Sierra C.A.: Linear autonomous compartmental models as continuous-time Markov chains: transit-time and age distributions. Math. Geosci., 50, 1-34, 2018

NASA LP DAAC Land Cover Type Yearly L3 Global 0.05 Deg CMG (MCD12C1), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, available at: https://lpdaac.usgs.gov/products/modis products table/land cover/yearly l3 global 0.05 deg cmg/mcd12c1, 2008.

Parry, M., Parry, M. L., Canziani, O., Palutikof, J., Van der Linden, P., and Hanson, C.: Climate Change 2007: Impacts, Adaptation and Vulnerability (eds Parry, M. L. et al.) Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge Univ. Press, Cambridge, UK, 211–272, 2007.

Poulter, B., Frank, D., Ciais, P., Myneni, R.B., Andela, N., Bi, J., Broquet, G., Canadell, J.G., Chevallier, F., Liu, Y.Y. and Running, S.W.: Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle. Nature 509(7502), 600-603, https://doi: 10.1038/nature13376, 2014.

Sanderman, J. Ronald, G. A. and Dennis, D. B.: Application of eddy covariance measurements to the temperature dependence of soil organic matter mean residence time. Glob. Biogeochem. Cycles, 17, 301-3015, https://doi: 10.1029/2001GB001833, 2003.

Schmidt, M.W., Torn, M.S., Abiven, S., Dittmar, T., Guggenberger, G., Janssens, I.A., Kleber, M., Kögel-Knabner, I., Lehmann, J., Manning, D.A. and Nannipieri, P.: Persistence of soil organic matter as an ecosystem property. Nature, 478(7367), 49–56, https://doi: 10.1038/nature10386, 2011.

Schuur, E.A.G., McGuire, A.D., Schädel, C., Grosse, G., Harden, J.W., Hayes, D.J., Hugelius, G., Koven, C.D., Kuhry, P., Lawrence, D.M. and Natali, S.M.: Climate change and the permafrost carbon feedback. Nature 520(7546), 171-179, https://doi: 10.1038/nature14338, 2015.

Shao, P., Zeng, X., Sakaguchi, K., Monson, R.K. and Zeng, X.: Terrestrial carbon cycle: climate relations in eight CMIP5 earth system models. J. Clim., 26(22), 8744-8764, https://doi: 10.1175/JCLI-D-12-00831.1,2013.

Sierra, C. A., and Markus, M.: A general mathematical framework for representing soil organic matter dynamics. Ecological Monographs, 85, 505-524, https://doi: 10.1890/15-0361.1, 2015.

Sierra, C.A., Müller, M., Metzler, H., Manzoni, S. and Trumbore, S.E.: The muddle of ages, turnover, transit, and residence times in the carbon cycle. Glob.Change Biol., 23(5), 1763–1773, https://doi: 10.1111/gcb.13556, 2017.

Sierra, C.A., Ceballos-Núñez, V., Metzler, H., Müler, M.: Representing and understanding the carbon cycle using the theory of compartmental dynamical systems. J. Adv. Model. Earth Sy., https://doi.org/10.1029/2018MS001360, 2018.

Six, J., and Jastrow, J. D.: Organic matter turnover. Encycl. of soil science: 936-942, 2002

Smith, W.K., Reed, S.C., Cleveland, C.C., Ballantyne, A.P., Anderegg, W.R., Wieder, W.R., Liu, Y.Y. and Running, S.W.: Large divergence of satellite and Earth system model estimates of global terrestrial CO2 fertilization. Nat.Clim.Change, 6(3), 306-310, https://doi: 10.1038/nclimate2879, 2016.

Spohn, M., Sierra, C.A.: How long do elements cycle in terrestrial ecosystems? Biogeochemistry, 139, 69-83, https://doi.org/10.1007/s10533-018-0452-z, 2018.

Stewart, C.E., Paustian, K., Conant, R.T., Plante, A.F. and Six, J.: Soil carbon saturation: evaluation and corroboration by long-term incubations. Soil Biol.Biochem. 40(7), 1741-1750, https://doi: 10.1016/j.soilbio.2008.02.014, 2008.

Tarnocai, C., Canadell, J.G., Schuur, E.A.G., Kuhry, P., Mazhitova, G. and Zimov, S.: Soil organic carbon pools in the northern circumpolar permafrost region, Glob. Biogeochem. Cy., 23(2), https://doi: 10.1029/2008GB003327, 2009.

Todd-Brown, K.E., Randerson, J.T., Post, W.M., Hoffman, F.M., Tarnocai, C., Schuur, E.A. and Allison, S.D.: Causes of variation in soil carbon simulations from CMIP5 Earth system models and comparison with observations. Biogeosciences, 10, 1717-1736, https://doi: 10.5194/bg-10-1717-2013.

Trumbore, S.E.: Comparison of carbon dynamics in tropical and temperate soils using radiocarbon measurements. Glob. Biogeochem. Cycles, 7(2), 275-290, https://doi: 10.1029/93GB00468, 1993.

Trumbore, S. E., O. A. Chadwick, and Amundson, R.: Rapid exchange between soil carbon and atmospheric carbon dioxide driven by temperature change. Science, 272, 393-396, https://doi: 10.1126/science.272.5260.393, 1996.

Wieder, W.R., Bonan, G.B. and Allison, S.D.: Global soil carbon projections are improved by modelling microbial processes. Nat. Clim. Change 3(10), 909-912, https://doi:. 10.1038/nclimate1951, 2013.

Xia, J., Luo, Y., Wang, Y.P. and Hararuk, O.: Traceable components of terrestrial carbon storage capacity in biogeochemical models. Glob.Change Biol. 19, 2104-2116, https://doi: 10.1111/gcb.12172, 2013.

Xia, J., et al. (2017), Terrestrial ecosystem model performance in simulating productivity and its vulnerability to climate change in the northern permafrost region. J. Geophys. Res. 122, 430-446, https://doi: 10.1002/2016JG003384.

Xu, X., Shi, Z., Li, D., Rey, A., Ruan, H., Craine, J.M., Liang, J., Zhou, J. and Luo, Y.: Soil properties control decomposition of soil organic carbon: results from dataassimilation analysis. Geoderma, 262(2016), 235-242, https://doi: 10.1016/j.geoderma.2015.08.038, 2016.

Zhang, K., Dang, H., Zhang, Q. and Cheng, X.: Soil carbon dynamics following landuse change varied with temperature and precipitation gradients: evidence from stable isotopes. Glob. Change Biol., 21(7), 2762-2772, https://doi: 10.1111/gcb.12886, 2015.

Biogeosciences Discuss., https://doi.org/10.5194/bg-2018-342
Manuscript under review for journal Biogeosciences
Discussion started: 15 August 2018

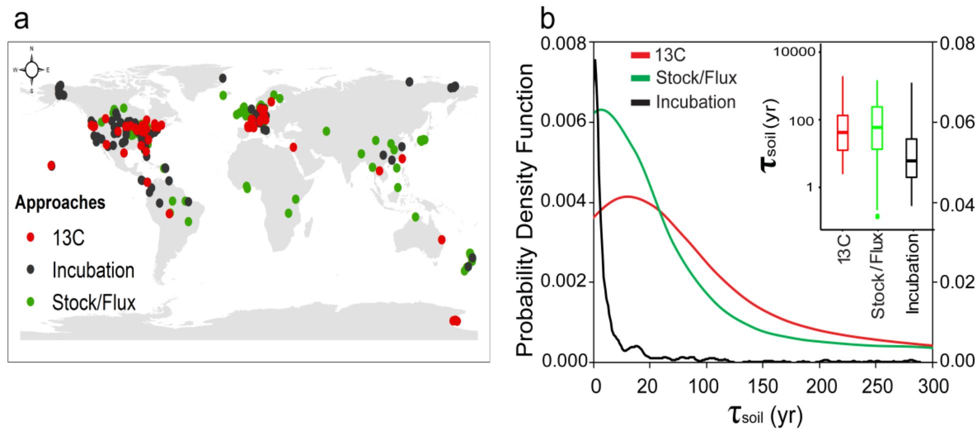

Figure 1. Spatial distributions of observational sites for estimates of SOC transit time (τ_{soil}, year). a, The site locations of measurements with different approaches. b, Probability density functions of τ_{soil} measured by different approaches. Note that the left axis is for ^{13}C and *stock-over-flux* approaches, and the right axis is for laboratory incubation studies.

Biogeosciences Discuss., https://doi.org/10.5194/bg-2018-342
Manuscript under review for journal Biogeosciences
Discussion started: 15 August 2018

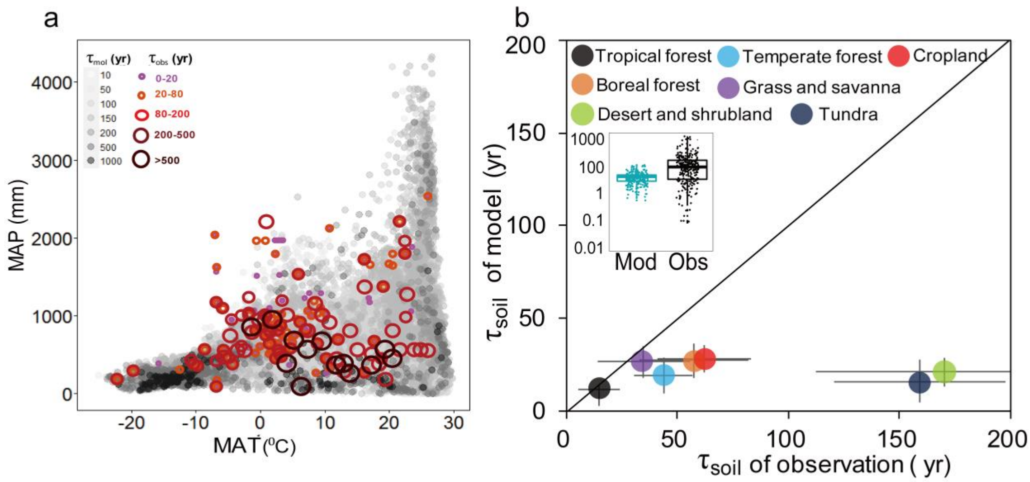

Figure 2. Global spatial variation of SOC transit time (τ_{soil}) with climate and the difference of τ_{soil} estimation between observations and models. a, Spatial variation of τ_{soil} with mean annual temperature (MAT) and mean annual precipitation (MAP). b, Comparisons of modelled against observed transit time; c and d are the comparisons of modelled against observed transit time at the biome level, respectively. Details for the classification of biomes are provided in the method section.

Biogeosciences Discuss., https://doi.org/10.5194/bg-2018-342
Manuscript under review for journal Biogeosciences
Discussion started: 15 August 2018

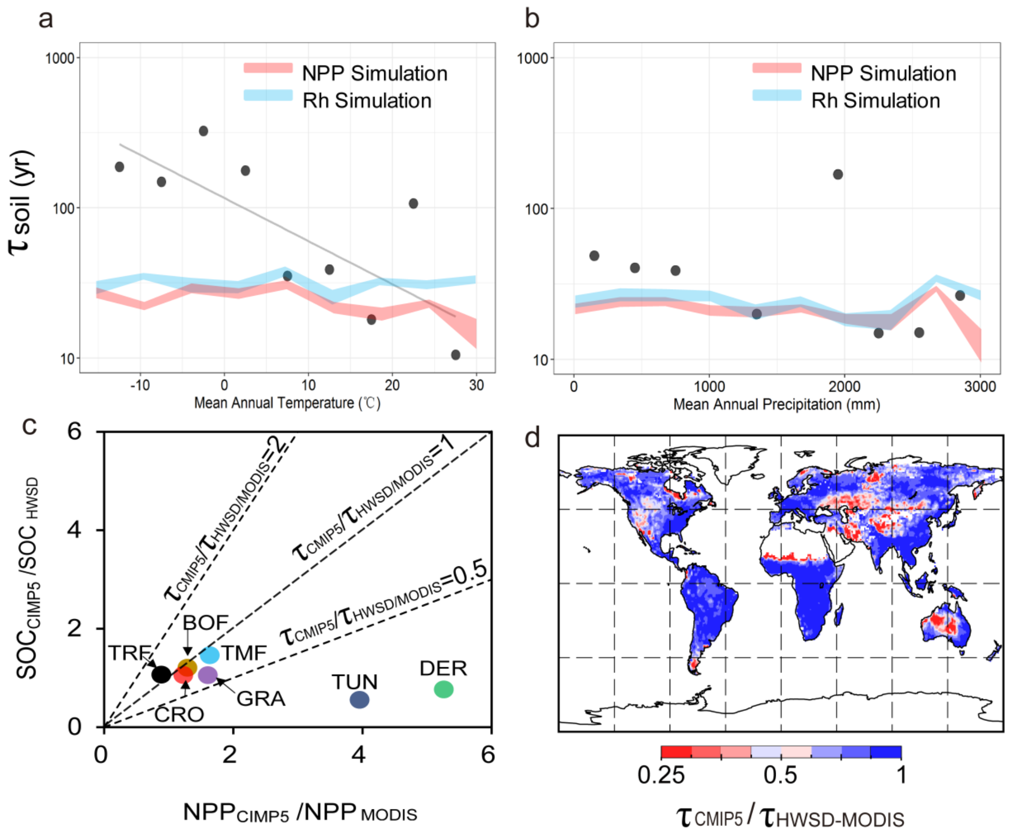

Figure 3. Relationships between τ_{soil} and climate factors in both observations and CIMP5 models. The black solid line in the panel (a) show the negative correlation between τ_{soil} and mean annual temperature (y= -5.28x+156.04, r^2 = 0.48, P<0.01). The black dots indicate the aggregated τ_{soil} over each category of MAT (panel a) or MAP (panel b). The red and blue areas present the standard errors of the estimated τ_{soil} among multiple models based on the ratios of C stock over NPP and R_h, respectively. Panel c shows the bias of NPP and SOC between CMIP5 and HWSD/MODIS. Panel d shows the difference of τ_{soil} between outputs from CMIP5 and gridded results (HWSD/MODIS) in each 1°×1° grid pixel at the global scale. TRF: Tropical forest; TMF: Temperate forest; BOF: Boreal forest; DER: Desert and shrubland; GRA: Grass and savanna; TUN: Tundra; CRO: Cropland.

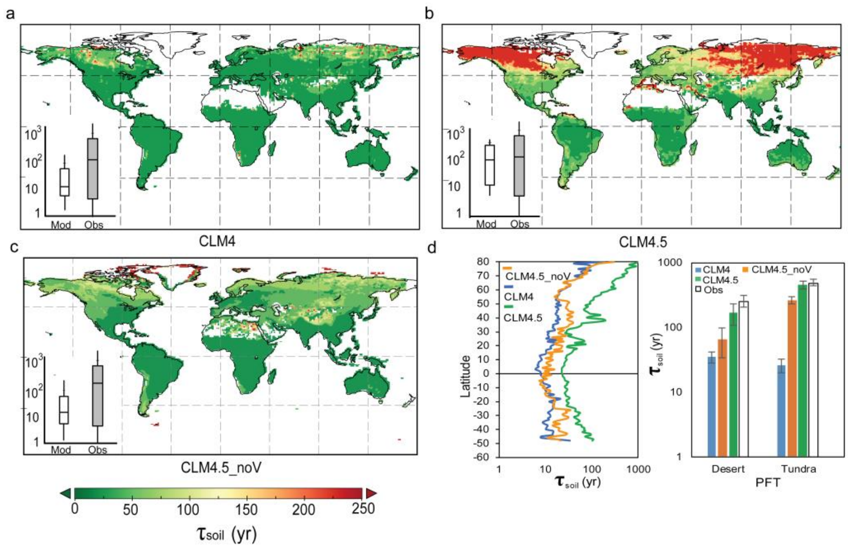

Figure 4. Simulated τ_{soil} by CLM4 (a; median global τ_{soil} = 20.56 years), CLM4.5 (b; median global τ_{soil} =127.50 years) and CLM4.5_noV (c; median global τ_{soil} =22.24 years). The panel d shows the latitudinal spatial distribution of the mean τ_{soil} of different models in desert and tundra. The insert figures in panels a-c compare the τ_{soil} between models and observations. The bottom and top of the box represent the first and third quartiles.