



**HAL**  
open science

# Evaluation of CMIP5 Earth System Models for the Spatial Patterns of Biomass and Soil Carbon Turnover Times and Their Linkage with Climate

Donghai Wu, Shilong Piao, Yongwen Liu, Philippe Ciais, Yitong Yao

► **To cite this version:**

Donghai Wu, Shilong Piao, Yongwen Liu, Philippe Ciais, Yitong Yao. Evaluation of CMIP5 Earth System Models for the Spatial Patterns of Biomass and Soil Carbon Turnover Times and Their Linkage with Climate. *Journal of Climate*, 2018, 31 (15), pp.5947-5960. 10.1175/JCLI-D-17-0380.1 . hal-02900790

**HAL Id: hal-02900790**

**<https://hal.science/hal-02900790>**

Submitted on 11 Jun 2021

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Evaluation of CMIP5 Earth System Models for the Spatial Patterns of Biomass and Soil Carbon Turnover Times and Their Linkage with Climate

DONGHAI WU, SHILONG PIAO, AND YONGWEN LIU

*Sino-French Institute for Earth System Science, College of Urban and Environmental Sciences, Peking University, Beijing, China*

PHILIPPE CIAIS

*Laboratoire des Sciences du Climat et de l'Environnement, CEA CNRS UVSQ, Gif-sur-Yvette, France*

YITONG YAO

*Sino-French Institute for Earth System Science, College of Urban and Environmental Sciences, Peking University, Beijing, China*

(Manuscript received 5 June 2017, in final form 26 March 2018)

## ABSTRACT

Earth system models (ESMs) from phase 5 of the Coupled Model Intercomparison Project (CMIP5) were diagnosed as having large discrepancies in their land carbon turnover times, which partly explains the differences in the future projections of terrestrial carbon storage from the models. Carvalhais et al. focused on evaluation of model-based ecosystem carbon turnover times  $\tau_{\text{eco}}$  in relation with climate factors. In this study,  $\tau_{\text{eco}}$  from models was analyzed separately for biomass and soil carbon pools, and its spatial dependency upon temperature and precipitation was evaluated using observational datasets. The results showed that 8 of 14 models slightly underestimated global biomass carbon turnover times  $\tau_{\text{veg}}$  (modeled median of 8 yr vs observed 11 yr), and 11 models grossly underestimated the soil carbon turnover time  $\tau_{\text{soil}}$  (modeled median of 16 yr vs observed 26 yr). The underestimation of global carbon turnover times in ESMs was mainly due to values for  $\tau_{\text{veg}}$  and  $\tau_{\text{soil}}$  being too low in the high northern latitudes and arid and semiarid regions. In addition, the models did not capture the observed spatial climate sensitivity of carbon turnover time in these regions. Modeled  $\tau_{\text{veg}}$  and  $\tau_{\text{soil}}$  values were generally weakly correlated with climate variables, implying that differences between carbon cycle models primarily originated from structural differences rather than from differences in atmospheric climate models (i.e., related to temperature and precipitation). This study indicates that most models do not reproduce the underlying processes driving regional  $\tau_{\text{veg}}$  and  $\tau_{\text{soil}}$ , highlighting the need for improving the model parameterization and adding key processes such as biotic disturbances and permafrost–carbon climate responses.

## 1. Introduction

Natural terrestrial ecosystems, excluding those subject to land use change, have sequestered about 30% of cumulative anthropogenic carbon emissions since 2005 (Le Quéré et al. 2015). The global terrestrial carbon sink is sensitive to climate variability and climate

trends (Forkel et al. 2016; Peylin et al. 2005; Piao et al. 2013; Xuhui Wang et al. 2014). A positive feedback between the terrestrial carbon reservoir and climate change is projected by Earth system models (ESMs), but the magnitude of this feedback differs among models (Friedlingstein et al. 2014, 2006). How to reduce this uncertainty has received increasing attention recently (Cox et al. 2013).

The carbon turnover time, defined as the ratio of mass and outgoing flux from a carbon pool, is one of the key parameters determining terrestrial carbon balance (He et al. 2016; Koven et al. 2015; Todd-Brown et al. 2013). The structure of land carbon cycle models can be

Supplemental information related to this paper is available at the Journals Online website: <https://doi.org/10.1175/JCLI-D-17-0380.s1>.

Corresponding author: Shilong Piao, [slpiao@pku.edu.cn](mailto:slpiao@pku.edu.cn)

summarized by a cascade of pools, each with a different turnover, for different grid points. For example, for live biomass, carbon turnover time in forest is longer than in grasslands; and for dead organic carbon, turnover time in Arctic tundra is much longer than in tropical forests (Bloom et al. 2016). It has been suggested that uncertain carbon turnover time as an emerging property of models dominates the uncertainty in terrestrial vegetation responses to future climate change and rising atmospheric CO<sub>2</sub> concentration (Friend et al. 2014). Furthermore, the soil carbon turnover times in ESMs were shown to be significantly underestimated compared to radiocarbon measurements, leading to overestimation of soil carbon sequestration by a factor of nearly 2 (40% ± 27%) (He et al. 2016).

Terrestrial carbon turnover time is closely linked with climate factors such as temperature and precipitation (Carvalhais et al. 2014; Chen et al. 2013; Knorr et al. 2005). For example, Carvalhais et al. (2014) found a negative correlation between temperature and ecosystem carbon turnover time  $\tau_{\text{eco}}$  across most of the regions in the world, with the exception of tropical forests and warm arid regions. In the warm arid regions, precipitation showed stronger correlations with  $\tau_{\text{eco}}$  than with temperature. In tropical regions, both temperature and precipitation showed a weak spatial correlation with  $\tau_{\text{eco}}$  (Carvalhais et al. 2014). It should be noted that since vegetation and soil carbon turnover have different physiological processes and climate responses (Bradford et al. 2016; De Kauwe et al. 2014), vegetation and soil carbon turnover time may have different spatial patterns of correlation with climate, which was not fully investigated by Carvalhais et al. (2014). Furthermore, it is difficult to draw a clear picture of the terrestrial carbon cycle model performance on the magnitude of the sensitivity of carbon turnover time to climate variation from the current literature.

In addition to the uncertainties in the climate sensitivity of carbon turnover time, the bias of ESM climate fields also influences the modeled carbon turnover times. The simulations from phase 5 of the Coupled Model Intercomparison Project (CMIP5) showed large differences between climate models (Flato et al. 2013). For example, the CMIP5 global land annual temperature  $T$  during the period of 1986–2005 differed by approximately 3°C among models, and global land annual precipitation  $P$  by approximately 250 mm (Anav et al. 2013). This invites the question whether large differences of turnover times between CMIP5 ESMs mainly result from differences between climate models or from structural differences between carbon cycle models.

In this study, we evaluated the spatial patterns of carbon turnover time and its response to climate

variation derived from 14 CMIP5 ESMs against observation-based results. Unlike previous studies such as Carvalhais et al. (2014), here we evaluate biomass and soil carbon turnover time separately. Annual net primary production instead of gross primary production was used to calculate carbon turnover time.

## 2. Dataset and methods

### a. Vegetation carbon storage

The spatial distribution of total biomass carbon was derived from recently published global maps of above-ground biomass carbon (ABC) over the period of 1993–2010 (Liu et al. 2015) and biome-specific conversion factors between total biomass carbon (TBC) and ABC (Flato et al. 2013; Liu et al. 2015; Robinson 2007). The global ABC product of Liu et al. (2015) was derived based on global vegetation optical depth (VOD) retrievals from harmonized series of passive microwave satellite sensors (Liu et al. 2011). Similar to Liu et al. (2015), in order to retrieve the TBC we simply multiplied ABC values by vegetation-specific ratios of TBC/ABC, provided by Table 1 in Liu et al. (2015). The information on the spatial distribution of vegetation type was determined using the Moderate Resolution Imaging Spectroradiometer (MODIS) International Geosphere–Biosphere Program (IGBP) land-cover map (Friedl et al. 2010). Our estimation of the global TBC stock was 570 PgC, comparable to the 560 PgC from Gibbs et al. (2006).

### b. Soil organic carbon storage

Previous studies usually used the best traditional soil carbon map provided by the Harmonized World Soil Database (HWSD) (FAO/IIASA/ISRIC/ISSCAS/JRC 2012) and the Northern Circumpolar Soil Carbon Database (NCSCD) (Hugelius et al. 2013; Tarnocai et al. 2009) for estimating soil carbon turnover time (Todd-Brown et al. 2013). In this study, we chose the latest global soil carbon dataset provided by the World Inventory of Soil Emission Potentials (WISE) project (Batjes 2016) based on approximately 21 000 available profiles and soil geographical data. The WISE soil carbon dataset has more accurate spatial patterns of soil organic carbon (SOC) especially for the northern circumpolar regions, and reported SOC density for seven depth intervals (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). Because the CMIP5 models did not include vertically resolved soil profiles, and did not consider carbon cycle processes for burying carbon below the active layer, we used the top 1 m of soil carbon storage to compute soil carbon turnover time as in Todd-Brown et al. (2013). To compare with modeled results,

we also used the global litter carbon stock from Bloom et al. (2016) output by a diagnostic ecosystem carbon balance model, Data Assimilation Linked Ecosystem Carbon Model version 2 (DALEC2) (Bloom and Williams 2015). In this study, soil organic carbon storage was calculated from the sum of soil carbon from Batjes (2016) and litter carbon from Bloom et al. (2016).

### c. NPP and climate data

The global distribution of net primary production (NPP) with 1-km spatial resolution from 2000 to 2010 was provided by the Numerical Terradynamic Simulation Group (NTSG) at the University of Montana (<https://www.ntsug.umt.edu/>; Zhao and Running 2010). This NPP product was not an observation but a model with a light-use efficiency formulation driven by satellite-based estimates of the fraction of photosynthetically active radiation, shortwave downward solar radiation, vapor pressure deficit (VPD), and low daily minimum temperature for gross primary production (GPP), and a model for maintenance and growth components respirations to derive NPP from GPP. Detailed information on the techniques used for modeling NPP can be found in related publications (Zhao and Running 2010; Zhao et al. 2005).

The temperature and precipitation data were from the Climatic Research Unit (CRU) time series version 3.24 datasets (Harris et al. 2014) with a spatial resolution of 0.5°. These gridded datasets were obtained from more than 4000 meteorological stations and interpolated based on spatial autocorrelation functions (Mitchell and Jones 2005; New et al. 2000).

### d. CMIP5 ESM simulations

We used historical simulations (“historical” experiment, 1850–2005) from the CMIP5 ESMs forced by observed atmospheric composition changes and time-variable land cover (Taylor et al. 2012). Output of biomass carbon, soil organic carbon, litter carbon, NPP, air temperature, and precipitation (cVeg, cSoil, cLitter, npp, tas, and pr in the CMIP5 variable list) from 14 ESMs (see Table S1 in the supplemental information) were used. These monthly output variables were downloaded from the PCMDI server (Cinquini et al. 2014; <http://cmip-pcmdi.llnl.gov/cmip5>). For models with multiple simulations, all members of the ensemble were averaged following Todd-Brown et al. (2013, 2014). All ESM data were regridded to 1° × 1° spatial resolution using a first-order conservative remapping scheme (Jones 1999) in Climate Data Operators (<https://code.zmaw.de/projects/cdo>).

### e. Analyses

Carbon turnover time is usually defined as the ratio between the mass of a carbon pool and its output flux

(Koven et al. 2015). In general, the output flux for biomass corresponds to litter fall (including tree mortality) and fires, while heterotrophic respiration corresponds to the output flux of soil carbon and litter. Because of the lack of observed information on the global distribution of output flux related materials (vegetation litter fall and heterotrophic respiration), here we used the input flux of annual NPP to calculate biomass and soil carbon turnover time [see Eqs. (1) and (2)]:

$$\tau_{\text{veg}} = \frac{C_{\text{veg}}}{\text{NPP}} \quad \text{and} \quad (1)$$

$$\tau_{\text{soil}} = \frac{C_{\text{soil}}}{\text{NPP}}, \quad (2)$$

where  $\tau_{\text{veg}}$  and  $\tau_{\text{soil}}$  refer to the biomass and soil turnover times;  $C_{\text{veg}}$  and  $C_{\text{soil}}$  refer to the biomass and soil carbon storage (cSoil + cLitter, from CMIP5). Under the assumption that the difference between carbon input and output in near steady state is small compared to the magnitude of each gross flux, the net primary production and loss from vegetation and heterotrophic respiration from soil are close to each other. The time frame of the variables used in estimating the carbon turnover times was from 2000 to 2005, the common period between satellite-based NPP fluxes and historical simulation results from CMIP5. At the global and biome scales,  $\tau_{\text{veg}}$  and  $\tau_{\text{soil}}$  were derived from the total carbon storage ( $C_{\text{veg}}$  and  $C_{\text{soil}}$ ) and NPP fluxes.

In Carvalhais et al. (2014), the association between climate variables (temperature and precipitation) and  $\tau_{\text{eco}}$  was determined by analyzing correlation coefficients to identify the dominant climate factors in local ecosystems. In contrast, we are interested here in both the sign and magnitude of the spatial sensitivities of carbon turnover times. Thus, we estimated the local spatial sensitivity (linear regression slope) of  $\tau_{\text{veg}}$  and  $\tau_{\text{soil}}$  to mean annual temperature (MAT) and mean annual precipitation (MAP) in 5° × 5° moving windows around each 1° grid cell, using the following multiple regression:

$$y = \gamma x_T + \delta x_P + c + \varepsilon, \quad (3)$$

where  $y$  is  $\tau_{\text{veg}}$  or  $\tau_{\text{soil}}$ ;  $x_T$  and  $x_P$  represent MAT and MAP, respectively;  $\gamma$  and  $\delta$  define the apparent sensitivities of carbon turnover to spatial gradients in temperature and precipitation, respectively (Piao et al. 2013);  $c$  is a constant; and  $\varepsilon$  is the residual error term. Here “apparent” indicates the empirical partial derivative of carbon turnover time to each climate variable, but in reality these factors covary. We tested the statistical significance of  $\gamma$  and  $\delta$  at the 0.05 level. If model-based spatial sensitivity values of carbon turnover times were beyond the 5th–95th uncertainty

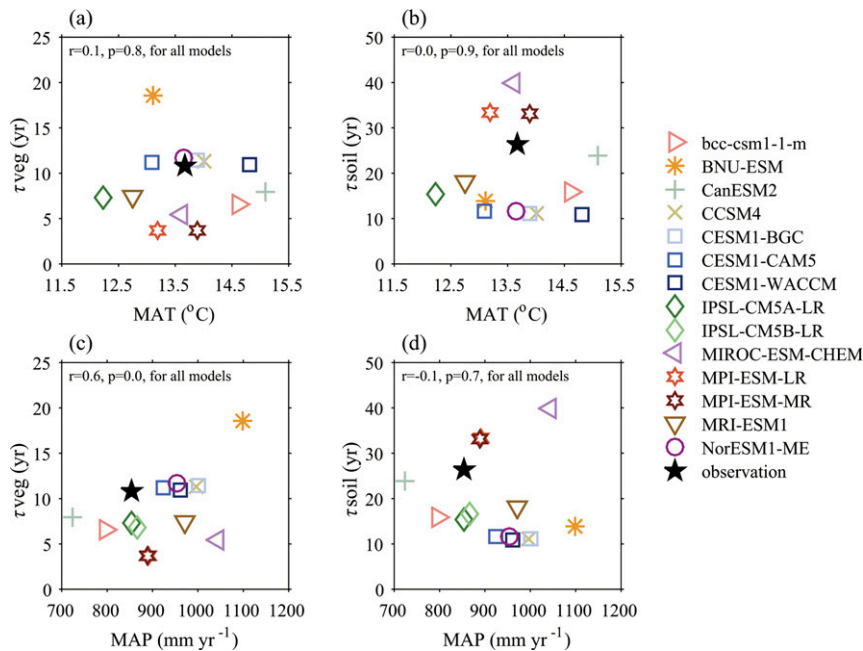


FIG. 1. The magnitude of global MAT and MAP with  $\tau_{veg}$  and  $\tau_{soil}$  estimated by 14 CMIP5 ESMs and observational data, (a) MAT and  $\tau_{veg}$ ; (b) MAT and  $\tau_{soil}$ ; (c) MAP and  $\tau_{veg}$ ; and (d) MAP and  $\tau_{soil}$ . Note that  $r$  is the Pearson correlation coefficient between MAT or MAP and  $\tau_{veg}$  or  $\tau_{soil}$  for all models;  $p$  is the corresponding significance.

range of the observation-based spatial sensitivity, we supposed that the model failed to capture the observation at corresponding regional grids. Furthermore, we have checked the robustness of spatial sensitivity of carbon turnover time to climate in a  $7^\circ \times 7^\circ$  moving window, and again in a  $9^\circ \times 9^\circ$  moving window.

### 3. Results

#### a. Carbon turnover time at the global and biome scale

Compared to observation-based  $\tau_{veg}$  ( $\sim 11$  yr), 8 of the 14 CMIP5 ESMs [BCC\_CSM1.1(m), CanESM2, IPSL-CM5A-LR, IPSL-CM5B-LR, MIROC-ESM-CHEM, MPI-ESM-LR, MPI-ESM-MR, and MRI-ESM1] underestimate  $\tau_{veg}$ , and 5 ESMs [CCSM4, CESM1(BGC), CESM1(CAM5), CESM1(WACCM), and NorESM1-ME] have a value comparable to observed (Figs. 1a,c). Among the 14 models, the shortest global  $\tau_{veg}$  is simulated by MPI-ESM-MR (4 yr), and BNU-ESM predicted the longest  $\tau_{veg}$  (19 yr), with a factor of 4.8 across the models. As shown in Figs. 1a and 1c, the large differences of  $\tau_{veg}$  across ESMs are correlated with precipitation ( $r = 0.6, p = 0.0$ ) but not with temperature differences ( $r = 0.1, p = 0.8$ ), implying that the bias of modeled precipitation rather than temperature may explain some of the differences in  $\tau_{veg}$  at the global scale.

Global  $\tau_{soil}$  based on the WISE soil dataset is 26 yr (Fig. 1). The 14 CMIP5 ESMs estimated  $\tau_{soil}$  ranging from

11 yr [CESM1(WACCM)] to 40 yr (MIROC-ESM-CHEM), with a median value of 16 yr, thus grossly underestimating  $\tau_{soil}$  (even though 3 models—MIROC-ESM-CHEM, MPI-ESM-LR, and MPI-ESM-MR—overestimate  $\tau_{soil}$ ). The model-estimated global  $\tau_{soil}$  is weakly positively correlated with temperature ( $r = 0.0, p = 0.9$ ) and negatively correlated with precipitation ( $r = -0.1, p = 0.7$ ) across the models (Figs. 1b,d), indicating that the differences of  $\tau_{soil}$  between models primarily originate from structural differences in terrestrial carbon cycle models rather than from errors in climate models.

For different biomes (see Fig. S1 in the supplemental material), we observed that most models largely underestimated  $\tau_{veg}$  and  $\tau_{soil}$  in tundra (modeled median of 7 yr vs observed 12 yr for  $\tau_{veg}$  and 40 vs 118 yr for  $\tau_{soil}$ ; Fig. 2a) and in desert and shrubland (modeled median of 4 yr vs observed 14 yr for  $\tau_{veg}$  and 18 vs 54 yr for  $\tau_{soil}$ ; Fig. 2e). In other biomes, model-based carbon turnover times showed large variation, but the median of the models provides similar values to observations for tropical forest (12 vs 14 yr for  $\tau_{veg}$  and 9 vs 11 yr for  $\tau_{soil}$ ; Fig. 2c) and temperate forest (10 vs 9 yr for  $\tau_{veg}$  and 17 vs 18 yr for  $\tau_{soil}$ ; Fig. 2d).

#### b. Spatial distribution of $\tau_{veg}$ and $\tau_{soil}$

The carbon turnover times derived from observational data show spatial gradients (Figs. 3a and 4a). Longer  $\tau_{veg}$  ( $>20$  yr) prevail in boreal forests and arid

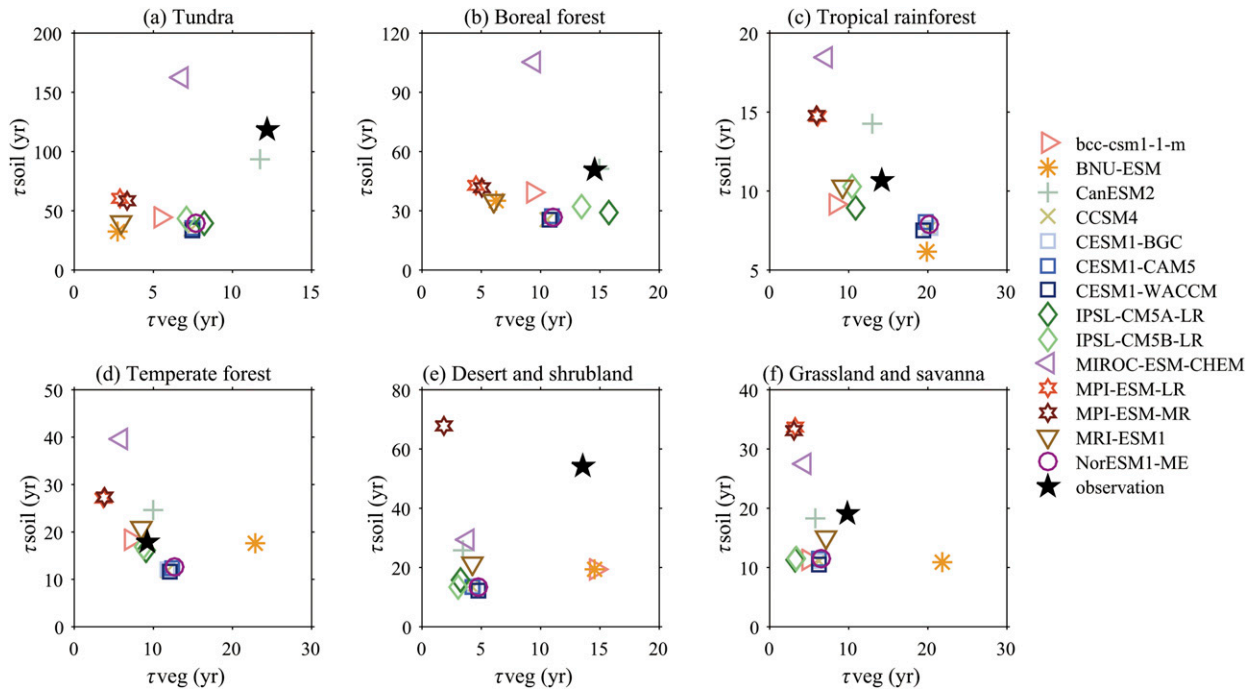


FIG. 2. The magnitude of  $\tau_{veg}$  vs  $\tau_{soil}$  of six biomes estimated by 14 CMIP5 ESMs and observational data, for (a) tundra, (b) boreal forest, (c) tropical rain forest, (d) temperate forest, (e) desert and shrubland, and (f) grassland and savanna.

and semiarid regions (western United States, western China, the sub-Saharan region, and central Australia), while temperate cropland-dominated regions (e.g., central North America, eastern Europe, and eastern China) have short  $\tau_{veg}$  ( $<4$  yr). The  $\tau_{veg}$  of tropical forests is longer than 12 yr. Similar spatial patterns of  $\tau_{veg}$  are reproduced by most ESMs (except BNU-ESM and MRI-ESM1; Fig. S2 in the supplemental material), although there are large differences in the spatial gradients of  $\tau_{veg}$  (Fig. 3). In fact,  $\tau_{veg}$  is underestimated over more than half the land area ( $\Delta\tau_{veg} < -3$  yr, where  $\Delta\tau_{veg}$  is the difference between observation-based and model-based  $\tau_{veg}$ ) for 13 out of 14 models (excluding BNU-ESM). The two models with the largest areas of underestimated  $\tau_{veg}$  are MPI-ESM-LR and MPI-ESM-MR. BNU-ESM has the largest area of mismatch with the observations. It is noticeable that most models underestimate biomass turnover times in arid and semiarid regions as well as in northeastern Siberia, but overestimate  $\tau_{veg}$  in eastern North America, southern Europe, and eastern China (Fig. 3). Across tropical forested regions, 5 of 14 models [CCSM4, CESM1(BGC), CESM1(CAM5), CESM1(WACCM), and NorESM1-ME] largely overestimate  $\tau_{veg}$  ( $\Delta\tau_{veg} > 5$  yr). Model-based  $\tau_{veg}$  is weakly correlated with temperature (5.3% land area,  $p < 0.05$ ; Fig. S4) and with precipitation (4.3% land area,  $p < 0.05$ ; Fig. S4) across local climate gradients, confirming that differences of  $\tau_{veg}$  mainly

generate from the coupled land models rather than climate models.

In contrast with  $\tau_{veg}$  (Fig. 3a), tropical forested area show lowest  $\tau_{soil}$  ( $<20$  yr). As shown in Fig. 4a, the largest  $\tau_{soil}$  are mainly in the temperate arid and semiarid regions as well as high-latitude tundra regions, where  $\tau_{soil} > 80$  yr. Note that  $\tau_{soil}$  in most ESMs generally show similar spatial patterns, with the shortest  $\tau_{soil}$  in tropical forest regions and longest  $\tau_{soil}$  in the Arctic tundra region (Fig. S3 in the supplemental material). Compared with  $\tau_{soil}$  derived from observation, 9 out of 14 models [BCC\_CSM1.1(m), BNU-ESM, CCSM4, CESM1(BGC), CESM1(CAM5), CESM1(WACCM), IPSL-CM5A-LR, IPSL-CM5B-LR, and NorESM1-ME] systematically underestimate  $\tau_{soil}$  ( $\Delta\tau_{soil} < -5$  yr, where  $\Delta\tau_{soil}$  is the difference between observation-based and model-based  $\tau_{soil}$ ), with CCSM4 showing the largest underestimated area. On the contrary, MIROC-ESM-CHEM (Fig. 4k), MPI-ESM-LR (Fig. 4l), and MPI-ESM-MR (Fig. 4m) overestimate  $\tau_{soil}$  ( $\Delta\tau_{soil} > 5$  yr) in about half of the land area. All models largely underestimate  $\tau_{soil}$  ( $\Delta\tau_{soil} < -50$  yr) in arid and semiarid regions across southwestern North America, western China, the sub-Saharan region, and Australia (Figs. 4b–o). In northern high-latitude regions with permafrost, shorter  $\tau_{soil}$  than observed ( $\Delta\tau_{soil} < -10$  yr) is predicted by most models except MIROC-ESM-CHEM, which significantly overestimates  $\tau_{soil}$  ( $\Delta\tau_{soil} > 50$  yr) (Fig. 4k).

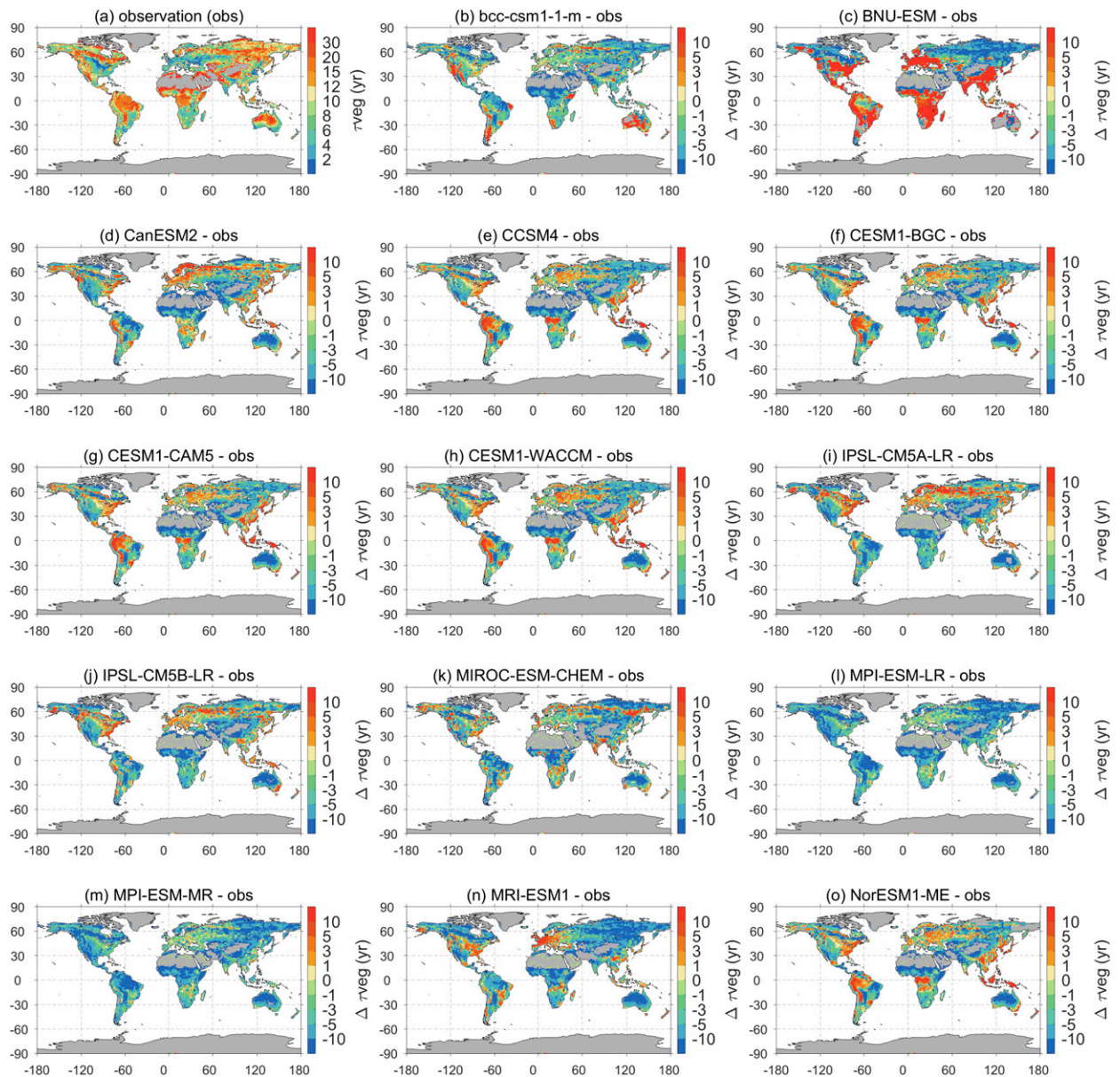
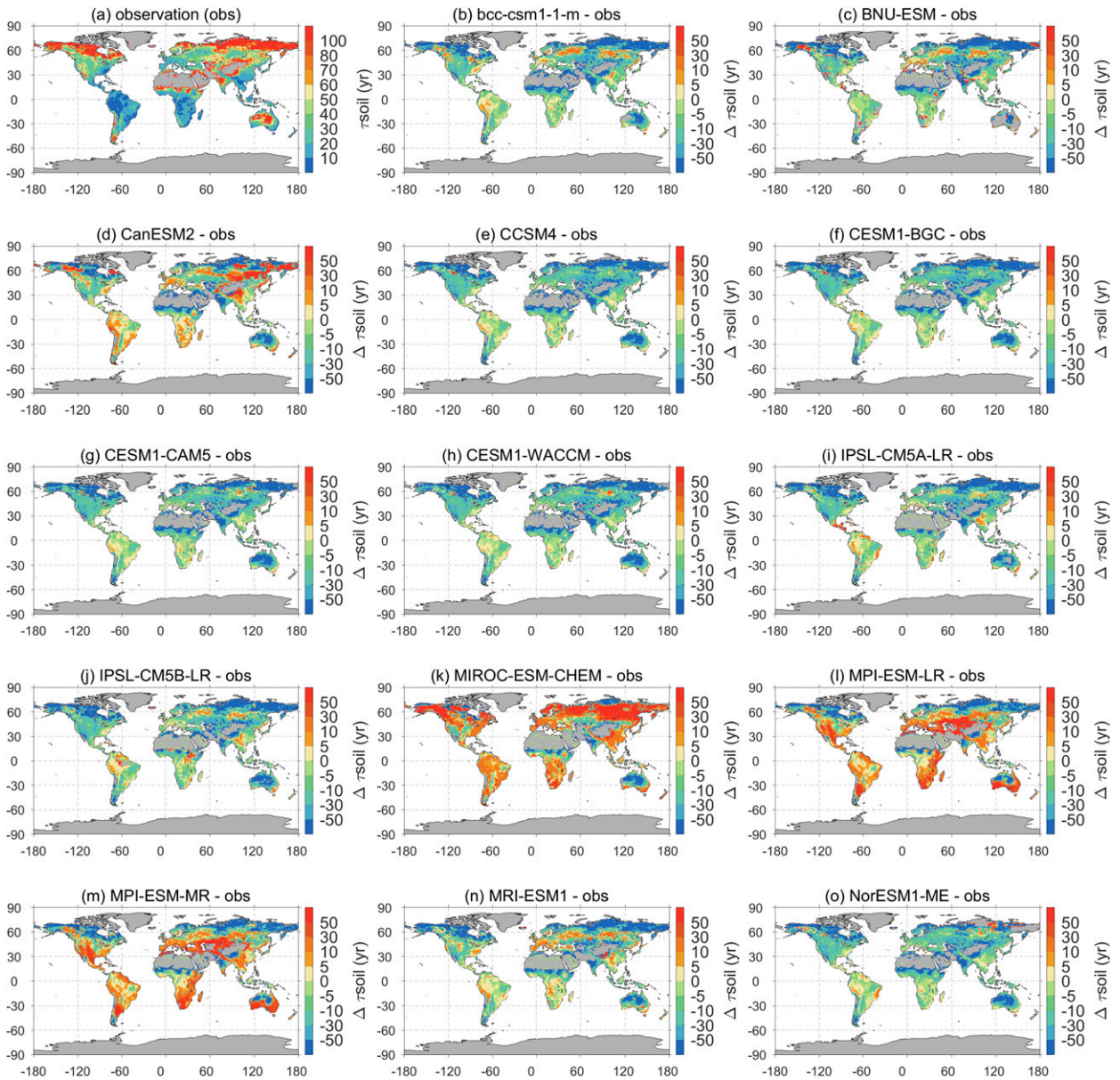


FIG. 3. (a) Global spatial patterns of  $\tau_{veg}$  derived from observation data (obs) and (b)–(o) observation differences with model-based  $\tau_{veg}$ . Areas with no biomass (mean annual NDVI below 0.1) are masked with gray shading.

For spatial correlations between model-based  $\tau_{soil}$  and climate, there is only a small area showing significant values at the  $p < 0.05$  level for  $\tau_{soil}$  and temperature (6.2% land area; Fig. S4) and for  $\tau_{soil}$  and precipitation (5.3% land area; Fig. S4).

As shown in Fig. 5a, model-based  $\tau_{soil}$  show higher spatial correlation with observation than  $\tau_{veg}$  (correlation coefficients with  $\tau_{soil}$  generally larger than 0.4 except for BNU-ESM, and correlation coefficients smaller than 0.3 for all models for  $\tau_{veg}$ ), implying that ESMs have better performance in the simulation of spatial

patterns of  $\tau_{soil}$  than  $\tau_{veg}$ . Overall, among the 14 models, MIROC-ESM-CHEM shows the highest spatial correlation of  $\tau_{soil}$  with the observation ( $r = 0.7$ ), while NorESM1-ME has the highest spatial correlation of  $\tau_{veg}$  with the observation ( $r = 0.3$ ). In terms of root-mean-square error (RMSE) between the observation and simulations across the globe (Fig. 5b), we found that NorESM1-ME and MPI-ESM-LR show the lowest RMSE for  $\tau_{veg}$  (8 yr) and  $\tau_{soil}$  (38 yr), respectively. The highest RMSE appears in BNU-ESM for both  $\tau_{veg}$  (36 yr) and  $\tau_{soil}$  (77 yr).

FIG. 4. As in Fig. 3, but for  $\tau_{\text{soil}}$ .

### c. Spatial sensitivities of carbon turnover times to climate

To further study the spatial sensitivities of  $\tau_{\text{veg}}$  and  $\tau_{\text{soil}}$  to climate (temperature and precipitation), we performed multiple linear regression analysis as explained in the method section. As shown in Fig. 6a, the observation-based sensitivities of  $\tau_{\text{veg}}$  to temperature (denoted as  $\gamma_T^{\text{veg}}$ ) varied across different regions, with 95% confidence interval values in the range from  $-4$  to approximately  $5 \text{ yr}^\circ\text{C}^{-1}$ . Significant negative  $\gamma_T^{\text{veg}}$  ( $< -1 \text{ yr}^\circ\text{C}^{-1}$ ) are generally observed across boreal forests and tundra of

northern Siberia, indicating faster biomass carbon turnover with increasing temperature. In contrast, tropical forests (except South Asia) and drylands in Australia show significant positive  $\gamma_T^{\text{veg}}$  ( $> 1 \text{ yr}^\circ\text{C}^{-1}$ ). The sign of  $\gamma_T^{\text{veg}}$  estimated by most ESMs is opposite to observations in the Amazon forest and in the tundra region of northern Siberia. Although most ESMs (except BNU-ESM) correctly capture the sign of  $\gamma_T^{\text{veg}}$  in other regions, the magnitude of model-based  $\gamma_T^{\text{veg}}$  is also lower than that of observation (Figs. 6a,c and Fig. S5 in the supplemental material).

Observation-based precipitation sensitivities of  $\tau_{\text{veg}}$  (denoted as  $\delta_P^{\text{veg}}$ ) also show large spatial heterogeneity



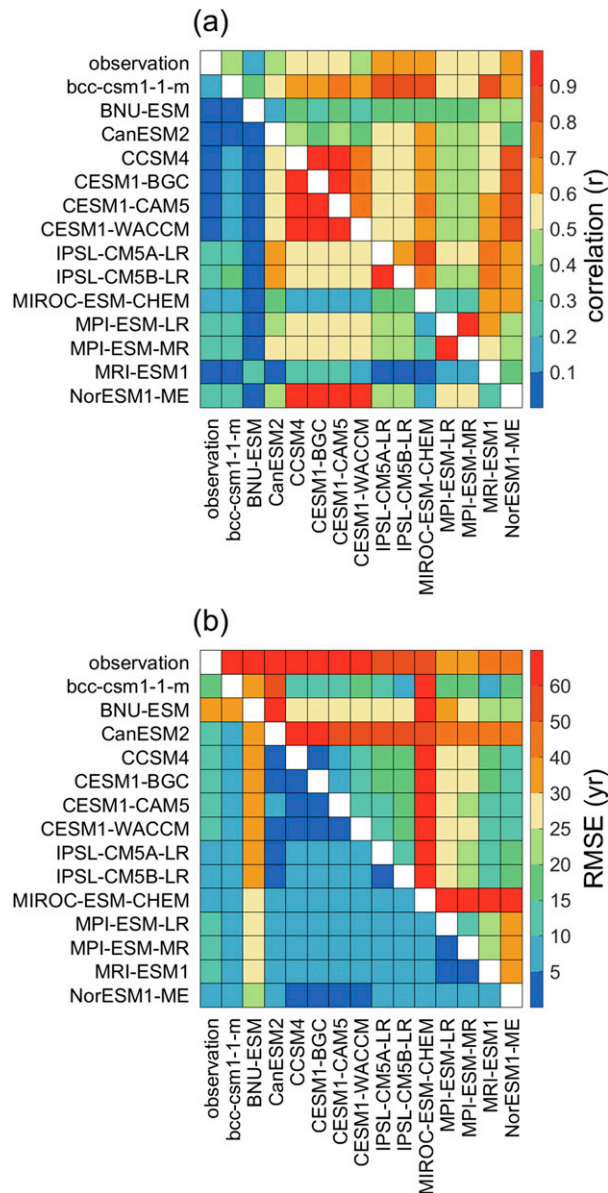


FIG. 5. Matrices of (a)  $r$  and (b) RMSE for carbon turnover times between each CMIP5 ESM and observation and between CMIP5 ESMs at the grid cells. Lower-triangular matrix represents  $r$  or RMSE for  $\tau_{\text{veg}}$ , and upper-triangular matrix represents  $r$  or RMSE for  $\tau_{\text{soil}}$ .

(Fig. 6b). Across boreal and Arctic regions, observation-based sensitivities to precipitation are positive  $\delta_p^{\tau_{\text{veg}}}$  [ $>5 \text{ yr } (100 \text{ mm})^{-1}$ ]. This longer  $\tau_{\text{veg}}$  with increasing precipitation is correctly represented by several ESMs including BCC\_CSM1.1(m), CanESM2, CCSM4, CESM1(BGC), CESM1(CAM5), CESM1(WACCM), and MIROC-ESM-CHEM (Fig. S6). In contrast, relative large negative values  $\delta_p^{\tau_{\text{veg}}}$  [ $<-5 \text{ yr } (100 \text{ mm})^{-1}$ ] are found in arid and semiarid regions (central Asia, the sub-Saharan region,

and northern Australia) where 13 of 14 models [except BCC\_CSM1.1(m), which overestimates  $\delta_p^{\tau_{\text{veg}}}$  in Australia] show opposite sensitivities of  $\tau_{\text{veg}}$  to precipitation compared to observation-based values (Figs. 6b,d and Fig. S6 in the supplemental material).

Figure 7 shows the spatial sensitivities of observation-based  $\tau_{\text{soil}}$  to temperature (denoted as  $\gamma_T^{\tau_{\text{soil}}}$ ) and precipitation (denoted as  $\delta_p^{\tau_{\text{soil}}}$ ). Similar to the spatial patterns of observed  $\gamma_T^{\tau_{\text{veg}}}$  (Fig. 6a),  $\tau_{\text{soil}}$  generally decreases with increasing temperature across spatial climate gradients (with values  $<-5 \text{ yr } ^\circ\text{C}^{-1}$ ) in boreal and Arctic regions, but the sensitivities to temperature are positive in tropical forests (except South Asia) and drylands, such as in Australia ( $>5 \text{ yr } ^\circ\text{C}^{-1}$ ) (Fig. 7a). As shown in Fig. 7c and Fig. S7 in the supplemental material, most ESMs perform better in simulating  $\gamma_T^{\tau_{\text{soil}}}$  over boreal and arctic regions than over tropical regions. For example, 12 of 14 models (except BNU-ESM and MRI-ESM1) also show negative values of  $\gamma_T^{\tau_{\text{soil}}}$  across boreal and Arctic regions, while only one model (IPSL-CM5B-LR) captured parts of the observation-based dramatic positive  $\gamma_T^{\tau_{\text{soil}}}$  in tropical regions.

In terms of  $\delta_p^{\tau_{\text{soil}}}$ , a relatively weak sensitivity is observed in tropical regions (Fig. 7b), consistent with most ESMs (Fig. 7d and Fig. S8 in the supplemental material). In temperate arid and semiarid regions, a negative  $\delta_p^{\tau_{\text{soil}}}$  is observed with the highest sensitivity lower than  $-10 \text{ yr } (100 \text{ mm})^{-1}$ . Although most of ESMs also predict negative  $\delta_p^{\tau_{\text{soil}}}$  in these regions, they underestimate the magnitude of the negative sensitivity (Figs. 7d and S8). A heterogeneous distribution of  $\delta_p^{\tau_{\text{soil}}}$  is observed in boreal and Arctic regions (Fig. 7b), and there is a poor agreement between observation and ESMs.

Furthermore, we have conducted spatial sensitivity of carbon turnover time to climate in a  $7^\circ \times 7^\circ$  moving window (Figs. S9 and S10 in the supplemental material) and in a  $9^\circ \times 9^\circ$  moving window (Figs. S11 and S12). In results, most of the spatial patterns are similar based on the three moving window methods, which emphasizes the robustness of the spatial sensitivities of carbon turnover time to climate. Here, we chose the results based on the  $5^\circ \times 5^\circ$  moving window, similar to Carvalho et al. (2014), because larger moving windows, containing more nonuniform biome types and environmental factors, would induce greater uncertainties, especially for the transitional zones of different vegetation types.

## 4. Discussion

### a. Observed global carbon turnover time

Compared to the previous study ( $\tau_{\text{veg}} = 4 \text{ yr}$  based on GPP) of Carvalho et al. (2014), a much longer global  $\tau_{\text{veg}}$  (11 yr) is obtained in this study. This difference is

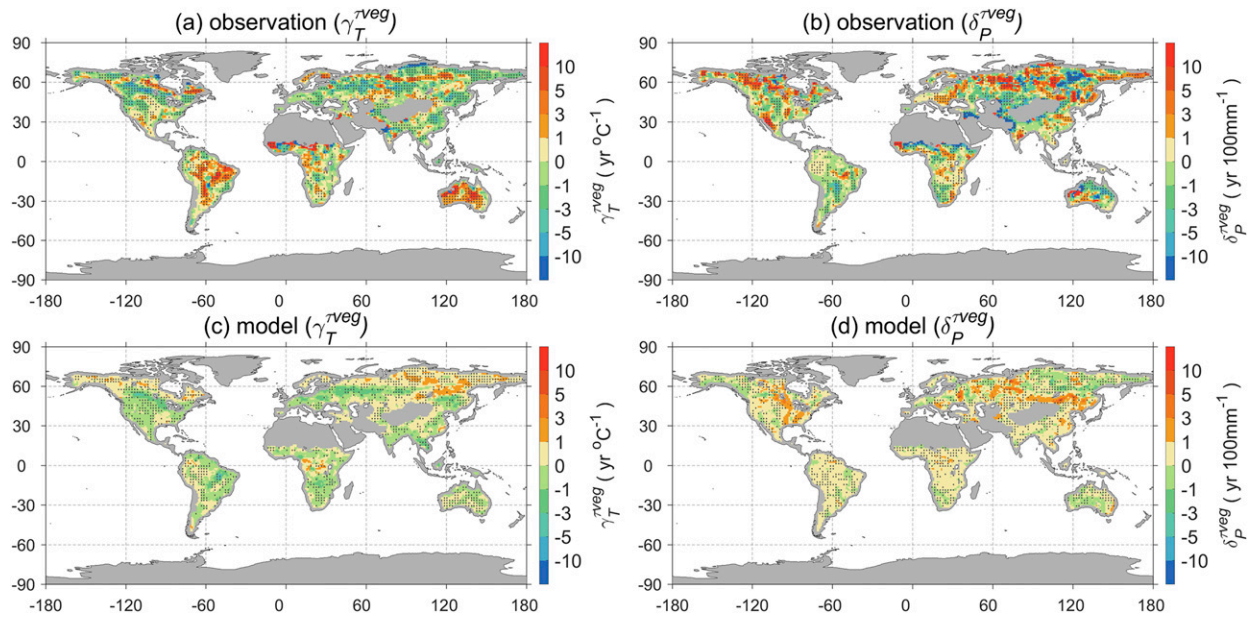


FIG. 6. Spatial sensitivity of  $\gamma_T^{\text{veg}}$  and  $\delta_P^{\text{veg}}$  in a  $5^\circ \times 5^\circ$  moving window using a multiple linear regression approach, sensitivity of observation-based (a)  $\gamma_T^{\text{veg}}$  and (b)  $\delta_P^{\text{veg}}$  and median sensitivity of model-based (c)  $\gamma_T^{\text{veg}}$  and (d)  $\delta_P^{\text{veg}}$ . For example, positive  $\gamma_T^{\text{veg}}$  suggests that warmer temperature is associated with longer  $\tau_{\text{veg}}$ , and the value represents the change of  $\tau_{\text{veg}}$  with a temperature gradient of  $1^\circ\text{C}$ . In (a) and (b), stippling indicates locations where observation-based sensitivity is significant ( $p < 0.05$ ); in (c) and (d), stippling indicates where fewer than one-quarter of the models are within the 5th–95th uncertainty range of the observed sensitivity. Areas with no biomass (mean annual NDVI below 0.1) are masked with gray shading.

mainly due to the different definition of  $\tau_{\text{veg}}$  as we used NPP instead of GPP. NPP is arguably more relevant for the fate of carbon being removed from the atmosphere on time scales longer than a year and stored into terrestrial pools. In contrast to  $\tau_{\text{veg}}$ , our estimation of the global value of  $\tau_{\text{soil}}$  (26 yr) is much smaller than derived by [Carvalhais et al. \(2014\)](#) (46 yr). This is because [Carvalhais et al. \(2014\)](#) estimated  $\tau_{\text{soil}}$  using total soil stocks for full depth, while we used soil stocks for 1-m depth. As mentioned in [section 2](#), the main purpose of this study is to evaluate ESMs estimated carbon turnover time, and the CMIP5 ESMs did not consider processes to burying carbon below the active layer ([Tian et al. 2015](#); [Todd-Brown et al. 2013](#)). Our estimates are in consistent with the global  $\tau_{\text{veg}}$  of 10 yr in [Jiang et al. \(2015\)](#) and with the global  $\tau_{\text{soil}}$  of 24 yr in [Todd-Brown et al. \(2013\)](#).

#### b. Comparison of observed and ESMs estimated carbon turnover time

Compared with observations, ESMs generally underestimate  $\tau_{\text{veg}}$ , particularly in the high northern latitudes and arid and semiarid regions ([Fig. 3](#)), where models also do not capture the observation-based spatial climate sensitivity of  $\tau_{\text{veg}}$  ([Fig. 6](#)). The spatial  $\gamma_T^{\text{veg}}$  estimated from observations indicate a decrease of  $\tau_{\text{veg}}$  in response to higher temperature in the northern high

latitudes, while models produce a sensitivity of opposite sign, particularly in northern Siberia. It has been suggested that drought driven by increases in temperature enhance fire risks and insect attacks ([Raffa et al. 2008](#); [Williams et al. 2010, 2013](#)), which increase mortality rate and accelerate biomass carbon turnover ([Allen et al. 2010](#); [Van Mantgem and Stephenson 2007](#)). However, climate-induced mortality and biotic disturbances are largely ignored in current ecosystem models ([Andregg et al. 2015](#); [Thurner et al. 2016, 2017](#)). In addition to drought-induced increase in tree mortality, most ESMs do not consider carbon–nitrogen interactions, which may also indirectly explain the opposite temperature sensitivity of  $\tau_{\text{veg}}$  between observation and ESMs in boreal regions ([Friedlingstein et al. 2014](#); [Piao et al. 2013](#)). Northern ecosystems are generally limited by low temperature and nitrogen ([Janssens et al. 2010](#); [Melillo et al. 2002](#); [Nemani et al. 2003](#)). Higher temperature enhance nitrogen mineralization, and thus increase in soil nitrogen availability for vegetation carbon assimilation and biomass growth ([Melillo et al. 2002](#)). The enhanced nitrogen availability also leads to more NPP allocated in parts of aboveground biomass (e.g., foliar and wood) ([Greaver et al. 2016](#); [Janssens et al. 2010](#)), which may eventually result in faster plant metabolism ([Niu et al. 2010](#)), also accompanied by vulnerability to attack (e.g., wind,

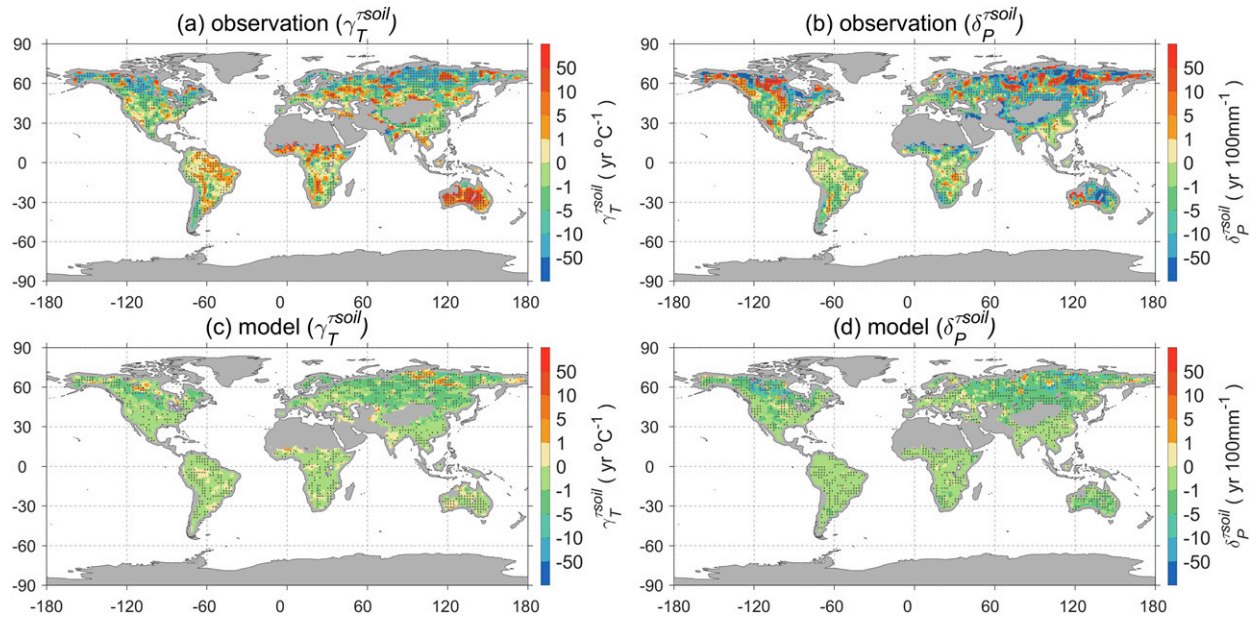


FIG. 7. Spatial sensitivity of  $\gamma_T^{\text{soil}}$  and  $\delta_P^{\text{soil}}$  in a  $5^\circ \times 5^\circ$  moving window using a multiple linear regression approach, sensitivity of observation-based (a)  $\gamma_T^{\text{soil}}$  and (b)  $\delta_P^{\text{soil}}$  and median sensitivity of model-based (c)  $\gamma_T^{\text{soil}}$  and (d)  $\delta_P^{\text{soil}}$ . For example, positive  $\delta_P^{\text{soil}}$  suggests that increasing precipitation is associated with longer  $\tau_{\text{soil}}$ , and the value represents the change of  $\tau_{\text{soil}}$  with a precipitation gradient of 100 mm. In (a) and (b), stippling indicates locations where observation-based sensitivity is significant ( $p < 0.05$ ); in (c) and (d), stippling indicates where fewer than one-quarter of the models are within the 5th–95th uncertainty range of the observed sensitivity. Areas with no biomass (mean annual NDVI below 0.1) and data are masked with gray shading.

insects, and pathogens) (Franklin et al. 1987; Stephenson et al. 2011). All these causes may increase the forest mortality rates, suggesting a negative apparent climatic  $\gamma_T^{\text{veg}}$ . In contrast to boreal regions, growing season temperature is close to a high temperature threshold of vegetation growth in tropical forests (Corlett 2011; Piao et al. 2013). Accordingly, regions with higher temperature generally have lower vegetation productivity (Doughty and Goulden 2008; Tribuzy 2005). It has been also suggested that tree mortality rates are positively correlated with forest NPP through many mechanisms including trade-offs between growth and defense and between reproduction and persistence (Stephenson et al. 2011). These ecological processes may induce positive  $\gamma_T^{\text{veg}}$  in tropical forests.

Similar to  $\tau_{\text{veg}}$ , ESMs generally underestimate the  $\tau_{\text{soil}}$ . As shown in Fig. 4, 13 out of 14 models predicted shorter  $\tau_{\text{soil}}$  in the northern high latitudes with permafrost, compared with observation. This may be related to the fact that permafrost processes were not taken into account in the CMIP5 ESMs (Burke et al. 2013; Schuur et al. 2015). Permafrost soil contains large amounts of organic carbon, which would be vulnerable with higher decomposition rates under rapid global warming (Koven et al. 2011). Combined reductions in the thawed season length and thawed soil depth during the warm season in these cold regions compared to warm climates could result in higher  $\gamma_T^{\text{soil}}$  (Koven et al. 2017). However, most models

used a fixed quotient of change in respiration caused by change in temperature by  $10^\circ\text{C}$  ( $Q_{10}$ ) and a single layer with soil decomposition closely related to near-surface temperature, which fail to capture the soil freeze–thaw processes affecting decomposition rates and underestimate the apparent  $\tau_{\text{soil}}$  (Koven et al. 2017; Wieder et al. 2018). In contrast to high latitudes, a positive value of  $\gamma_T^{\text{soil}}$  is generally observed in arid and semiarid regions including southwestern China, western Asia, western North America, and Australia. This is because lower soil moisture associated with temperature limits soil organic carbon decomposition (Xin Wang et al. 2014). Indeed, a negative value of  $\delta_P^{\text{soil}}$  was observed across most of these dry regions (Fig. 7b). The ESMs sensitivity is opposite to observed for  $\gamma_T^{\text{soil}}$  in arid and semiarid regions. It is not clear, however, if this is induced by an inaccurate representation of soil moisture by models. In addition, most patterns of relationships between climate and  $\tau_{\text{soil}}$  are similar to that between climate and  $\tau_{\text{eco}}$  in Carvalhais et al. (2014), which also implies that  $\tau_{\text{soil}}$  plays a dominant role in the terrestrial carbon turnover processes.

In Carvalhais et al. (2014), negative correlations were found between forest cover and  $\tau_{\text{eco}}$ , suggesting that  $\tau_{\text{eco}}$  does not increase with higher forest density. Here, we performed a similar analysis for  $\tau_{\text{veg}}$  and  $\tau_{\text{soil}}$  in boreal forest, temperate forest, and tropical rain forest. Five

CMIP5 models were used because they output a forest cover variable. In the results (Fig. S13 in the supplemental material), we found that  $\tau_{\text{veg}}$  increased with higher forest cover in the three biomes across all the five models; however, there were no consistent relationships between forest cover and  $\tau_{\text{soil}}$  for most models. For observation-based results,  $\tau_{\text{veg}}$  showed an increasing trend along with increased forest cover in temperate forest;  $\tau_{\text{veg}}$  in boreal forest suggested an increasing trend at a threshold of 35% forest cover and then became flat beyond the threshold; and  $\tau_{\text{veg}}$  did not show obvious changes with increasing forest cover in tropical rain forest. Observation-based  $\tau_{\text{soil}}$  decreases with increasing forest cover in boreal forests, while there were no significant relationships between forest cover and  $\tau_{\text{soil}}$  in temperate and tropical rain forest. The differences between the patterns based on observation and model mainly emerged for the relationships between forest cover and  $\tau_{\text{veg}}$ . This may be because current land surface models largely simplified the real terrestrial ecosystems, while the observation-based apparent  $\tau_{\text{veg}}$  reflects processes including resource competition (Stephenson et al. 2011), fire (Stephenson et al. 2011; Thonicke et al. 2001), insects (Anderegg et al. 2015), and other natural and anthropogenic disturbances (Erb et al. 2016; Fahey et al. 2005) in response to forest density. These underlying mechanisms are difficult to quantify in the present day, and require future research.

### c. Uncertainties

It should be noted that there still exist large uncertainties in the estimation of global biomass and soil carbon turnover time. First, biomass carbon stock used in this study from Liu et al. (2015) was indirectly based on aboveground biomass (AGB) and a biome specific conversion factor from AGB to total biomass. It has been suggested that the ratios of above to belowground biomass varied with environmental conditions (Mokany et al. 2006). In addition, AGB derived with satellite-based passive microwave data in Liu et al. (2015) may saturate at a high biomass density (e.g., tropical rain forests) although it remains sensitive to biomass variations in these regions. These may contribute potential uncertainties of  $\tau_{\text{veg}}$ . Here, we compared the  $\tau_{\text{veg}}$  using TBC from Liu et al. (2015) and the  $\tau_{\text{veg}}$  derived from the benchmark map of forest carbon stocks in tropical regions from Saatchi et al. (2011). The results suggested similar histogram patterns between the two (Fig. S14 in the supplemental material), implying that our estimates of  $\tau_{\text{veg}}$  in the tropical rain forest are reliable.

Second, although efforts have been made to make global inventories of soil carbon, bias due to the

interpolation of point-scale observations remains in the WISE dataset. Most current soil carbon storage data are mainly from temperate and tropical ecosystems, and more inventory data in regions such as Arctic regions are needed. We compared our global estimate of  $\tau_{\text{soil}}$  with that based on soil carbon (using HWSD) and NPP from Bloom et al. (2016). The distribution of  $\tau_{\text{soil}}$  (Fig. S15 in the supplemental material) was found to be similar between the two estimates.

Third, satellite-based NPP data were estimated with a radiation-based approach, through deducting the autotrophic respiration from the GPP (Zhao and Running 2010). Although this NPP observation-based product has been extensively used, including for investigating carbon turnover times (Koven et al. 2017; Thurner et al. 2016) and for benchmarking ecosystem models (Kolby Smith et al. 2016; Todd-Brown et al. 2013), it is subject to uncertainties. For example, satellite-based NPP datasets have large uncertainties in tropical regions (Cleveland et al. 2015), such as from saturation of the fraction of photosynthetically active radiation (FPAR) in high vegetation density areas, cloud and aerosol contamination, scarce meteorological data in tropical regions, and improper parameterization of the maximum light-use efficiency ( $\text{LUE}_{\text{max}}$ ).

Fourth, in this study, we calculated  $\tau_{\text{veg}}$  and  $\tau_{\text{soil}}$  based on the steady-state assumption (input equals output), as in previous studies. This seems as an imperative choice because there is no direct measurement on the global distribution of litter fall and heterotrophic respiration. Uncertainties from the steady-state assumption are difficult to quantify from the observations in the present day, such an analysis can be conducted based on modeling output by estimating carbon turnover times from the outflux  $\tau_{\text{out}}$  (Carvalhais et al. 2014). Here, outflux from biomass was calculated as in Friend et al. (2014), and outflux from soil is heterotrophic respiration. In the results, the comparisons between NPP and outflux (Figs. S16 and S17 in the supplemental material) and between carbon turnover time and  $\tau_{\text{out}}$  (Figs. S18 and S19) show a strong similarity, which emphasizes the robustness of turnover time being defined from input or output under the steady-state assumption.

Fifth, when we evaluate the model-based  $\tau_{\text{veg}}$  and  $\tau_{\text{soil}}$  at grid scale, potential discrepancies of vegetation type and forest cover between ESMs and observation increase uncertainties. These differences limit the accuracy of the evaluation of current models for representing the spatial carbon turnover times. Because most of the CMIP5 ESMs did not report the simulated vegetation type and forest cover maps, we are still unable to evaluate the discrepancies in current time. Future model intercomparison projects are recommended to provide

these variables. Reducing these apparent influences will help us better understand and improve the internal parameterization and structure related to carbon turnover processes in current ESMs.

#### d. Conclusions

In summary, our results show that current ESMs underestimate biomass and soil carbon turnover times. This result implies that current ESMs may overestimate the carbon sequestration potential of biomass and soil in response to elevated atmospheric CO<sub>2</sub> concentration (He et al. 2016), which has been generally predicted to be the main driver of the enhancement of vegetation productivity (Zhu et al. 2016) and the terrestrial ecosystem carbon sink by ESMs (Cramer et al. 2001; Sitch et al. 2008). To reduce the large bias in the relationships between climate factors and biomass or soil carbon turnover times compared to observation, ESM developers need to calibrate the key processes affecting carbon turnover, especially in the high northern latitudes and arid and semiarid regions, so that ESMs are more closely comparable to the real world. Current limitations include the lack of representation of biotic disturbances, carbon–nutrient interactions, and permafrost–carbon climate responses. In addition, more accurate descriptions of hydrological processes and water–carbon interactions remain as a high priority for the carbon cycle modeling community.

*Acknowledgments.* This study was supported by the National Key R&D Program of China (2017YFA0604702), the National Natural Science Foundation of China (41530528 and 31621091), and the 111 Project (B14001).

#### REFERENCES

- Allen, C. D., and Coauthors, 2010: A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. *For. Ecol. Manage.*, **259**, 660–684, <https://doi.org/10.1016/j.foreco.2009.09.001>.
- Anav, A., and Coauthors, 2013: Evaluating the land and ocean components of the global carbon cycle in the CMIP5 Earth system models. *J. Climate*, **26**, 6801–6843, <https://doi.org/10.1175/JCLI-D-12-00417.1>.
- Anderegg, W. R. L., and Coauthors, 2015: Tree mortality from drought, insects, and their interactions in a changing climate. *New Phytol.*, **208**, 674–683, <https://doi.org/10.1111/nph.13477>.
- Batjes, N. H., 2016: Harmonized soil property values for broad-scale modelling (WISE30sec) with estimates of global soil carbon stocks. *Geoderma*, **269**, 61–68, <https://doi.org/10.1016/j.geoderma.2016.01.034>.
- Bloom, A. A., and M. Williams, 2015: Constraining ecosystem carbon dynamics in a data-limited world: Integrating ecological “common sense” in a model–data fusion framework. *Biogeosciences*, **12**, 1299–1315, <https://doi.org/10.5194/bg-12-1299-2015>.
- , J.-F. Exbrayat, I. R. van der Velde, L. Feng, and M. Williams, 2016: The decadal state of the terrestrial carbon cycle: Global retrievals of terrestrial carbon allocation, pools, and residence times. *Proc. Natl. Acad. Sci. USA*, **113**, 1285–1290, <https://doi.org/10.1073/pnas.1515160113>.
- Bradford, M. A., W. R. Wieder, G. B. Bonan, N. Fierer, P. A. Raymond, and T. W. Crowther, 2016: Managing uncertainty in soil carbon feedbacks to climate change. *Nat. Climate Change*, **6**, 751–758, <https://doi.org/10.1038/nclimate3071>.
- Burke, E. J., C. D. Jones, and C. D. Koven, 2013: Estimating the permafrost-carbon climate response in the CMIP5 climate models using a simplified approach. *J. Climate*, **26**, 4897–4909, <https://doi.org/10.1175/JCLI-D-12-00550.1>.
- Carvalho, N., and Coauthors, 2014: Global covariation of carbon turnover times with climate in terrestrial ecosystems. *Nature*, **514**, 213–217, <https://doi.org/10.1038/nature13731>.
- Chen, S., Y. Huang, J. Zou, and Y. Shi, 2013: Mean residence time of global topsoil organic carbon depends on temperature, precipitation and soil nitrogen. *Global Planet. Change*, **100**, 99–108, <https://doi.org/10.1016/j.gloplacha.2012.10.006>.
- Cinquini, L., and Coauthors, 2014: The Earth System Grid Federation: An open infrastructure for access to distributed geospatial data. *Future Gener. Comput. Syst.*, **36**, 400–417, <https://doi.org/10.1016/j.future.2013.07.002>.
- Cleveland, C. C., and Coauthors, 2015: A comparison of plot-based satellite and Earth system model estimates of tropical forest net primary production. *Global Biogeochem. Cycles*, **29**, 626–644, <https://doi.org/10.1002/2014GB005022>.
- Corlett, R. T., 2011: Impacts of warming on tropical lowland rainforests. *Trends Ecol. Evol.*, **26**, 606–613, <https://doi.org/10.1016/j.tree.2011.06.015>.
- Cox, P. M., D. Pearson, B. B. Booth, P. Friedlingstein, C. Huntingford, C. D. Jones, and C. M. Luke, 2013: Sensitivity of tropical carbon to climate change constrained by carbon dioxide variability. *Nature*, **494**, 341–344, <https://doi.org/10.1038/nature11882>.
- Cramer, W., and Coauthors, 2001: Global response of terrestrial ecosystem structure and function to CO<sub>2</sub> and climate change: Results from six dynamic global vegetation models. *Global Change Biol.*, **7**, 357–373, <https://doi.org/10.1046/j.1365-2486.2001.00383.x>.
- De Kauwe, M. G., and Coauthors, 2014: Where does the carbon go? A model–data intercomparison of vegetation carbon allocation and turnover processes at two temperate forest free-air CO<sub>2</sub> enrichment sites. *New Phytol.*, **203**, 883–899, <https://doi.org/10.1111/nph.12847>.
- Doughty, C. E., and M. L. Goulden, 2008: Are tropical forests near a high temperature threshold? *J. Geophys. Res.*, **113**, G00B07, <https://doi.org/10.1029/2007JG000632>.
- Erb, K.-H., and Coauthors, 2016: Biomass turnover time in terrestrial ecosystems halved by land use. *Nat. Geosci.*, **9**, 674–678, <https://doi.org/10.1038/ngeo2782>.
- Fahey, T. J., and Coauthors, 2005: The biogeochemistry of carbon at Hubbard Brook. *Biogeochemistry*, **75**, 109–176, <https://doi.org/10.1007/s10533-004-6321-y>.
- FAO/IIASA/ISRIC/ISSCAS/JRC, 2012: Harmonized World Soil Database (version 1.2). Food and Agriculture Organization of the United Nations (FAO) and International Institute for Applied Systems Analysis (IIASA), <http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/>.
- Flato, G., and Coauthors, 2013: Evaluation of climate models. *Climate Change 2013: The Physical Science Basis*, T. F. Stocker et al., Eds., Cambridge University Press, 741–866.

- Forkel, M., N. Carvalhais, C. Rödenbeck, R. Keeling, M. Heimann, K. Thonicke, S. Zaehle, and M. Reichstein, 2016: Enhanced seasonal CO<sub>2</sub> exchange caused by amplified plant productivity in northern ecosystems. *Science*, **351**, 696–699, <https://doi.org/10.1126/science.aac4971>.
- Franklin, J. F., H. Shugart, and M. E. Harmon, 1987: Tree death as an ecological process. *BioScience*, **37**, 550–556, <https://doi.org/10.2307/1310665>.
- Friedl, M. A., D. Sulla-Menashe, B. Tan, A. Schneider, N. Ramankutty, A. Sibley, and X. Huang, 2010: MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sens. Environ.*, **114**, 168–182, <https://doi.org/10.1016/j.rse.2009.08.016>.
- Friedlingstein, P., and Coauthors, 2006: Climate–carbon cycle feedback analysis: Results from the C<sup>4</sup>MIP model intercomparison. *J. Climate*, **19**, 3337–3353, <https://doi.org/10.1175/JCLI3800.1>.
- , M. Meinshausen, V. K. Arora, C. D. Jones, A. Anav, S. K. Liddicoat, and R. Knutti, 2014: Uncertainties in CMIP5 climate projections due to carbon cycle feedbacks. *J. Climate*, **27**, 511–526, <https://doi.org/10.1175/JCLI-D-12-00579.1>.
- Friend, A. D., and Coauthors, 2014: Carbon residence time dominates uncertainty in terrestrial vegetation responses to future climate and atmospheric CO<sub>2</sub>. *Proc. Natl. Acad. Sci. USA*, **111**, 3280–3285, <https://doi.org/10.1073/pnas.1222477110>.
- Gibbs, H. K., L. Olsen, and T. Boden, 2006: Major world ecosystem complexes ranked by carbon in live vegetation: An updated database using the GLC2000 land cover product. Oak Ridge National Laboratory, <https://doi.org/10.3334/CDIAC/lue.ndp017.2006>.
- Greaver, T. L., and Coauthors, 2016: Key ecological responses to nitrogen are altered by climate change. *Nat. Climate Change*, **6**, 836–843, <https://doi.org/10.1038/nclimate3088>.
- Harris, I., P. Jones, T. Osborn, and D. Lister, 2014: Updated high-resolution grids of monthly climatic observations—The CRU TS3.10 dataset. *Int. J. Climatol.*, **34**, 623–642, <https://doi.org/10.1002/joc.3711>.
- He, Y., S. E. Trumbore, M. S. Torn, J. W. Harden, L. J. S. Vaughn, S. D. Allison, and J. T. Randerson, 2016: Radiocarbon constraints imply reduced carbon uptake by soils during the 21st century. *Science*, **353**, 1419–1424, <https://doi.org/10.1126/science.aad4273>.
- Hugelius, G., C. Tarnocai, G. Broll, J. Canadell, P. Kuhry, and D. Swanson, 2013: The Northern Circumpolar Soil Carbon Database: Spatially distributed datasets of soil coverage and soil carbon storage in the northern permafrost regions. *Earth Syst. Sci. Data*, **5**, 3–13, <https://doi.org/10.5194/essd-5-3-2013>.
- Janssens, I. A., and Coauthors, 2010: Reduction of forest soil respiration in response to nitrogen deposition. *Nat. Geosci.*, **3**, 315–322, <https://doi.org/10.1038/ngeo844>.
- Jiang, L., and Coauthors, 2015: Scale-dependent performance of CMIP5 Earth system models in simulating terrestrial vegetation carbon. *J. Climate*, **28**, 5217–5232, <https://doi.org/10.1175/JCLI-D-14-00270.1>.
- Jones, P. W., 1999: First- and second-order conservative remapping schemes for grids in spherical coordinates. *Mon. Wea. Rev.*, **127**, 2204–2210, [https://doi.org/10.1175/1520-0493\(1999\)127<2204:FASOCR>2.0.CO;2](https://doi.org/10.1175/1520-0493(1999)127<2204:FASOCR>2.0.CO;2).
- Knorr, W., I. C. Prentice, J. I. House, and E. A. Holland, 2005: Long-term sensitivity of soil carbon turnover to warming. *Nature*, **433**, 298–301, <https://doi.org/10.1038/nature03226>.
- Kolby Smith, W., S. C. Reed, C. C. Cleveland, A. P. Ballantyne, W. R. L. Anderegg, W. R. Wieder, Y. Y. Liu, and S. W. Running, 2016: Large divergence of satellite and Earth system model estimates of global terrestrial CO<sub>2</sub> fertilization. *Nat. Climate Change*, **6**, 306–310, <https://doi.org/10.1038/nclimate2879>.
- Koven, C. D., B. Ringeval, P. Friedlingstein, P. Ciais, P. Cadule, D. Khvorostyanov, G. Krinner, and C. Tarnocai, 2011: Permafrost carbon–climate feedbacks accelerate global warming. *Proc. Natl. Acad. Sci. USA*, **108**, 14 769–14 774, <https://doi.org/10.1073/pnas.1103910108>.
- , and Coauthors, 2015: Controls on terrestrial carbon feedbacks by productivity vs. turnover in the CMIP5 Earth system models. *Biogeosciences*, **12**, 5211–5228, <https://doi.org/10.5194/bg-12-5757-2015>.
- , G. Hugelius, D. M. Lawrence, and W. R. Wieder, 2017: Higher climatological temperature sensitivity of soil carbon in cold than warm climates. *Nat. Climate Change*, **7**, 817–822, <https://doi.org/10.1038/nclimate3421>.
- Le Quéré, C., and Coauthors, 2015: Global carbon budget 2015. *Earth Syst. Sci. Data*, **7**, 349–396, <https://doi.org/10.5194/essd-7-349-2015>.
- Liu, Y. Y., R. A. M. de Jeu, M. F. McCabe, J. P. Evans, and A. I. J. M. van Dijk, 2011: Global long-term passive microwave satellite-based retrievals of vegetation optical depth. *Geophys. Res. Lett.*, **38**, L18402, <https://doi.org/10.1029/2011GL048684>.
- , A. I. J. M. van Dijk, R. A. M. de Jeu, J. G. Canadell, M. F. McCabe, J. P. Evans, and G. Wang, 2015: Recent reversal in loss of global terrestrial biomass. *Nat. Climate Change*, **5**, 470–474, <https://doi.org/10.1038/nclimate2581>.
- Melillo, J. M., and Coauthors, 2002: Soil warming and carbon-cycle feedbacks to the climate system. *Science*, **298**, 2173–2176, <https://doi.org/10.1126/science.1074153>.
- Mitchell, T. D., and P. D. Jones, 2005: An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *Int. J. Climatol.*, **25**, 693–712, <https://doi.org/10.1002/joc.1181>.
- Mokany, K., R. Raison, and A. S. Prokushkin, 2006: Critical analysis of “root : shoot” ratios in terrestrial biomes. *Global Change Biol.*, **12**, 84–96, <https://doi.org/10.1111/j.1365-2486.2005.001043.x>.
- Nemani, R. R., C. D. Keeling, H. Hashimoto, W. M. Jolly, S. C. Piper, C. J. Tucker, R. B. Myneni, S. W. Running, 2003: Climate-driven increases in global terrestrial net primary production from 1982 to 1999. *Science*, **300**, 1560–1563, <https://doi.org/10.1126/science.1082750>.
- New, M., M. Hulme, and P. Jones, 2000: Representing twentieth-century space–time climate variability. Part II: Development of 1901–96 monthly grids of terrestrial surface climate. *J. Climate*, **13**, 2217–2238, [https://doi.org/10.1175/1520-0442\(2000\)013<2217:RTCSTC>2.0.CO;2](https://doi.org/10.1175/1520-0442(2000)013<2217:RTCSTC>2.0.CO;2).
- Niu, S., M. Wu, Y. I. Han, J. Xia, Z. H. E. Zhang, H. Yang, and S. Wan, 2010: Nitrogen effects on net ecosystem carbon exchange in a temperate steppe. *Global Change Biol.*, **16**, 144–155, <https://doi.org/10.1111/j.1365-2486.2009.01894.x>.
- Peylin, P., and Coauthors, 2005: Multiple constraints on regional CO<sub>2</sub> flux variations over land and oceans. *Global Biogeochem. Cycles*, **19**, 1–21, <https://doi.org/10.1029/2003GB002214>.
- Piao, S., and Coauthors, 2013: Evaluation of terrestrial carbon cycle models for their response to climate variability and to CO<sub>2</sub> trends. *Global Change Biol.*, **19**, 2117–2132, <https://doi.org/10.1111/gcb.12187>.
- Raffa, K. F., B. H. Aukema, B. J. Bentz, A. L. Carroll, J. A. Hicke, M. G. Turner, and W. H. Romme, 2008: Cross-scale drivers of natural disturbances prone to anthropogenic amplification: The dynamics of bark beetle eruptions. *BioScience*, **58**, 501–517, <https://doi.org/10.1641/B580607>.
- Robinson, D., 2007: Implications of a large global root biomass for carbon sink estimates and for soil carbon dynamics. *Proc. Biol. Sci.*, **274**, 2753–2759, <https://doi.org/10.1098/rspb.2007.1012>.

- Saatchi, S. S., and Coauthors, 2011: Benchmark map of forest carbon stocks in tropical regions across three continents. *Proc. Natl. Acad. Sci. USA*, **108**, 9899–9904, <https://doi.org/10.1073/pnas.1019576108>.
- Schuur, E. A. G., and Coauthors, 2015: Climate change and the permafrost carbon feedback. *Nature*, **520**, 171–179, <https://doi.org/10.1038/nature14338>.
- Sitch, S., and Coauthors, 2008: Evaluation of the terrestrial carbon cycle, future plant geography and climate-carbon cycle feedbacks using five dynamic global vegetation models (DGVMs). *Global Change Biol.*, **14**, 2015–2039, <https://doi.org/10.1111/j.1365-2486.2008.01626.x>.
- Stephenson, N. L., P. J. van Mantgem, A. G. Bunn, H. Bruner, M. E. Harmon, K. B. O'Connell, D. L. Urban, and J. F. Franklin, 2011: Causes and implications of the correlation between forest productivity and tree mortality rates. *Ecol. Monogr.*, **81**, 527–555, <https://doi.org/10.1890/10-1077.1>.
- Tarnocai, C., J. Canadell, E. Schuur, P. Kuhry, G. Mazhitova, and S. Zimov, 2009: Soil organic carbon pools in the northern circumpolar permafrost region. *Global Biogeochem. Cycles*, **23**, GB2023, <https://doi.org/10.1029/2008GB003327>.
- Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment design. *Bull. Amer. Meteor. Soc.*, **93**, 485–498, <https://doi.org/10.1175/BAMS-D-11-00094.1>.
- Thonicke, K., S. Venevsky, S. Sitch, and W. Cramer, 2001: The role of fire disturbance for global vegetation dynamics: Coupling fire into a dynamic global vegetation model. *Global Ecol. Biogeogr.*, **10**, 661–677, <https://doi.org/10.1046/j.1466-822X.2001.00175.x>.
- Turner, M., C. Beer, N. Carvalhais, M. Forkel, M. Santoro, M. Tum, and C. Schmullius, 2016: Large-scale variation in boreal and temperate forest carbon turnover rate related to climate. *Geophys. Res. Lett.*, **43**, 4576–4585, <https://doi.org/10.1002/2016GL068794>.
- , and Coauthors, 2017: Evaluation of climate-related carbon turnover processes in global vegetation models for boreal and temperate forests. *Global Change Biol.*, **23**, 3076–3091, <https://doi.org/10.1111/gcb.13660>.
- Tian, H., and Coauthors, 2015: Global patterns and controls of soil organic carbon dynamics as simulated by multiple terrestrial biosphere models: Current status and future directions. *Global Biogeochem. Cycles*, **29**, 775–792, <https://doi.org/10.1002/2014GB005021>.
- Todd-Brown, K., J. Randerson, W. Post, F. Hoffman, C. Tarnocai, E. Schuur, and S. Allison, 2013: Causes of variation in soil carbon simulations from CMIP5 Earth system models and comparison with observations. *Biogeosciences*, **10**, 1717–1736, <https://doi.org/10.5194/bg-10-1717-2013>.
- , and Coauthors, 2014: Changes in soil organic carbon storage predicted by Earth system models during the 21st century. *Biogeosciences*, **11**, 2341–2356, <https://doi.org/10.5194/bg-11-2341-2014>.
- Tribuzy, E. S., 2005: Variações da temperatura foliar do dossel e o seu efeito na taxa assimilatória de CO<sub>2</sub> na Amazônia Central. Ph.D. thesis, Universidade de São Paulo, 102 pp., <https://doi.org/10.11606/T.91.2005.tde-15072005-144011>.
- Van Mantgem, P. J., and N. L. Stephenson, 2007: Apparent climatically induced increase of tree mortality rates in a temperate forest. *Ecol. Lett.*, **10**, 909–916, <https://doi.org/10.1111/j.1461-0248.2007.01080.x>.
- Wang, X., and Coauthors, 2014: Soil respiration under climate warming: Differential response of heterotrophic and autotrophic respiration. *Global Change Biol.*, **20**, 3229–3237, <https://doi.org/10.1111/gcb.12620>.
- Wang, X., and Coauthors, 2014: A two-fold increase of carbon cycle sensitivity to tropical temperature variations. *Nature*, **506**, 212–215, <https://doi.org/10.1038/nature12915>.
- Wieder, W. R., M. D. Hartman, B. Sulman, Y.-P. Wang, C. D. Koven, and G. B. Bonan, 2018: Carbon cycle confidence and uncertainty: Exploring variation among soil biogeochemical models. *Global Change Biol.*, **24**, 1563–1579, <https://doi.org/10.1111/gcb.13979>.
- Williams, A. P., C. D. Allen, C. I. Millar, T. W. Swetnam, J. Michaelsen, C. J. Still, and S. W. Leavitt, 2010: Forest responses to increasing aridity and warmth in the southwestern United States. *Proc. Natl. Acad. Sci. USA*, **107**, 21 289–21 294, <https://doi.org/10.1073/pnas.0914211107>.
- , and Coauthors, 2013: Temperature as a potent driver of regional forest drought stress and tree mortality. *Nat. Climate Change*, **3**, 292–297, <https://doi.org/10.1038/nclimate1693>.
- Zhao, M., and S. W. Running, 2010: Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. *Science*, **329**, 940–943, <https://doi.org/10.1126/science.1192666>.
- , F. A. Heinsch, R. R. Nemani, and S. W. Running, 2005: Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sens. Environ.*, **95**, 164–176, <https://doi.org/10.1016/j.rse.2004.12.011>.
- Zhu, Z., and Coauthors, 2016: Greening of the Earth and its drivers. *Nat. Climate Change*, **6**, 791–795, <https://doi.org/10.1038/nclimate3004>.