Improvement of Soil Respiration Parameterization in a Dynamic Global Vegetation Model and Its Impact on the Simulation of Terrestrial Carbon Fluxes

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January 12, 2017

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Abstract

Soil decomposition is one of the critical processes in maintaining terrestrial ecosystem and global carbon cycle. Soil respiration (Rs) sensitivity to temperature so called the Q10 value required for parameterizing soil decomposition process is assumed to be a constant in conventional numerical models, while it is not so in the realistic case with spatiotemporal heterogeneity. This study develops a new parameterization method for determining Q_{10} by considering the soil respiration dependence on soil temperature and moisture obtained by multiple regression. This study further investigates the impacts of the new parameterization on the global terrestrial carbon flux. Our results show that non-uniform spatial distribution of Q_{10} tends to represent the dependence of the soil respiration process on heterogeneous surface vegetation type compared with the control simulation using a uniform Q_{10}. Moreover, it tends to improve the simulation of the observed relationship between soil respiration and soil temperature and moisture, particularly over cold and dry regions. The homogenous distribution of decomposition processes tended to change carbon assimilation over land. This change of ununiformed spatial distribution of carbon assimilation improves the simulation of gross primary production (GPP) by enhanced nutrient assimilation from soil to vegetation. It leads to a more realistic spatial distribution of GPP, particularly over high latitudes (60–80 N) where the original model has a significant underestimation bias. In addition, overestimation bias of GPP in the tropics and the midlatitudes is significantly reduced. Improvement in the spatial distribution of GPP leads to a substantial reduction of global mean bias of GPP from + 9.11 to + 1.68 GtC yr^{-1} compared with the FLUXNET-MTE observation data. The modified Q_{10} parameterization is possible to improve the simulation of global carbon cycle in CMIP5 ESMs which are based on the soil decomposition with constant Q_{10} values.

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1. Introduction

Vegetated land surface affects climate (Foley et al., 1998; Sellers et al., 1986) and is affected by climate significantly (Bonan, 2008), forming complex interactions and feedback loops critical to climate change (Friedlingstein et al., 2006; Gregory et al., 2009). The land surface components of Earth System Models (ESMs) have evolved from only representing biophysical processes (i.e., hydrology and energy cycling) to including biogeochemical processes, such as dynamic vegetation change and carbon and nutrient cycles driven by ecosystems (Oleson et al., 2013; Sitch et al., 2003; Wang et al., 2010). The carbon balance of terrestrial ecosystems is the result of the balance between carbon uptake and loss by plants and soil respiration (Beer et al., 2010; Malhi et al., 1999; Le Que re et al., 2009, 2014; Luyssaert et al., 2007; Trumbore, 2006). Which terrestrial ecosystems act dominantly as sinks or sources has been a subject of considerable interest in studies of future climate change. Precise evaluation for each sink and source component and their responses to environmental factors are essential for reliable projection of future climate change by ESMs.

Future climate change projection by various ESMs driven by identical anthropogenic emissions is diverse and highly uncertain in the prediction of atmospheric CO2 concentration (Friedlingstein et al., 2006, 2014; Hoffman et al., 2013). Many previous studies (Friedlingstein et al., 2006; Hoffman et al., 2013; Anav et al., 2013; Aroa et al., 2013; Friedlingstein et al., 2014) suggested that the uncertainty of CO2 concentrations simulated by the emission-driven ESMs should be attributed to the carbon cycle over land rather than over ocean. In particular, One of the main causes seems to be related to our poor knowledge on carbon exchange by soil, leading to significant diversity among the model simulations (Todd-Brown et al., 2013). Diversity in the parameterization of photosynthesis at the leaf level is small compared with that of the soil decomposition process in contemporary ESMs with an interactive carbon cycle. Microbial decomposition of soil organic matter produces a major carbon flux from the

subsurface biosphere. Many studies investigated the response of soil respiration (Rs) under global warming, and most of them suggested the warming would accelerate the release of CO2 from soil in future (Cox et al., 2000; Dufresne et al., 2002; Friedlingstein et al, 2003; Suseela et al., 2012). However, the amplitude of soil decomposition process has not been quantified through direct field measurements in the global domain, and highly uncertain, mostly due to the lack of observation data and poor estimates of it indirectly from soil temperature (Sussela et al., 2012). Moreover, Luo et al., (2016) suggested that the optimal parameter calibration in the model parameterization based on observation is needed to improve the soil carbon projection in ESMs. The reduction of uncertainty in the soil biogeochemical process remains a challenge for the ESM modeling community.

Soil respiration (Rs) is considered a significant source of CO_2 from terrestrial ecosystems. Recent studies suggest that CO_2 emission change by soil should be largely driven by surface temperature change (Bond-Lamberty and Thomson, 2010). At global, regional and local scales, soil temperature and soil moisture are considered the most important abiotic parameters determining Rs (Kutsch et al., 2009). Empirical response functions based on heterogeneous field measurements are commonly used to derive annual estimates of Rs (Tang et al., 2005).

The sensitivity of soil respiration (Rs) to temperature, the so-called Q_{10} value, is required for parameterizing the soil decomposition process. Whether this value is a global constant or variable in space is still under debate and the conclusions from the previous studies are diverse, which reflect our limited understanding to the soil respiration process. For example, Mahech et al. (2010) suggested that the Q_{10} value is independent of mean annual temperature and biomes. Karhu et al. (2014) also mentioned that the Q_{10} is approximately a global constant about 1.4 in the high latitude regions in the northern hemisphere. Another studies, on the other hand, suggested that Q_{10} may vary in space (Zhou et al., 2009; Xu and Qi, 2001; Qi et al., 2002). Belay-Tedla et al. (2009) suggested that warming-induced changes in plant growth and

community structure can considerably influence the quality and quantity of substrates which in turn regulates the responses of soil respiratory C release to rising temperature. All the abiotic and biotic factors such as soil temperature (Lloyd and Taylor, 1994; Kirschbaum, 1995; Luo et al., 2001), moisture (Davidson et al., 1998; Reichstein et al., 2002; Hui and Luo, 2004), and soil organic matter (Taylor et al., 1989; Liski et al., 1999; Wan and Luo, 2003) are heterogeneous, showing substantial spatial variation globally. Accordingly, estimated Q_{10} from measured soil respiration possibly varies at various geographic locations (Xu and Qi, 2001).

Based on the aforementioned studies, Zhao et al. (2009) developed an inverse model to retrieve the global pattern of heterogeneous Q_{10} values by assimilating soil organic carbon data with a process-based biogeochemical model. They suggested that spatial distribution of Q_{10} values changes according to vegetation type, with an increasing tendency as latitude increases. The impact on the estimation of carbon release due to Q_{10} variation in space is a significant change of approximately 25–40 % compared with the use of a constant Q_{10} value in Zhao et al. (2009). This result suggests that the determination of Q_{10} value is very important for the simulation of carbon-climate feedback and future climate change. However, most advanced ESMs partcipated in Coupled Model Intercomparison Project Phase 5 (CMIP5) still use a globally-constant Q_{10} value in the dynamic global vegetation models (Anav et al. 2013; Todd-Brown et al. 2013). In this case, the sensitivity of subsurface carbon flux under global warming condition would not be reflected in the model simulation.

Motivated by the above, this study developed a new parameterization method for determining Q_{10} by considering the dependence of soil respiration on soil temperature and moisture, the relationship of which was obtained from multiple regression with those two predictors. The variation of dominant vegetation type for the given area was also considered when determining Q_{10}. Community Land Model version 4 (CLM4) has the parameterization of the interactive carbon and nitrogen (C-N) cycle for the dynamic vegetation model, which was

used to derive realistic spatial distributions of Q_{10}. Moreover, the realistic soil carbon decomposition processes affect not only Rs but also primary production by improving nitrogen assimilation from soil to vegetation. This study further investigates the impacts of the new parameterization on the global carbon cycle.

Section 2 describes the observation and modeling data used in this study and the modeling method used to obtain the distribution of Q_{10}. Section 3 provides the results from the off-line dynamic vegetation model test with prescribed atmospheric states. In addition, the results from a fully interactive ESM model test with the modified Q_{10} are provided in that section. Summary and further discussion are provided in Section 4.

2. Data, Methods, and Experiments

2.1. Data

FLUXNET-MTE (Multi Tree Ensemble) data (Jung et al., 2009) is used to validate GPP. FLUXNET provides the global distribution of carbon and water fluxes in the vegetated land surface and its temporal variation, which were derived from upscaling eddy covariance measurements at the flux tower sites using a statistical machine-learning algorithm. The data provide the information on terrestrial carbon and water cycles globally (Jung et al. 2009). The data's spatial resolution is 0.5° X 0.5° (lat./lon.) and time resolution is monthly for 23 years (1983–2009).

This study also used the Moderate Resolution Imaging Spectroradiometer (MODIS) GPP and net primary production (NPP) data. Autotrophic respiration (Ra) by plants was determined by subtracting NPP from GPP by definition. This study used the gridded data for the global domain at 0.5° X 0.5° horizontal resolution. These data are originally from MODIS17A3 GPP and NPP products in HDF EOS (Hierarchical Data Format – Earth Observing System) format with a native resolution of 1 km (Running et al., 2004).

When GPP is compared between in situ observation-based FLUXNET-MTE and satellite-based MODIS, the two datasets show a minor difference for the overlapping period (2000–2006). The global GPP of FLUXNET-MTE is 101.13 GtC yr^{-1} and that of MODIS is 100.51 GtC yr^{-1}, which is less than 1 % of the total value.

Simulations of soil respiration (Rs) by CLM4 will be verified using the gridded reanalysis dataset from Hashimoto et al. (2015), which has the data period of 1983-2005. The data were also used for the parameterization of soil respiration (described in detail in section 2.2 in Hashimoto et al., 2015). Although only directly observed soil respiration is available from soil respiration database (SRDB) version 3 (Bond-Lamberty and Thomson, 2010), it has limited sampling for boreal cold regions (i.e., tundra and northern Siberian) as well as unpopulated regions in the tropics, covering a significant portion of the global biosphere. The data from Hashimoto et al. were derived using SRDB data and the empirical soil respiration model with specified climate conditions for surface air temperature and precipitation. The model was modified and updated from the original version of Raich et al. (2002). Global land use data in a synergetic land cover product (SYNMAP, Jung et al., 2006) using a Bayesian calibration scheme were used to determine the best parameter set for deriving the climate-driven model of soil respiration. The climate-forcing data were obtained from CRU version 3.21 climate data (University of East Anglia Climatic Research Unit, 2013). These data was applied monthly at a spatial resolution of 0.5° X 0.5° (lat./lon.).

All the data were regridded onto 1.9° X 2.5° lat./lon. grids for comparison with the CLM4 simulation at this resolution.

2.2. Q_{10} Parameterization

Most dynamic vegetation models implemented in current ESMs, including CLM4, adopt a simple type of empirical equation for Rs, which is proportional to the soil decomposition flux

199 of carbon at the root zone. The decomposition flux is calculated by multiplying the carbon
200 amount from litters by the rate scalar (R_{scalar}), representing the effects of the physical
201 environmental condition such as soil temperature (T_{scalar}) and moisture (W_{scalar}) as:

202 $$R_{scalar} = T_{scalar} * W_{scalar} , \quad (1)$$

203 where T_{scalar} is basically an exponential function of temperature from van't Hoff (1898). It is
204 implemented in CLM4 as in the following equation:

205 $$T_{scalar} = Q_{10}^{[\frac{T_j - T_{ref}}{10}]}, \quad (2)$$

206 where T_j is the temperature at the *j*-th soil level, and T_{ref} is the reference temperature of 25
207 °C. CLM4 considers temperature for the top 5 soil levels as representing the root zone (approx.
208 29 cm depth). Q_{10} is specified as a constant value of 1.5 in the standard CLM4 model. The
209 moisture scalar (W_{scalar}) is based on Andren and Paustian (1987), which describes the water
210 potential for soil decomposition as

211 $$W_{scalar} = \sum_{j=1}^{5} \frac{\log(\frac{\Psi_{min}}{\Psi_j})}{\log(\frac{\Psi_{min}}{\Psi_{max}})} , \quad (3)$$

212 where Ψ_j is the soil water potential at the level *j* defined from the exponential of volumetric
213 soil moisture (m^3 m^{-3}). Ψ_{max} is the maximum potential depending on soil type, and Ψ_{min} is
214 the minimum value of -10 MPa, regardless of soil type. The range of W_{scalar} is 0 to 1 by
215 setting to 0 when the Ψ_j is below Ψ_{min}, and setting to 1 when Ψ_j is above Ψ_{max}.

216 For improving the *Rs* parameterization in CLM4, this study considers a spatiotemporal
217 change of Q_{10} in (2). We developed a multiple regression model for Q_{10} based on Qi et al.
218 [2002], which assumes that the rate of R_s change depends entirely on soil temperature (*T*) and
219 soil moisture (*M*). These two physical variables are well-known important factors for soil

biological processes. The fractional instantaneous change of R_S by soil temperature q is defined as

$$\mathrm{q(T,M)} = \frac{1}{R_s}\frac{dR_s}{dT} \qquad (4)$$

Q_{10} is defined as the relative change of R_s at a temperature increase of 10 degrees, which can be described in the following equations:

$$Q_{10}\mathrm{(T,M)} = \frac{R_s(T+5,X)}{R_s(T-5,X)} \quad , \qquad (5)$$

$$Q_{10} = \mathrm{e}\int_{T-5}^{T+5} q(T,X)\ dT \quad , \qquad (6)$$

where X is any additional independent variable to predict Rs. In this case, only soil moisture (M) is considered. From (6), Q_{10} is a monotonic function of q, and the factor affecting q also influences Q_{10}. Therefore, the change of Rs is decomposed into the change by temperature and the change by moisture:

$$\frac{dR_s}{dT} = \frac{\partial R_s(T,M)}{\partial M}\frac{dM}{dT} + \frac{\partial R_s(T,M)}{\partial T} \quad . \qquad (7)$$

Inserting (7) into (4), the equation for q is rewritten as

$$\mathrm{q(T,M)} = \frac{1}{R_s}\left[\frac{\partial R_s(T,M)}{\partial M}\frac{dM}{dT} + \frac{\partial R_s(T,M)}{\partial T}\right] \quad , \qquad (8)$$

where dM/dT = -1/2.2 = -0.455, as suggested by Xu and Qi (2001).

Through a multiple regression analysis, the relationships between R_s and T and between R_s and M were obtained. In this study, multiple regression was conducted for each plant function type (PFT) for 16 classifications in CLM4. The Q_{10} multiple regression model developed in this study has an advantage over the treatment of constant value in the standard CLM4 model. First, the dependence of Rs on soil moisture and temperature can be dependent on PFT. In addition, this approach is able to consider the nonlinear relationship between R_s and the two major environmental variables of soil temperature and moisture, supported by

242 recent observational studies (Davidson et al., 1998; Raich et al., 2002).

243 Crucial for the parameterization of Q_{10} are the quality of the reference data and the degree
244 of fitting for multiple regression. The observation data for R_S were obtained from Hashimoto
245 et al. (2015) soil respiration data. The parametrization requires the dependence of soil
246 respiration on subsurface temperature and moisture; these data are also not available from in
247 situ observations. To obtain these variables, this study conducted the land surface reanalysis
248 for recent 30 years (1981 – 2010), using the off-line land surface model driven by observed
249 meteorological forcing data archived by Sheffield et al. (2006). The 3-hourly forcing data by
250 Sheffield et al. (2006) consists of the National Centers for Environmental Prediction–National
251 Center for Atmospheric Research reanalysis (Kalnay et al., 1996), which were corrected with
252 independent observations. For precipitation, the daily Global Precipitation Climatology Project
253 (GPCP, Huffman et al., 2001) data were processed into the 3-hourly data using the Tropical
254 Rainfall Measuring Mission (TRMM: Huffman et al., 2003) 3B42RT but constraining daily
255 mean amount from GPCP. Surface temperature was constrained by the observation from the
256 monthly Climatic Research Unit (CRU) 2.0 product (Mitchell et al., 2004). The observed
257 radiation was also used from the monthly NASA Langley surface radiation budget (Stackhouse
258 et al., 2004) data. Remaining meteorological conditions such as surface wind and humidity
259 were from the National Centers for Environmental Prediction–National Center for
260 Atmospheric Research (NCEP-NCAR) atmospheric reanalysis. Interested readers refer to
261 Sheffield et al. (2006) for the detail. Using this 3-hourly forcing data, this study integrated the
262 off-line land surface model with 3-hourly time steps and at a 0.5°×0.5° spatial resolution.

263 Figure 1 shows the r-squared values from the multiple regression for soil respiration for
264 various PFT types. In most vegetation types, the regression by soil temperature and moisture
265 tends to exhibit high values close to 1. The regression results are better than they are when the
266 multi-model ensemble average of soil temperature and moisture from 13 Global Soil Wetness

Project (GSWP2) land surface model outputs (Dirmeyer et al., 2006) were applied to the multiple regression. This difference is attributed mostly to a better quality of forcing data by Sheffield et al. (2006), such as the use of daily precipitation data instead of monthly values in GSWP2 and a longer training period from 1983–2010 than was used for GSWP2 data (1986–1995). The r-square value was found to be comparable when the period of forcing data was reduced.

2.3. Experiments

Two sets of off-line CLM4 simulations were conducted with identical meteorological forcing for 23 years (1983–2005), where the only difference was the specification of Q_{10} in the control run (CTL) and the state-dependent Q_{10} in every time interval (EXP). The offline simulations for GPP and soil respiration are also compared with those from the fully-interactive Community Earth System Model with Biogeochemistry (CESM-BGC) model simulation that used the identical land surface model (i.e., CLM4). The dataset was obtained from Earth System Grid – Center for Enabling Technologies (ESG-CET at http://pcmdi9.llnl.gov/). Figure 2 shows the time average of Q_{10} values, where the geographical change is clear according to the dominant PFTs and climate conditions. Generally, the regions of lower canopy plants with cold soil temperatures exhibit relatively higher values, significantly higher than the default value of 1.5 in CTL. In contrast, the regions of lower Q_{10} values are located at low latitudes in high temperatures, such as the Amazon and the Maritime Continent. This result suggests that soil respiration is more sensitive to the change of soil temperature in boreal vegetated regions in cold climates.

The time average of the off-line simulation from the standard run (CTL) in Figure 3 is very similar to the fully interactive integration of the same model in terms of the spatial bias pattern for the terrestrial carbon fluxes, presumably inherited by the deficiencies in the parametrization

of the dynamic vegetation model. Both simulations tend to overestimate GPP over the tropics and underestimate it in high latitudes. The bias pattern of Rs is also quite similar with no significant difference. Despite the fact that in the simulated climatic condition the fully interactive run should be different from the observation used to drive the off-line CLM4, much resemblance in the terrestrial carbon–flux bias pattern suggests that the deficiency in the dynamic vegetation model is overwhelming the bias rather than that systematic error is occurring in the climate condition. Therefore, our comparison in the following sections is mostly for the off-line simulation differences between CTL and EXP.

3. Results

This study further compares the simulation of GPP by various ESMs in CMIP5. Figure 4 compares the zonal mean distribution of GPP averaged for 23 years (1983–2005) between FLUXNET-MTE observations and the historical emission-driven simulations by 10 CMIP5 ESMs (Table 2). Among the models, the two ESMs from CESM-BGC and NorESM share an identical dynamic vegetation model with an interactive C-N cycle (Bonan et al., 2011). The global GPP simulated by the multi-model ensemble (MME) of CMIP5 ESMs is 119.28 GtC yr^{-1}, which is a slight overestimation by 18 GtC yr^{-1} from the FLUXNET-MTE observation. Overall, MME shows realistic meridional variation with large values in the tropics and small values in high latitudes. As identified in previous studies, however, the ESMs tend to overestimate GPP significantly in the tropics (Shao et al., 2013; Anav et al., 2013). Global GPP simulated by the two ESMs with an interactive C-N cycle is lower than the remainder of the ESMs (– 12 GtC yr^{-1}). Including typical biases of overestimation of GPP over tropical belts (20S–20N), the two models show the other GPP bias from the remainder of the ESMs, which tend to significantly underestimate GPP, even more so than other ESMs in the Northern Hemisphere high latitudes (> 60 N). These systematic biases are a common problem in the C-

N coupled models based on CLM4 (Bonan et al., 2011; Thornton et al., 2009). These systematic biases in the tropics and the Northern Hemisphere high latitudes are common in the C-N coupled models based on CLM4 (Bonan et al. 2009).

Figure 5a compares the Rs pattern between the observation and the offline model simulation. The simulated pattern also shows a general agreement with the observation, such as large soil respiration in warm and wet regions in low latitudes and less respiration in cold and dry regions in high latitudes. However, the simulation bias in CTL shows the uniform pattern of underestimation in almost every region except central China. This bias suggests that the parameterization of internal soil biological processes could be misrepresented in the standard CLM4 model.

The changes in Rs simulation by EXP are given in Figure 5b, in terms of global distribution as well as zonally-averaged distribution. Overall, the modification to Q10 tends to increase Rs in almost every region. This is an improvement from CTL, although the model now tends to overestimate Rs in some specific regions, such as the tropics and the high latitudes in the Northern Hemisphere, such as southern Siberia, Alaska and China. Overall the increase of Rs can be attributed to the increase of Q_{10} in most of the vegetated regions (Figure 2) from the standard value of 1.5. Despite the increase of Rs in EXP, the underestimation persists over the Amazon and other large biomass regions.

The sensitivity of Q_{10} parametrization depend on the surface vegetation types. For instance, boreal forest and shrub regions which has cold climate shows significant enhanced relationship between Rs and soil temperature. In contrast, temperate, tropical forest and Grass regions show relative higher positive relationship between Rs and temperature in CTL simulation comparing with EXP simulation (Table 3). Some regions in shrub and crop regions is unclear to show this relationship. Interestingly, PFTs of higher value of climatology averaged Q_{10} value (Table 1) comparing with standard value (1.5) enhanced relationship between Rs and soil temperature

such as boreal forest and boreal shrubs except for crop land. In boreal forest and shrub regions which has higher Q_{10} value comparing with global constant, the relationship between Rs and temperature in EXP are enhanced than CTL simulation. However, the tropical, temperate forests and grass regions (lower Q_{10} value than 1.5 in EXP simulation) is unclear for impacts of Q_{10} parameterization. One of possibility is that these regions are strong sensitivity of soil respiration to soil moisture. Figure S1 supported that this mechanism. In high temperature region, the sensitivity of Rs on the moisture is stronger than temperature. It reflected the unclear change of temperature sensitivity of Rs to soil temperature over tropical forest region.

Figure 7 compares the GPP bias patterns in CTL and EXP. CTL shows significant biases when sign and magnitude differ geographically. Among the biases, overestimation in the tropics and underestimation in Siberia is evident. Although the spatial structure of bias seems to be quite similar, implying intrinsic model deficiencies other than Q_{10}, EXP shows an improvement by reducing biases such as overestimation in southern Asia and China and underestimation in northern Eurasia in CTL. However, underestimation biases in the central part of North America and the Amazon are even larger in EXP. This change of spatial distribution of GPP is associated with sensitivity of Rs to soil temperature. Degradation of GPP simulation over Europe and North America is driven by the temperate plant type where the temperature sensitivity of Rs tends to decrease (Figure 6). On the other hand, the northern Eurasian and Chinese regions that have good improvement of GPP bias in EXP show an enhanced relationship between Rs and temperature. This result indicates that the change of Rs to soil temperature by Q10 variation affects not only the change in respiration but also the carbon production (GPP) flux. The variable Q_{10} in the parameterization of soil decomposition flux immediately affects the heterotrophic respiration from soil organic matter (SOM) as given by the model formulations in Eq. (1) and (2). Moreover, this modification changes the plant assimilation and GPP in the meantime in this carbon-nitrogen coupled model. A faster (slower)

carbon decomposition rate in the model tends to increase (decrease) nitrogen assimilation from soil to vegetation and plants, thereby increasing (decreasing) GPP. This aspect is illustrated well by comparing the turnover time of the soil carbon, which is defined as the ratio of soil carbon amount to the net primary production (NPP), between the CTL and EXP runs (Figure 8). As shown in the figure, the run with variable Q_{10} (EXP) makes shorter turnover time in northern hemisphere high latitudes and longer in the tropics compared with the control run(CTL). The shorter turnover time in high latitudes suggests the enhancement of nitrogen assimilation to vegetation in EXP, thereby enhancing net primary production by plants.

The improvement in the GPP simulation by the Q_{10} parameterization is illustrated better in Figure 9, which compares the regionally averaged GPP over major 4 regions. In the global average, EXP reduces the overestimation bias by approximately 10 % (103.81 GtC/yr) compared with CTL simulation (111.24 GtC/yr). Little plant cover over Southern Hemisphere (SH, 60S-20S) leads to a smaller contribution of global GPP. The improvement over this region is not clear in EXP. However, the overestimation bias in the tropical regions has been improved significantly. This result is caused by the suppression of the GPP amount in the Amazon region in EXP. This underestimation of GPP over the Amazon induces the improvement of the zonal mean terrestrial carbon budget in EXP. The middle latitude region (20N–60N), which is dominated by temperate forest and crop fields, also has a reduced overestimation of GPP bias compared with CTL. In addition, simulated GPP over high latitude regions (> 60N) were improved in EXP. Those were also the common areas of bias in the interactive C-N coupled ESM run.

The modification to the soil process parameterization can affect the rest of the terrestrial carbon cycle by changing the carbon pools and nitrogen pools in the soil system needed for plant nitrogen assimilation. For detailed investigation of the impact of the Q10 parameterization, this study further investigates the changes in the simulated terrestrial carbon

cycle of each vegetation type. Figure 10 compares the observation and the simulations using two offline runs for GPP, autotropic respiration by plants (Ra), and Rs depending on the primary vegetation type. For the comparisons of GPP and Ra, satellite-based MODIS data were used as the data separated GPP and Ra over vegetation areas. In the MODIS observations, the terrestrial carbon cycle is largely contributed to by vegetation response in tropical and temperate tree regions. Vegetation types with a short canopy height and trees with deciduous leaves contribute less in terms of absolute amount of carbon fluxes, although their relative changes are not trivial. Both CTL and EXP runs capture these observed differences in the magnitude of carbon fluxes realistically. Regarding the simulation of GPP, EXP tends to reduce the biases, particularly in temperate, tropical and crop zones. EXP also improves the simulation of Ra in those regions. The improvement is most evident in Rs, where the simulated values are close to the observed values in most vegetation types. Rs by EXP has been increased in every type of vegetation from CTL, reaching values closer to the reference observation data. According to this result, although the absolute magnitude of Rs is much smaller compared with that of GPP and Ra, the modification of Rs by the Q_{10} parameterization affects the entire terrestrial carbon cycle and improves their simulations.

4. Summary and Concluding Remarks

Soil respiration is a crucial process in maintaining terrestrial carbon cycles. Although its sensitivity to the physical environmental conditions such as soil temperature and moisture depends on the type of vegetation, as supported by observational data, most contemporary ESMs do not consider this dependence. These models thereby underestimate the effects of and feedbacks from soil respiration on terrestrial carbon cycles. Using the CLM4 land surface model with the interactive C-N cycle, this study developed a new parameterization method to consider the spatiotemporal variation of Q_{10} that represents the sensitivity of soil respiration to

417 the temperature change for each different vegetation type. This sensitivity has been treated as
418 constant with a uniform value regardless of plant type in the original CLM4 model.
419 The new parameterization changes the simulation of soil respiration and the rest of
420 terrestrial carbon fluxes significantly by enhancing the feedback to the plant production process.
421 The new parameterization calculates Q_{10} at every time interval for each location, and this state-
422 dependent prescription induces the overall increase of soil respiration in most locations and
423 most vegetation types, improving spatially uniform negative bias in the original CLM4
424 simulation with constant Q_{10} value. The simulated sensitivity of soil respiration to soil
425 temperature and moisture by the new method showed more realistic features, particularly in
426 the temperate and cold regions. This changed soil carbon fluxes at the subsurface and affected
427 the simulation of GPP, where the simulation of spatial distribution of GPP has been improved
428 particularly over high latitudes with short canopy heights and over the tropics and warm regions,
429 including southern Asia and China. The improved GPP simulation over cold regions was
430 mostly attributed to the increase in carbon decomposition in those regions. Due to the
431 advancement of both respiration and primary production, carbon balance between subsurface
432 and surface ecosystems with soil organic matter and plants were also improved by the new Q_{10}
433 parameterization. The observed ratio of soil respiration to GPP was represented better in the
434 new simulation, which clearly shows the dependence on the vegetation type.
435 The major findings from this study suggest that the modification of subsurface terrestrial
436 carbon cycle processes is important for improving the simulation of terrestrial carbon fluxes.
437 The parameterization of the photosynthetic process is still a major term crucially related to
438 primary production (Bonan et al. 2010; Bonan et al., 2011). Previous studies have suggested
439 that the improvement of canopy processes in the photosynthetic parameter in CLM4 was able
440 to improve the simulation by reducing the overestimation of GPP in the tropics. Despite the
441 improvement in the photosynthetic process in their models, respiration processes by plants and

soil are still largely uncertain due to a lack of reliable observational data and comprehensive studies (Bonan et al. 2010; Bonan et al., 2011). For this reason, this study approached the modification of the soil decomposition process, aiming to improve the terrestrial carbon cycle. In fact, the parameterization of photosynthesis in the state-of-the-art ESMs is implemented in a similar fashion with small differences, based on the formulations from Farquhar et al. (1980). Still, large uncertainties lie in the formulation of the respiration process and its parameters. This study suggested that the improved soil decomposition process induces a change in carbon-climate feedback intensity by changing soil respiration. In addition, the realistic description of Q_{10} variation in a numerical model will reduce the uncertainty of the magnitude of carbon-climate feedback due to accurate atmospheric CO2 simulation in ESMs.

Acknowledgement

This study is supported Basic Science Research Program through the National Research Foundation of Korea (NRF), funded by the Ministry of Education, Science and Technology (2012M1A2A2671851) and the Supercomputing Center/Korea Institute of Science and Technology Information with supercomputing resources including technical support (KSC-2015-C3-035).

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645 **Table 1.** Climatological averaged Q_{10} values by PFTs in CLM4

	Temperate	Boreal	Tropical	Shrub	B. Shrub	Grass	Crop
Averaged Q_{10} value	1.446	1.762	1.374	1.266	1.918	1.842	2.041

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653 **Table 2. List of ESMs used in this study and their features**

Number	Models	Modeling center	Horizontal resolution	ESM Reference	Land model	Photosynthesis	Autotropic Respiration	Nitrogen Cycle	Dynamic Vegetation
1	BCC-CSM 1	Beijing Climate Center, China	2.812° × 2.812°	Wu et al. (2013)	BCC-AVIM1	Farquhar et al., (1980)	Foley et al. (1996)	No	No
2	BCC-CSM 1M	Beijing Climate Center, China	1.125° × 1.125°	Wu et al. (2013)	BCC-AVIM1	Farquhar et al., (1980) Collatz et al. (1992)	Foley et al. (1996)	No	No
3	CanESM2	Canadian Centre for Climate Modeling and Analysis, Canada	2.812° × 2.812°	Arora et al. (2011)	CTEM	Farquhar et al., (1980) Collatz et al. (1992)	Ryan (1991)	No	No
4	CESM1-BGC	Community Earth System Model Contributors, NSF-DOE-NCAR, USA	1.25° ×0.9°	Long et al. (2013)	CLM4	Farquhar et al., (1980) Collatz et al. (1992)	Foley et al. (1996)	Yes	No
5	GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5° ×2°	Dunne et al. (2013)	LM3	Farquhar et al., (1980) Collatz et al. (1992)	Foley et al. (1996)	No	Yes
6	GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5° ×2°	Dunne et al. (2013)	LM3	Farquhar et al., (1980) Collatz et al (1992)	Ryan (1991)	No	Yes
7	MIROC-ESM	Japan Agency for Marine-Earth Science	2.812° × 2.812°	Watanabe et al. (2011)	MATSIRO+ SEIB-	Farquhar et al., (1980)	Ryan (1991)	No	No

		and Technology, Atmosphere and Ocean Research Institute, and National Institute for Environmental Studies, Japan			DGVM				
8	MPI-ESM LR	Max Planck Institute for Meteorology, Germany	2.812° × 2.812°	Ilyina et al. (2013)	JSBACH	Farquhar et al., (1980)	Obata (2007)	No	Yes
9	MRI-ESM1	Meteorological Research Institute, Japan	1.125° ×1.125°	Yukimoto et al. (2011)	HAL	Farquhar et al., (1980) Collatz et al. (1992)	Ryan (1997)	No	No
10	NorESM1-ME	Norwegian Climate Centre, Norway	2.5° ×1.875°	Tjiputra et al. (2013)	CLM4	Farquhar et al., (1980) Collatz et al. (1992)	Foley et al. (1996)	Yes	No

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Table 3. R-squared values between log Rs and soil temperature by PFTs in CTL and EXP

	Temperate	Boreal	Tropical	Shrub	B. Shrub	Grass	Crop
CTL	0.40	0.06	0.34	0.06	0.04	0.38	0.27
EXP	0.36	0.21	0.31	0.05	0.19	0.28	0.31

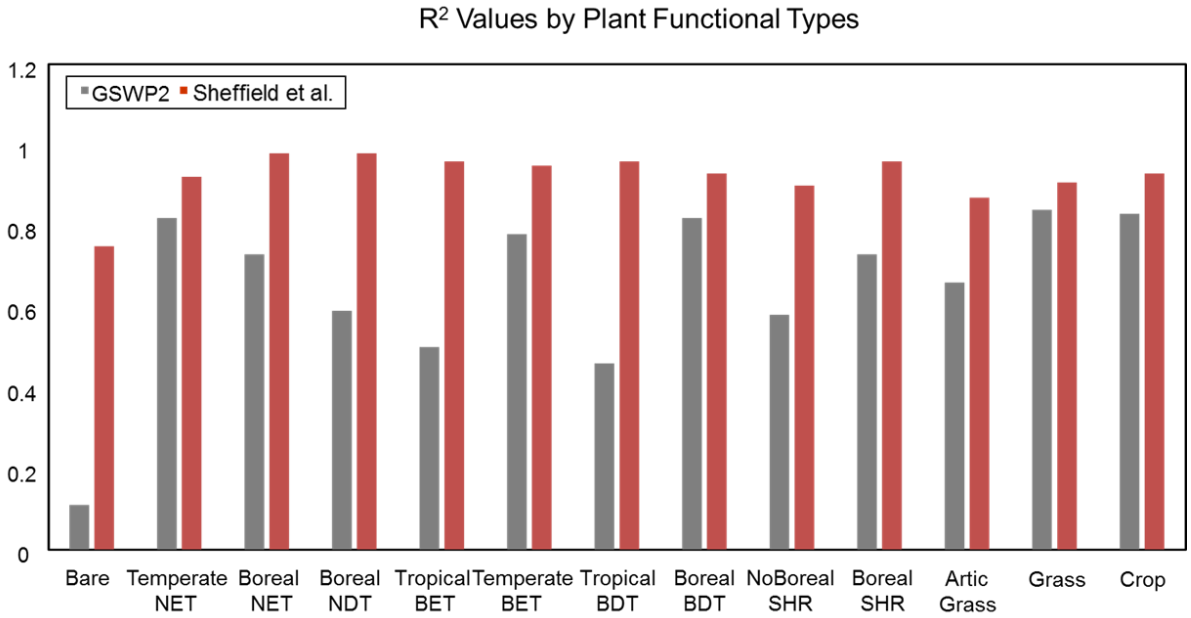


Figure 1. R-squared value in multiple regression by PFTs in CLM4 between soil respiration data and soil temperature and moisture from GSWP2 multiple ensemble model data (grey bars) and off-line model output forced by Sheffield data for 28 years (red bars).

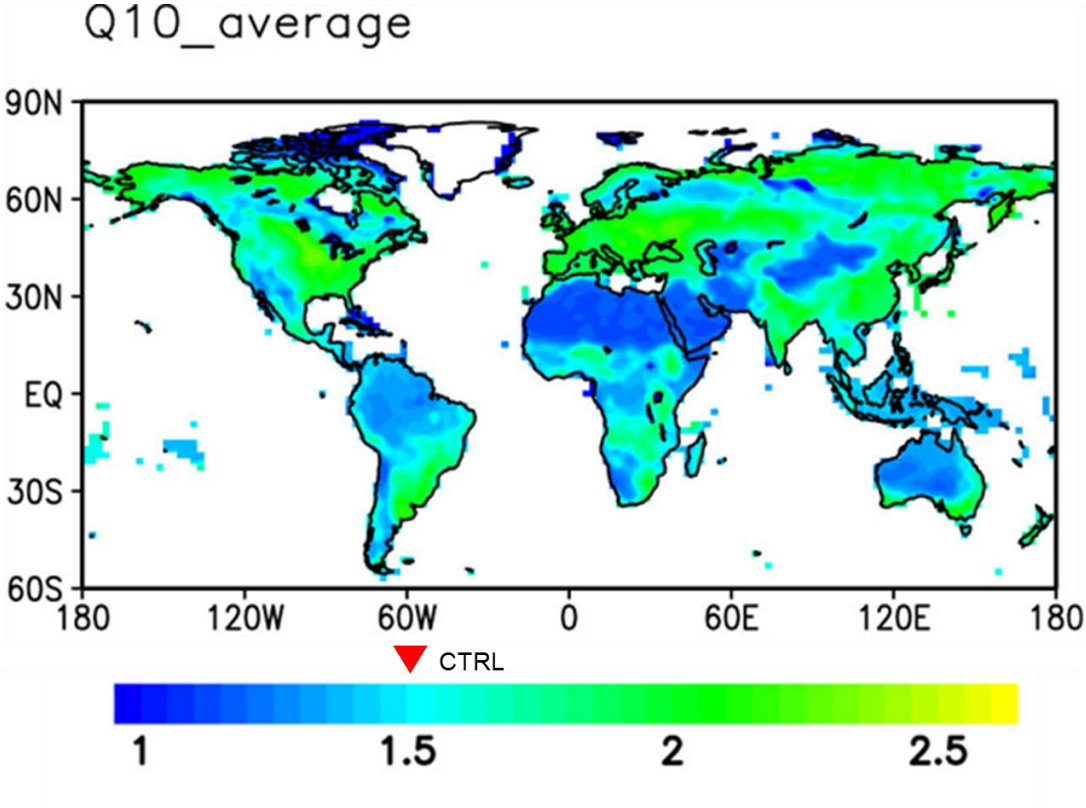
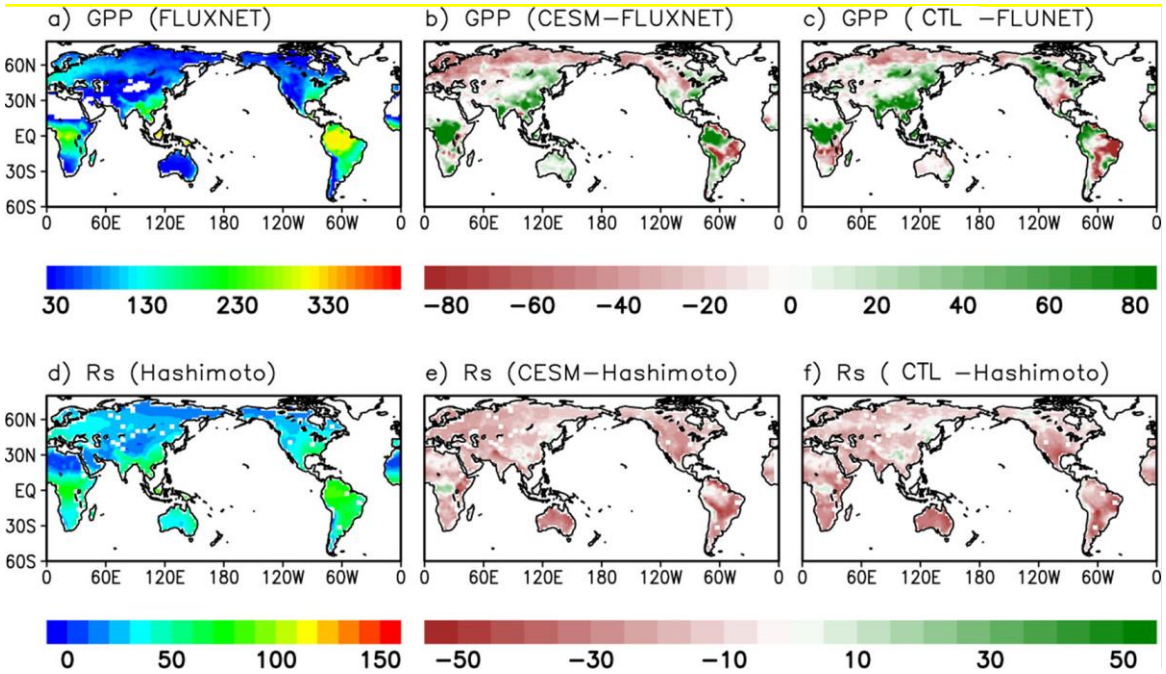


Figure 2. Climatological averaged Q_{10} spatial distribution in EXP experiment. Red filled triangle indicates standard value of Q_{10} in CTL experiment.



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687 **Figure 3.** Spatial distribution of GPP(upper) and Rs (bottom) in the observation and bias

688 patterns of online full interactive simulation (CESM) and off-line (CTR) experiment for 23

689 years (1983-2005). The unit is gC m^2 mon^{-1}.

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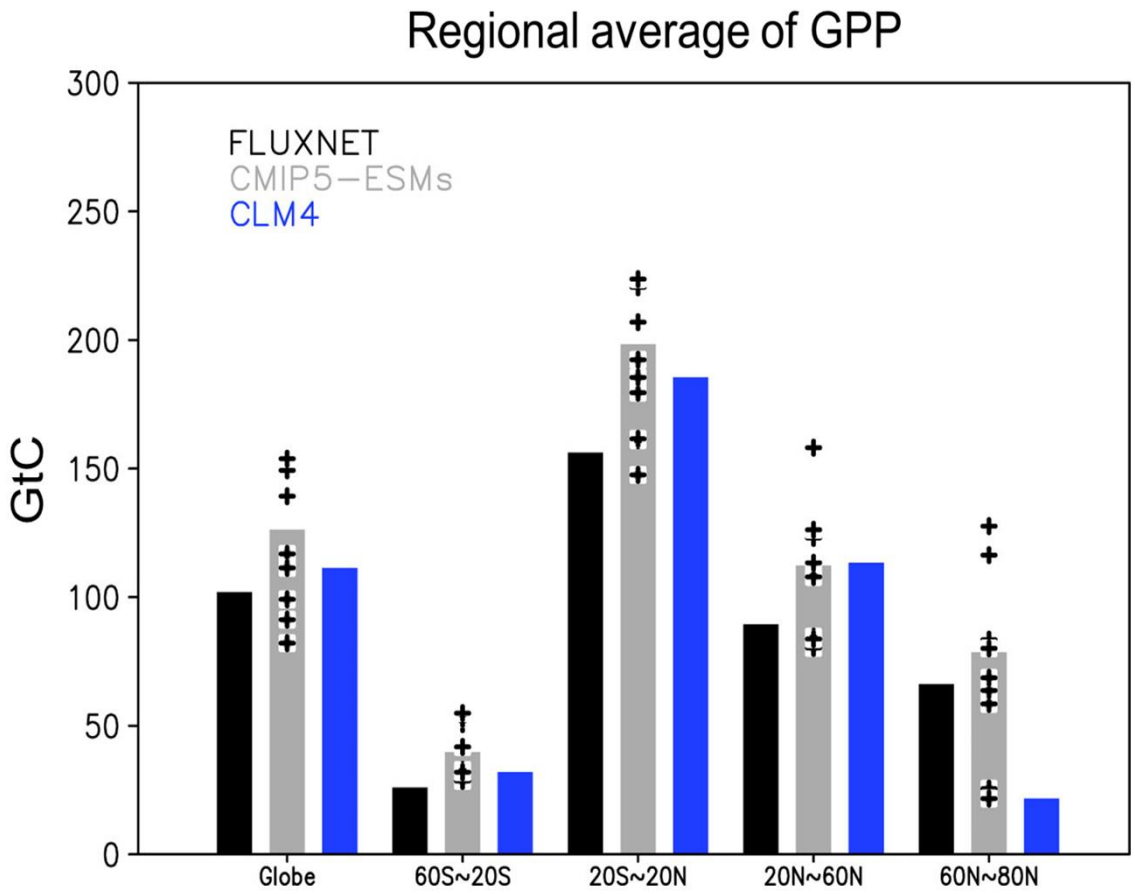


Figure 4. Regional averaged GPP in CMIP5 historical runs for 23 years (1983~2005). Black bars indicate the FLUXNET. Grey bars are multi-model ensemble (MME) mean of 10 CMIP5-ESMs and symbol dots are individual models. Blue bars show average of GPP simulated by ESMs which are coupled with CLM4 (CESM-BGC and NorESM).

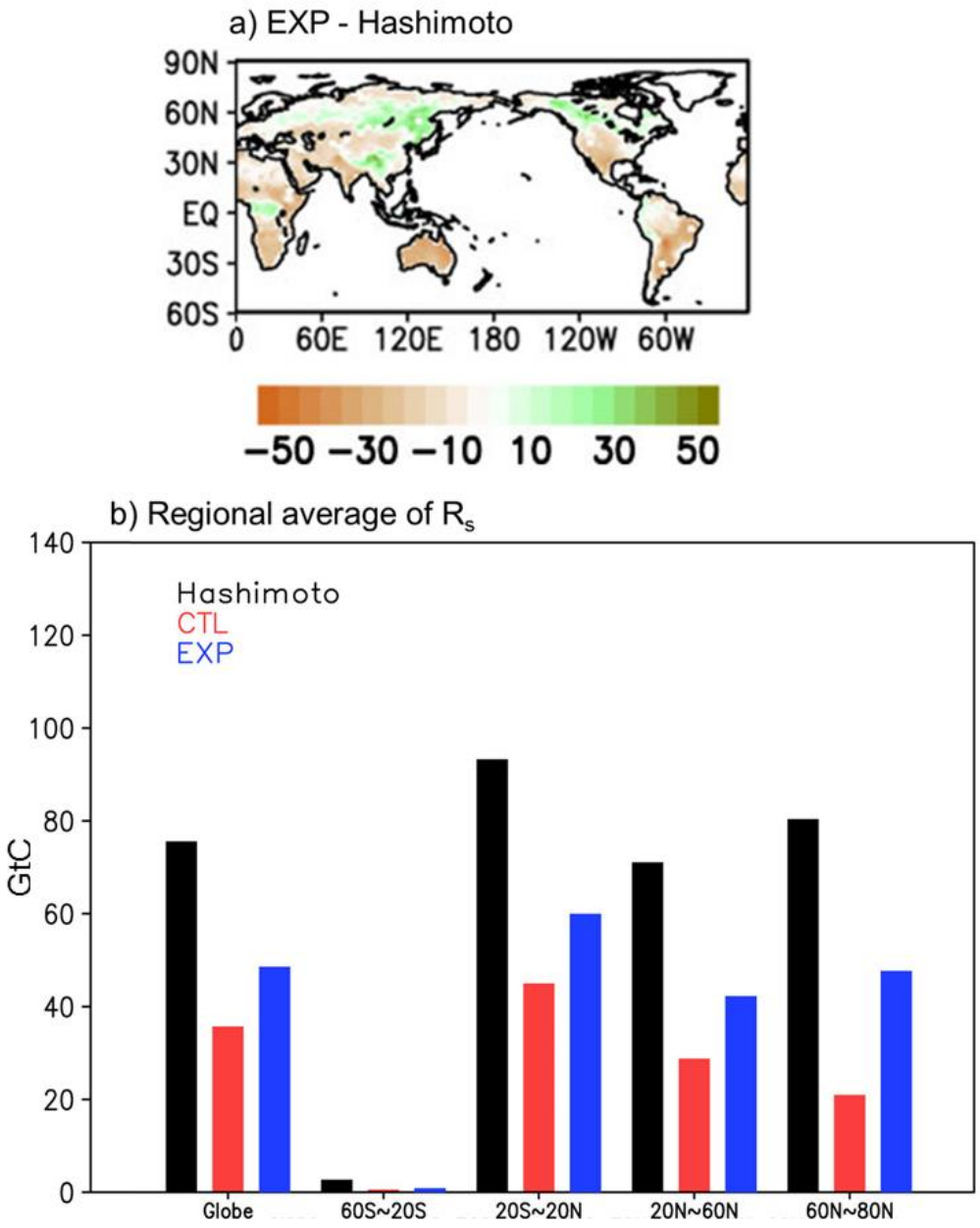
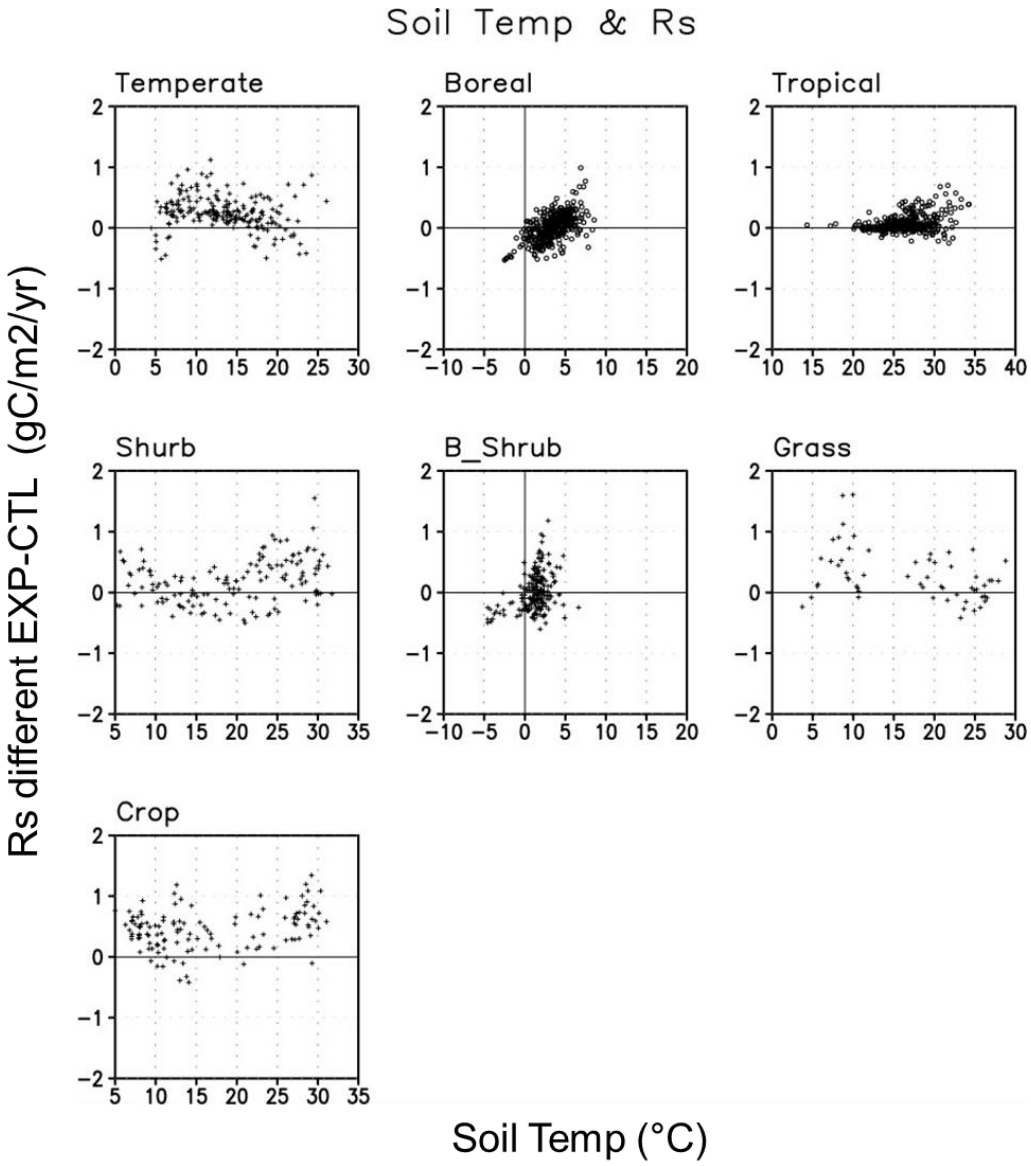


Figure 5. (a) shows the spatial distribution of bias pattern of Rs in EXP simulation. The unit is gC m2 mon-1. (b) indicates the comparison of the regional average of Rs between Hashimoto data (black bars), CTL simulation (red bars) and EXP experiment (blue bars).



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709 **Figure 6.** Scatter plots of change of Rs (y-axis) between EXP and CTL simulation as a
710 function of soil temperature (x-axis). Each panel shows the plots for different PFTs that include
711 temperate (temperate NET and BET), boreal (boreal NET, NDT, BDT), tropical (toprical BET,
712 BDT), Shrub, B_shrub (Boreal shrub), Grass(Grass) and Crop(Crop).

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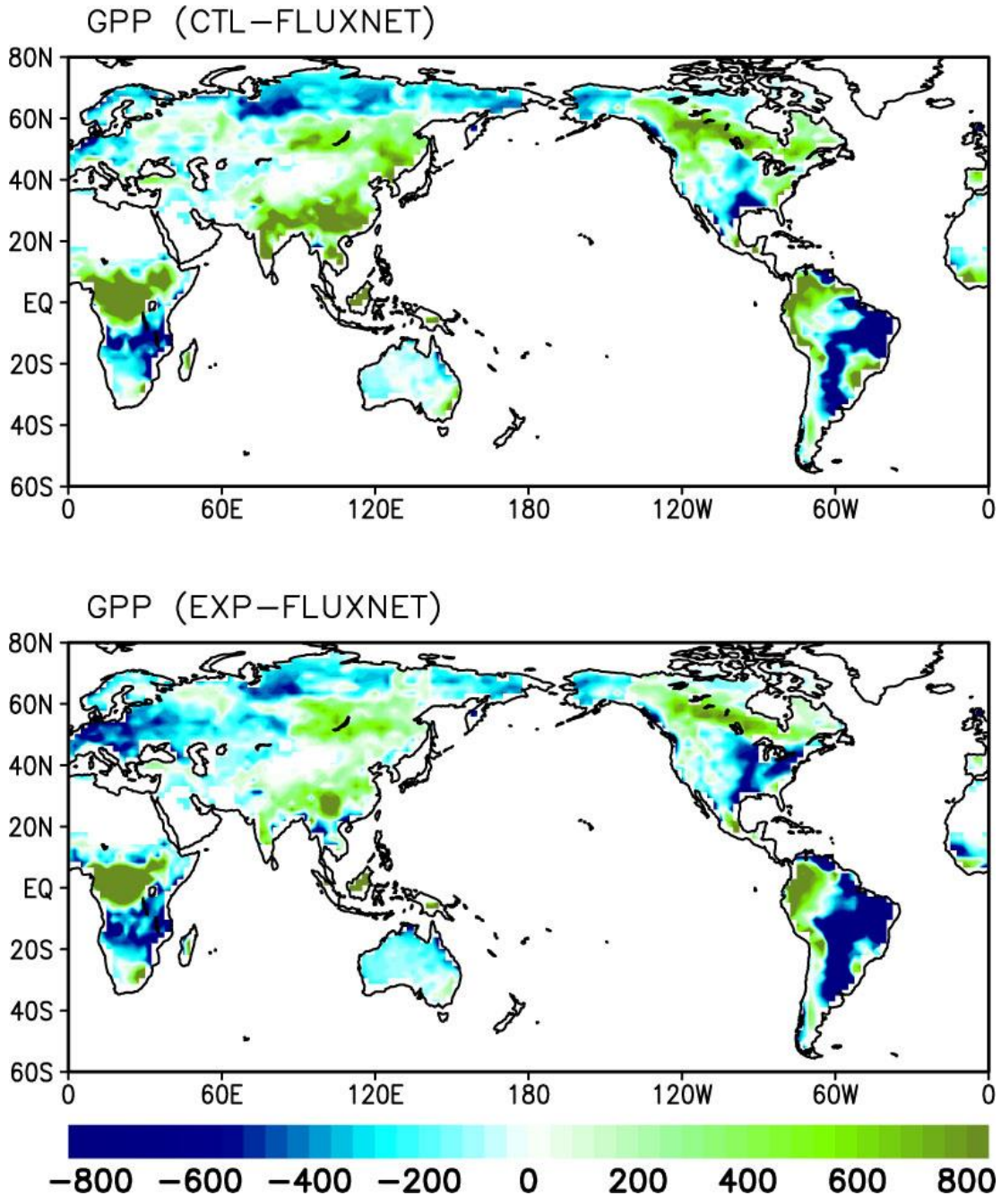

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715 **Figure 7.** Bias of GPP spatial distribution in CTL and EXP comparing with FLUXNET

716 during 23 years (1983-2005). Unit is gC/m2/yr.

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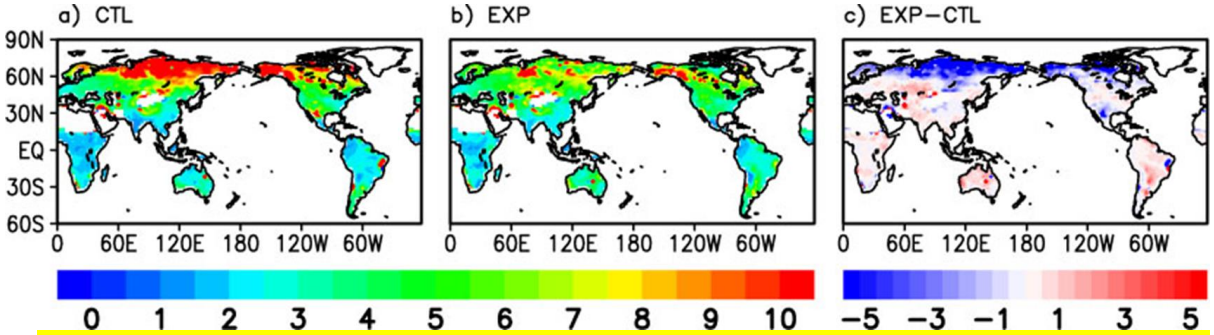


Figure 8. Spatial distribution of turnover time (year) of soil carbon in (a) CTL and (b) EXP. (c) indicates the difference between EXP and CTL simulation. The turnover time is defined as the ratio of the soil carbon amount to the net primary production (NPP).

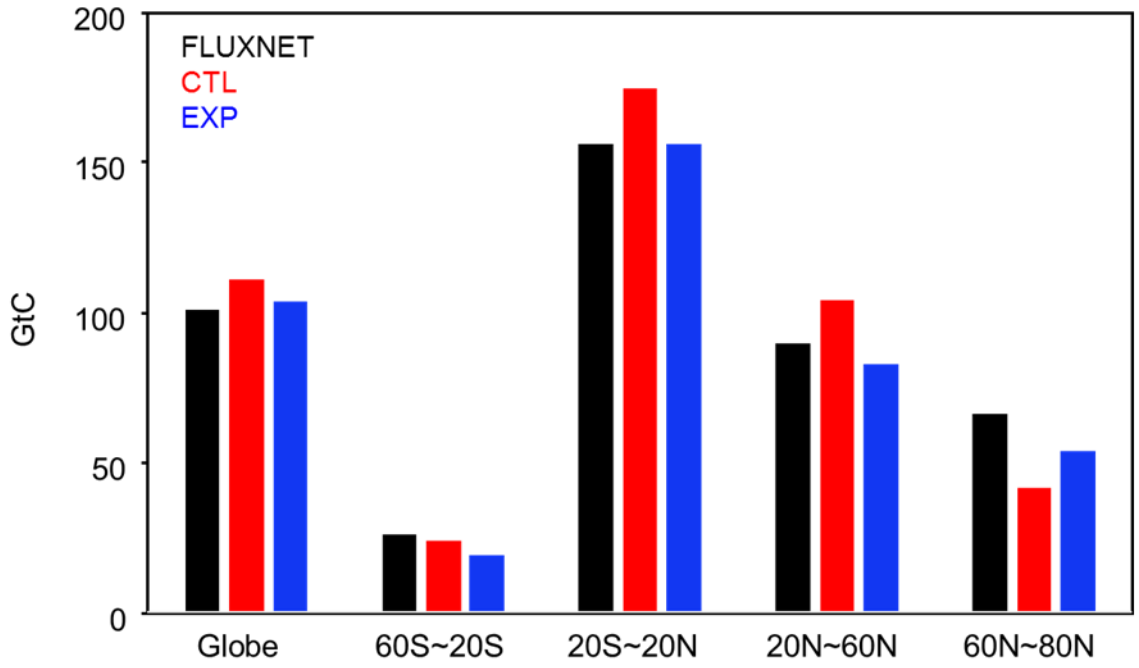
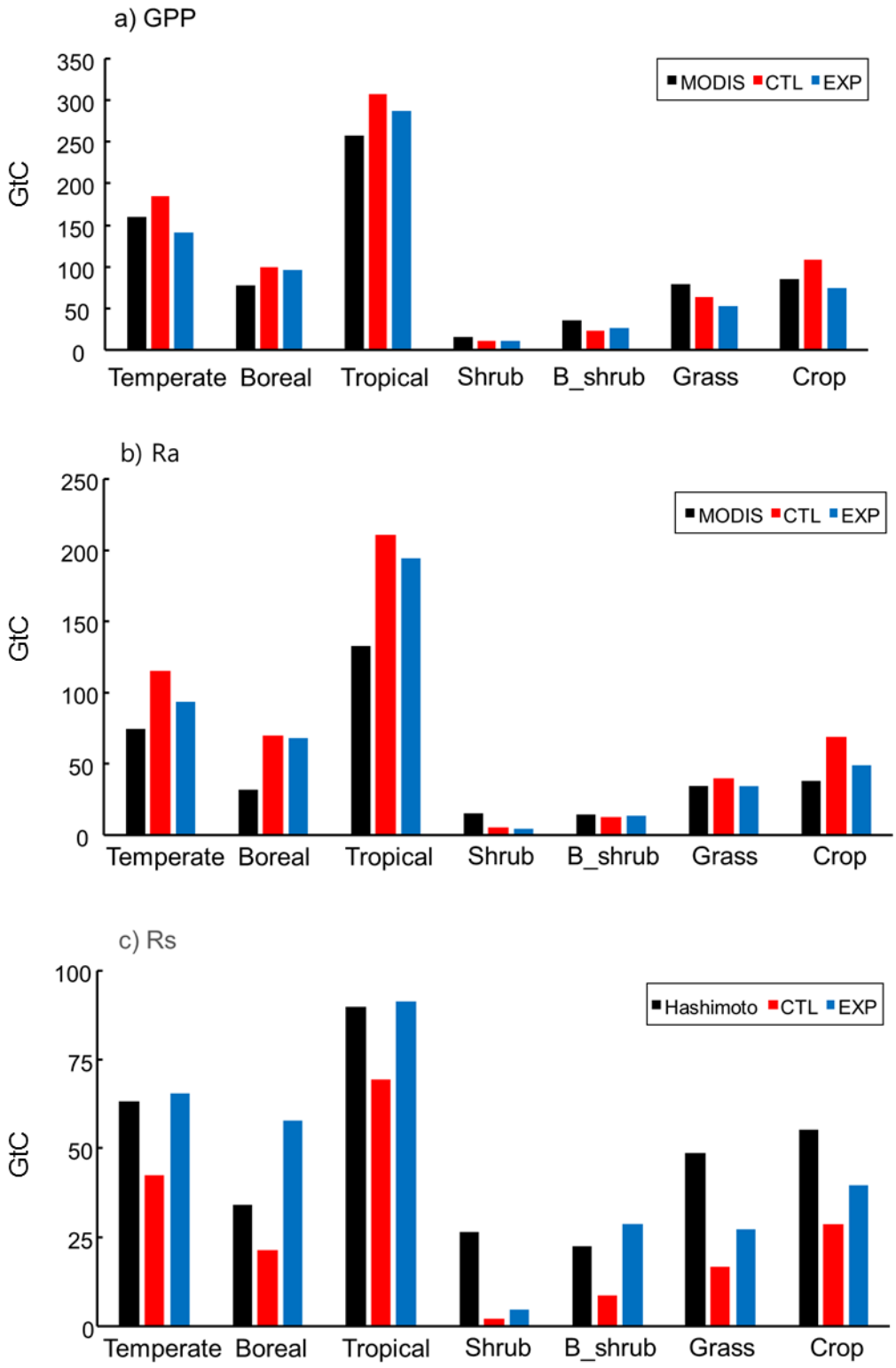


Figure 9. Regional averaged GPP in FLUXNET (black bars), CTL (red bars) and EXP (blue bars).



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733 **Figure 10.** Comparison of spatial average of GPP, Ra and Rs in observation (black bars),

734 CTL (red bars) and EXP (blue bars) by PFTs.

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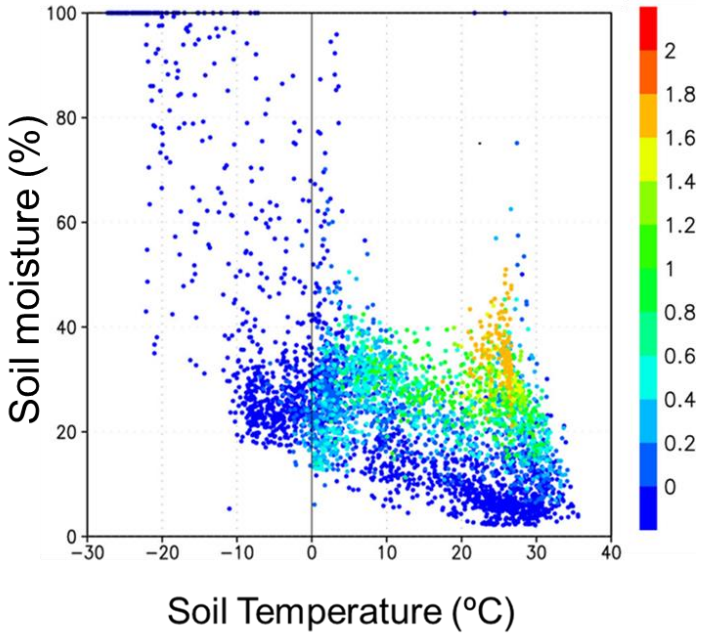

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737 **Figure S4**. Spatial Matrix between soil moisture (Y-axis) and soil temperature (X-axis) with
738 Rs (color dots) in the CTL simulation.

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