Spatial biases reduce the ability of earth system models to simulate soil heterotrophic respiration fluxes

Bertrand Guenet[1,*], Jérémie Orliac[1], Lauric Cécillon[1,2], Olivier Torres[3], Laura Sereni[4], Philip A. Martin[5], Pierre Barré[1], Laurent Bopp[3]

[1] Laboratoire de Géologie, Ecole normale supérieure, CNRS, IPSL, Université PSL, 24 Rue Lhomond, 75005 Paris, France

[2] Laboratoire ECODIV, Univ. Normandie, UNIROUEN, INRAE, Rouen, France.

[3] LMD-IPSL, Ecole Normale Supérieure, Université PSL, CNRS, Ecole Polytechnique,

10   Sorbonne Université, Paris, France.

[4] INRAE, AgroParisTech, Université Paris-Saclay, UMR1402 ECOSYS, Ecotoxicology Team, 78026, Versailles, France.

[5] Basque Centre for Climate Change (BC3), Edificio sede no 1, planta 1, Parque científico UPV/EHU, Barrio Sarriena s/n, 48940, Leioa, Bizkaia, Spain.

15   *Correspondence to*: Bertrand Guenet (guenet@geologie.ens.fr)

Abstract. Heterotrophic respiration (Rh) is, at a global scale, one of the largest CO_2 fluxes between the earth's surface and atmosphere and may increase in the future. Yet, the capacity of Earth System Models (ESMs) to reproduce this flux has never been evaluated, causing uncertainty in resulting CO_2 flux estimates. In this study, we combine recently released observational data on Rh and ESM simulations to evaluate, for the first time, the ability of 13 ESMs to reproduce Rh. Only

20   four of the 13 tested were able to reproduce the total Rh flux but spatial analysis underlined important bias compensation. We observed that mean annual precipitation was the most important driver explaining the difference between ESM simulations and observation-derived product of Rh with higher bias between ESM simulations and Rh products where precipitation was high. Based on our results, next-generation ESMs should focus on improving the response of Rh to soil moisture.

1 Introduction

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Stocks of soil organic carbon are estimated to represent around three times the amount of carbon in the atmosphere (Scharlemann et al., 2014). This soil carbon is used as a substrate by soil microorganisms to obtain their energy and feed their metabolism, which account for the majority of heterotrophic soil organism biomass. Annual fluxes that result from the respiration of these heterotrophic organisms (hereafter referred to as heterotrophic respiration) are estimated (Ciais et al.,

30   2021; Hashimoto et al., 2015; Konings et al., 2019; Warner et al., 2019) to be five times higher than annual anthropogenic emissions (Friedlingstein et al., 2020) and roughly similar to annual terrestrial net primary production (Zhao et al., 2005). Thus, due to the size of fluxes relating to heterotrophic respiration, even minor changes in soil organic carbon dynamics can lead to significant impacts on carbon feedbacks and, ultimately, on climatic changes. As a result, modification of soil organic carbon stocks due to human activities is considered to be an important driver of future climate trajectories (Chabbi et al.,

35   2017).

Despite the importance of heterotrophic fluxes, they have not been well characterized and incorporated into earth system models (ESMs), which aim to simulate the most important drivers of the earth's climate system. Although the carbon fluxes of oceans and plants have been well characterized and incorporated into earth system models (Luyssaert et al., 2018; Séférian et al., 2020) this is not true of fluxes resulting from heterotrophic respiration – and as such, these represent a key

40   source of uncertainty regarding carbon flux. Given the importance of carbon exchange between the earth's surface and atmosphere as a driver of atmospheric CO_2 it is vital that such exchanges are accurately represented in earth system models.

Assessing how accurately current ESMs reproduce the fluxes associated with heterotrophic respiration is therefore of major importance. Until now, it was not possible to undertake a robust spatial assessment because of the lack of observation-derived gridded products of Rh. In recent years, new gridded products derived either from (i) upscaling of local

45   observation or (ii) calculations using atmospheric inversions and satellite observations have filled this gap. These products provide the opportunity to evaluate the simulations of ESMs used within the Coupled Model Intercomparison Project Phase 6 (CMIP6) against observation-derived products for heterotrophic respiration. CMIP is a key initiative which aims to compare current ESMs and is a central element of national and international assessments of climate change(Masson-Delmotte et al., 2021).

50   In this study we have two major aims:

1. Compare predictions of the total flux of heterotrophic respiration from 13 earth system models with three recent gridded products of heterotrophic respiration derived from observations and identify the spatial biases of heterotrophic respiration in the models.

2. Identify the major drivers of the heterotrophic respiration bias in earth system models to propose way of
55   improvement for the next generation of earth system models.

2 Materials and Methods

2.1 Earth System Models simulations.

In this study, we used the model outputs from the 6th Coupled-Model Intercomparison Project (CMIP6) (Eyring et al., 2016) which coordinates global climate model simulations of the past, current, and future climate. CMIP6 proposes historical
60 simulation spanning from 1850 to 2014. Historical simulations are driven from an initial point chosen in control integration (*piControl*). We chose to use the latest CMIP6 results for basic initial state (r1i1p1f1). We choose outputs from thirteen ESMs that provide heterotrophic respiration fluxes (BCC-CSM2-MR, BCC-ESM1, CanESM5, CESM2, CNRM-ESM2-1, E3SM-1-1-ECA, IPSL-CM6A-LR, MIROC-ES2L, MPI-ESM1-2-LR, NorCPM1, NorESM2-LM, SAM0-UNICON and UKESM1-0-LL). The variable used is "rh" corresponding to the total heterotrophic respiration on land. We computed annual
65 average over the 1990-2010 period which corresponds to the period in which most of the observations in the global Soil Respiration Database (Bond-Lamberty and Thomson, 2010) v3.0 were made, which were used to derived two observation products we used.

2.2 Observation-derived products.

70 In this study we used three observation derived products (Hashimoto et al., 2015; Konings et al., 2019; Warner et al., 2019). In Warner et al. (2019), the authors predicted annual soil respiration and associated uncertainty across terrestrial areas at a resolution of 1 km using a quantile regression forest algorithm trained with observations from the global Soil Respiration Database (Bond-Lamberty and Thomson, 2010) v3.0 (commit number 651770 in GitHub, https://github.com/bpbond/srdb) spanning from 1961 to 2011 but mostly after 1990. Then they deduced Rh from the soil respiration using two different
75 methods (Bond-Lamberty et al., 2004; Subke et al., 2006). They therefore proposed two Rh maps derived from a unique mean map of Rs from quantile regression forest model. Here, we decided to use the mean of two approaches as a reference for Warner et al. (2019) Rh results. The second product we used (Hashimoto et al., 2015) called here Hashimoto et al. (2015) is also based on the Soil Respiration Database (Bond-Lamberty and Thomson, 2010) v3.0 but in this case they derived the Rh flux using a climate-driven model of soil respiration derived from the Raich's model (Raich et al., 2002). They provided
80 a 0.5◦ resolution product at a monthly step time between 1965 and 2012. In our case, we used the yearly average over the period. The third product used (Konings et al., 2019) called here Konings et al. (2019) estimated Rh as a residual remote-sensing data exploiting recent advance in carbon-flux estimations. In contrast with the two other products which can be considered as bottom up, the Konings et al., (2019) product propose a top-down approach combining net ecosystem productivity estimates from atmospheric inversions with an optimally scaled gross primary productivity dataset derived from
85 satellite observations. Rh is then derived using the CARbon DAta MOdel fraMework, (CARDAMOM). Their result is a monthly evaluation of Rh, between 2010-01 and 2012-12, at a resolution 4°×5°.

2.3 Data treatment and regriding.

All the ESMs outputs and products were not at the same resolution. Thus, we needed to choose a reference for map-grid
90   resolution. The coarser resolution was from Konings et al. (2019)'s product with a 4°×5° resolution grid. Degrading every
Rh map at such resolution would be a substantial loss of information. Thus, we increased the resolution of those datasets and
decreased the very fine scale maps to an arbitrary reference corresponding to the CNRM-ESM2-1 model which runs at 0.7°
resolution. We chose to set the reference at the maximum resolution available among CMIP6's ESMs predicting Rh. We
used the common regridding routine cdo remapdis (nco module) that performs regridding by distance-weighted average
95   remapping and conserve latitudinal and longitudinal means. To avoid coastal pixels encroaching into oceans, we weighted
each pixel by its proportion of land. The sum of Rh over the lands was compared before and after regridding to ensure that it
was conservative.

2.4 Comparison between models' outputs and heterotrophic respiration products.

100 To estimate the ability of the CMIP6's model to reproduce soil heterotrophic respiration, we first compared the global flux
summed over all the grid cells and averaged over 1990-2010 period in Pg C yr^{-1}. We also compared the Rh maps after
regridding averaged over the 1990-2010 period. We also performed latitudinal and longitudinal means calculus including
oceanic zero-values. Secondly, we wanted to assess spatial bias distribution. Therefore, we i) compare CMIP6 model
average with observation products and ii) compare each CMIP6 models with observation products. Thus, we first
105 represented the model average (over the period 1990-2010) and all the observation derived products on a same figure with
their associated latitudinal and longitudinal means. We also calculated the 25th and 75th quantiles of latitudinal and
longitudinal CMIP6 model means. Then, we computed the difference for each single CMIP6 models with the median of the
three observation products.

2.5 ESM's model residual analysis.

110 We defined here the ESM's model residuals as median of the difference between each single CMIP6's model output and the
observation-based products median calculated for each grid cell. We proceed with a two-step methodology. First, we
compared several linear generalized least square models with different spatial structures (gaussian, exponential, spherical,
linear or rational (gls package)) and without spatial structures. Based on AIC values we selected the rational quadratic spatial
115 correlation structure that had the smallest AIC values for the second step of the analysis. Then, we used generalized additive
mixed model with ESM's model residuals as variable to explain and mean annual temperature (MAT), mean annual
precipitation (MAP), observation derived SOC, ESM's model residuals on NPP and lithology as predictors variables. MAT
and MAP are derived from the Global Soil Wetness Project Phase 3 (GSWP3) reanalysis (http://hydro.iis.u-
tokyo.ac.jp/GSWP3/ last access: April 5 2022). SOC was taken from the Soilgrid250m product(Hengl et al., 2017). ESM's
120 model residuals on NPP are calculated as the median of the difference between ESM's NPP and NPP from the global
inventory monitoring and modelling studies group (GIMMS). Lithology maps from the global lithological map (GLiM)
(Hartmann and Moosdorf, 2012) was used but since lithology was not significant (p>0.05) and the model has a lower AIC

without it was not included in the final generalized additive mixed model presented here. All statistical analysis were made using R v3.5 (R Core Team, 2018).

3 Results

3.1 Global heterotrophic respiration flux and spatial biases

Global heterotrophic respiration flux simulated by the 13 ESMs ranges from 29 to 78 Pg C yr^{-1} (Fig. 1), whereas the equivalent estimates for observationally derived products estimate range from 43 to 51 Pg C yr^{-1}. The multi-model mean of the ESMs (49 Pg C yr^{-1}) falls within the range of the observation-derived products. However, only four out of 13 ESMs (BCC-CSM2-MR, CNRM-ESM2-1, IPSL-CM6A-LR, and SAM0-UNICOM) simulate an overall heterotrophic respiration flux that is within the range of the observation-derived products (Fig 1).

Despite similar global-scale values, regional-scale differences between the observation-derived products are much larger (Fig. 2). The Konings et al. (2019) product estimates large heterotrophic fluxes in the tropics and lower fluxes in other regions such as the west coast of Northern America or central Asia, as compared to the Warner et al. (2019) and the Hashimoto et al. (2015) products that share similar spatial patterns. The mean of the 13 ESMs simulations also gives a much larger heterotrophic respiration fluxes over the tropics in particular over South-East Asia compared to any of the three observation-derived products. In general, the heterotrophic respiration fluxes from the 13 ESMs mean is closer to Konings et al. (2019) product over the tropics but closer to the Warner et al. (2019) and the Hashimoto et al., (2015) products over temperate regions. For boreal regions, the three observations-derived products and the 13 ESMs means are very close.

To generate our best-estimate of heterotrophic respiration fluxes from the three observation-derived products we calculated the median for each cell. We then compared each ESM with the observation-derived products median (Fig. 3). This comparison indicates that, apart from the ESM NorCPM1, ESMs tend to overestimate heterotrophic respiration flux in tropical regions (approx. 1,000 gC m^{-2} yr^{-1} for MPI-ESM1-2-LR over the Amazon or 1,500 gC m^{-2} yr^{-1} for UKESM1-0-LL over South-East Asia, for instance). Models perform relatively well in temperate regions with for instance bias close to 0 gC m^{-2} yr^{-1} for BCC-ESM-1 over North America and Europe. Importantly, the four models that predict a global heterotrophic respiration flux within the range given by the observation-derived products (BCC-CSM2-MR, CNRM-ESM2-1, IPSL-CM6A-LR and SAM0-UNICOM), do not perform well at finer scales - with over estimation of the flux in some regions and under estimation in others. Therefore, this good global-scale performance masks spatial bias compensation.

3.2 Identification of the major drivers of the heterotrophic respiration bias in earth system models.

150   In order to improve predictions of heterotrophic respiration fluxes in future ESMs it is key that we understand the spatial biases we observed and what their causes are. To explore these biases, we performed a statistical analysis based on a generalized additive mixed model of the ESMs residuals defined as the median of the difference between each CMIP6's model output and the median of the observation-based products calculated in each grid cell (see online methods). We performed the residual analysis on the ESMs median rather on each individual model because the ESMs soil carbon module

155   share a very common approach based on first order kinetics with soil organic decomposition driven by soil moisture and temperature (Ito et al., 2020). This approach is derived from the very first attempts to describe soil organic decomposition with mathematical equations (Henin and Dupuis, 1945) and is still the most used to describe this process (Manzoni and Porporato, 2009; Wutzler et al., 2008). Thus, performing analysis on the median instead of each single model can provide broader suggestions to improve ESMs performances.

160   Since the drivers of heterotrophic respiration are soil carbon availability, soil moisture and temperature, carbon inputs and mineralogy (Doetterl et al., 2015), we used soil organic carbon, net primary production residuals calculated using similar methods to heterotrophic respiration flux residuals, mean annual precipitation, mean annual temperature and lithology as explaining variables. Our method identified the main drivers of ESMs residuals as soil organic carbon, net primary production residuals, mean annual precipitation, and mean annual temperature (Fig. 4). Lithology was not significant

165   ($p>0.05$) and the model has a lower AIC without this variable and so we did not include lithology in the final model presented here. We observed that the residuals due to soil organic carbon stock are close to zero for soil with a low carbon stock but heterotrophic respiration is under estimated by ESMs for soils rich in organic carbon (> 3,000 g C m^{-2}) (Fig. 4a). The model residuals on the heterotrophic respiration flux are partially explained by the model residuals on net primary production with a slight increase from model underestimation to model overestimation when model residual on net primary

170   production increase from -1,000 to 400 g C m^{-2} yr^{-1}. We noted that when net primary production fits well with satellite products (i.e model residuals close to 0 g C m^{-2} yr^{-1}), the ESM residuals on the heterotrophic respiration flux are also close to 0 g C m^{-2} yr^{-1}. For a few grid cells where ESMs largely overestimate net primary production (i.e. model residuals higher than 400 g C m^{-2} yr^{-1}), the ESMs residuals on heterotrophic respiration flux tend to be negative suggesting that ESM underestimate heterotrophic respiration flux. The clearest tendency we obtained was with mean annual precipitation, the

175   more it increases the more the models overestimate the heterotrophic respiration flux (Fig. 4c). The median ESMs residual was also partially controlled by mean annual temperature (Fig. 4d) with a relatively low overestimation by the models for cold temperatures such as those recorded in polar climate zones and in some continental climate zones (e.g. subartic climate), a relatively good fit for temperature between 270 and 290K corresponding to temperate and some continental climate zones (e.g. Hot summer continental climates) and then a sudden underestimation for warm temperatures above 290K

180   corresponding to tropical and dry climate zones.

4 Discussion

In this study we evaluated, for the first time, the ability of the ESMs to reproduce heterotrophic respiration flux. Indeed, so far heterotrophic respiration in ESMs could only by constraint indirectly by constraining net ecosystem exchange fluxes or through ecosystem respiration in which heterotrophic respiration is just one component among many others. We
185 showed that only four of 13 of the CMIP models produce global-scale estimates that are consistent with observation-derived products. However, we also showed that this consistency was due to spatial bias compensations driven by different environmental variables. Heterotrophic respiration represents a carbon flux that is roughly five times that of anthropogenic emissions (Friedlingstein et al., 2020) and, as such, it is vital that work is done to improve the ability of ESMs to reproduce this flux. Nevertheless, we also observed large discrepancies between observation-based products showing that our ability to
190 provide heterotrophic flux based on observations is not optimal. To better constrain ESMs projections, some efforts are needed to reduce uncertainties between observation-based products.

However, working only on heterotrophic respiration may not be sufficient to improve the entire soil organic carbon module of the ESMs. ESM capacities to reproduce observed soil organic carbon stocks also need to be improved (Ito et al., 2020; Varney et al., 2022). To improve both soil organic carbon stocks and heterotrophic respiration fluxes soil organic carbon
195 decomposition rates needs to be better constrained. The ESM residual analysis we performed here suggests some new research avenues and in particular for the response of the major drivers. First, it must be noted that most of the boundary conditions of the soil organic carbon modules of an ESM are calculated by the ESM itself. Thus, if soil moisture, soil temperature or litter production are incorrect, the soil organic carbon dynamic cannot be correct. We observed that when the residual of NPP was close to zero the residual on heterotrophic respiration is also close to zero. Thus, improving the plant
200 functioning scheme may ultimately improve the capacities of the ESMs to reproduce the heterotrophic respiration flux. Our study also showed that mean annual temperature is an important driver of the ESM residuals in particular for hot regions with large underestimations of the flux. It probably corresponds to very arid regions since for most of the ESMs, heterotrophic respiration fluxes from regions like Australia, Middle East or Northern Africa tend to be underestimated. The response of soil organic decomposition by microorganisms is likely to be temperature dependent, with lower rates of
205 decomposition seen in cold regions and higher rates in hot regions (Wang et al., 2010; Zhou et al., 2009). In contrast, the response of soil organic decomposition to temperature in ESMs is generally controlled by Q10 equations (Davidson and Janssens, 2006) with fixed parameters not dynamic and not spatially distributed (Ito et al., 2020). Having more flexible Q10 parameters may help to improve ESMs capacities to reproduce observation-derived products of heterotrophic respiration fluxes. Moreover, land surface scheme of ESMs are known to be very sensitive to Q10 values(Jones et al., 2003).

210 Finally, we observed a relatively linear, positive relationship between mean annual precipitation and the ESMs' residuals. This response is probably driven by soil moisture because it is a key driver of microbial activity and therefore of heterotrophic respiration fluxes (Moyano et al., 2012). ESMs use three main groups of soil moisture response function

(Falloon et al., 2011): i) some models do not represent soil moisture effect, ii) some models increase soil organic decomposition when soil moisture increases assuming less water limitation for microbial activity and iii) some models assume a humped relationship between soil moisture and soil organic decomposition, with high decomposition at intermediate soil moisture and low decomposition in very wet soils where microbial activity is reduced because of limitation by oxygen availability and in dry soils where microbial activity is reduced because of limitation by water. As with Q10, the land surface schemes are highly sensitive to the soil moisture response function chosen approach and most of the ESMs use option ii) (Varney et al., 2022). Soil incubations have repeatedly shown that the response of heterotrophic respiration fluxes to soil moisture is approximated by a bell-shaped function with parameters depending on soil organic carbon, soil clay content, and soil bulk density (Moyano et al., 2012). Thus, for wet soils, heterotrophic respiration fluxes are probably reduced because of oxygen limitation. Implementing this bell-shaped function approach is necessary to accurately represent the soil organic carbon stock of peatland in some land surface schemes used by ESMs (Qiu et al., 2019). Not considering the possible oxygen limitation effect on wet soils can explain why ESMs tends to overestimate the heterotrophic respiration flux when mean annual precipitation is high. Changing soil moisture function to better represent this effect should be relatively easy and may substantially improve the capacities of ESMs to reproduce the heterotrophic respiration flux.

Another important parameter controlling heterotrophic respiration flux is carbon use efficiency defined as the ratio between the carbon remaining in a system and the carbon entering that system (Manzoni et al., 2018). In our context this is the ratio between the carbon mineralized through microbial heterotrophic respiration and the carbon incorporated into the microbial biomass. The heterotrophic respiration flux therefore results from two processes in ESMs, the soil organic carbon decomposition and its allocation to other soil carbon pools or to heterotrophic respiration. Carbon use efficiency is highly variable and depends on several biotic and abiotic factors (Manzoni, 2017; Manzoni et al., 2012; Sinsabaugh et al., 2013). In ESMs, carbon use efficiency is not dynamic and not spatially distributed, thus having flexible carbon use efficiency control may help to reproduce observations (Zhang et al., 2018). A simple approach that may aid a better representation of heterotrophic respiration fluxes is optimizing the carbon use efficiency parameters of the ESMs using a Bayesian approach as is done for other land fluxes (Kuppel et al., 2012). This would result in a spatially distributed set of parameters for carbon use efficiency but this approach would not be dynamic. Another option might to benefit to the current large carbon use efficiency measures existing in the literature (Manzoni et al., 2012) to define statistical functions predicting carbon use efficiency based on explanatory variables that could themselves be dynamic (soil temperature, pH, soil C:N ratio, etc.). Thus, carbon use efficiency might be spatialized and dynamic.

A better representation of the heterotrophic respiration flux is also important for other biogeochemical variables in particular in ESMs with explicit nitrogen cycle representation in their land surface scheme. Indeed, heterotrophic respiration fluxes are indicators of soil organic carbon decomposition but when nitrogen is explicitly represented it also becomes an indicator of soil N mineralization (Vuichard et al., 2018). In the field, the soil organic matter is composed by complex molecules made of carbon and nitrogen among others (Cleveland and Liptzin, 2007). Microorganisms decompose soil organic matter releasing

CO_2 to the atmosphere and mineral nitrogen to the soil solution. Microbial activity is therefore a major driver of mineral nitrogen availability and partially control nitrogen limitation on primary production and therefore on land carbon sink (Bragazza et al., 2013). Since more and more ESM represent explicitly the nitrogen cycle in their land surface scheme (Davies-Barnard et al., 2020; Varney et al., 2022) constraining well the heterotrophic respiration flux may help to constrain

250 the nitrogen mineralization flux as they both come from the soil organic matter decomposition by extracellular enzymes. A better representation of the mineral N release flux would probably, in turn, improve the simulation of NPP.

5 Conclusion

Our study showed that despite the absence of constraint on the heterotrophic respiration flux before the CMIP6 exercise, a few current ESMs are fairly representing the total heterotrophic respiration flux but all failed at representing the spatial

255 distribution. Since heterotrophic fluxes are large and are a major determinant of whether land surfaces represent a carbon sink or source it is of major importance to better constrain these fluxes and how they will be impacted by climate and land use changes. We showed that current ESMs failed to reproduce heterotrophic respiration fluxes where precipitation is important probably because heterotrophic respiration responses to soil moisture are poor representations of reality. Nevertheless, it is important to note that soil moisture is not only driven by precipitation. Other water fluxes like runoff,

260 drainage and evapotranspiration affect the water balance in soils. In this study we did not directly consider soil moisture because it was not available for all the ESMs. Another limitation of our study is that we did not account for other important drivers of heterotrophic respiration in our model residual analysis like pH, microbial biomass, nitrogen availability, etc. We decided to focus on explanatory variables calculated by all the models because we aimed to identify biases due to feedbacks between ESMs variables rather than identifying missing mechanisms. We propose several options to improve the ESM

265 without deep modifications of the current schemes. Our propositions might be easily implemented in the next ESMs generation resulting in possible substantial improvements.

Data availability

 All data are available in the main text.

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Author contributions

BG, LC, PB and LB designed the study, BG, JO, OT and LS performed the analysis. All the authors participated to the results interpretention and to the writing.

275 ## Competing interests

All other authors declare they have no competing interests.

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420 **Figures**
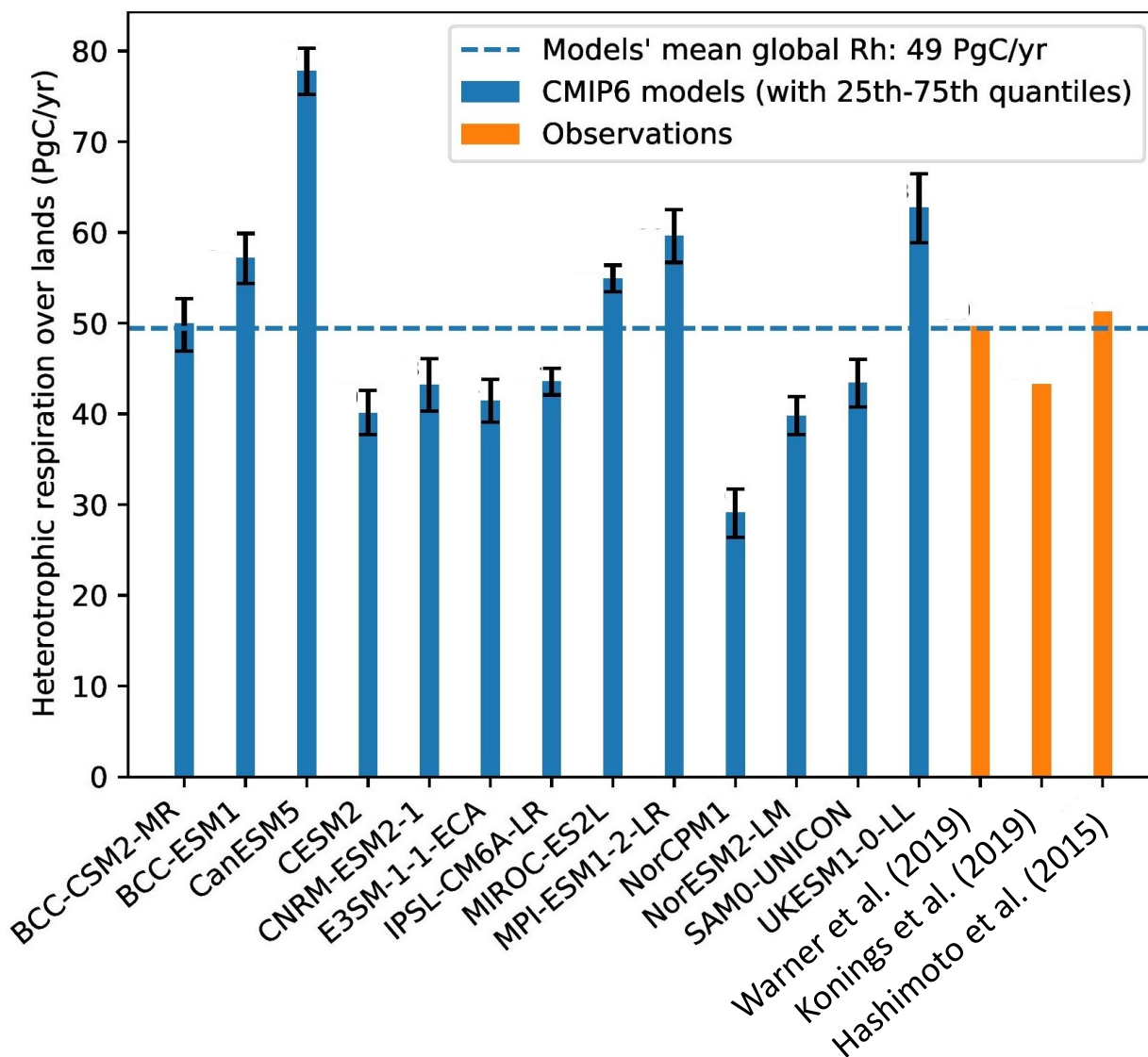
Fig. 1. Global estimations of soil heterotrophic respiration mean over 1990-2010 period.
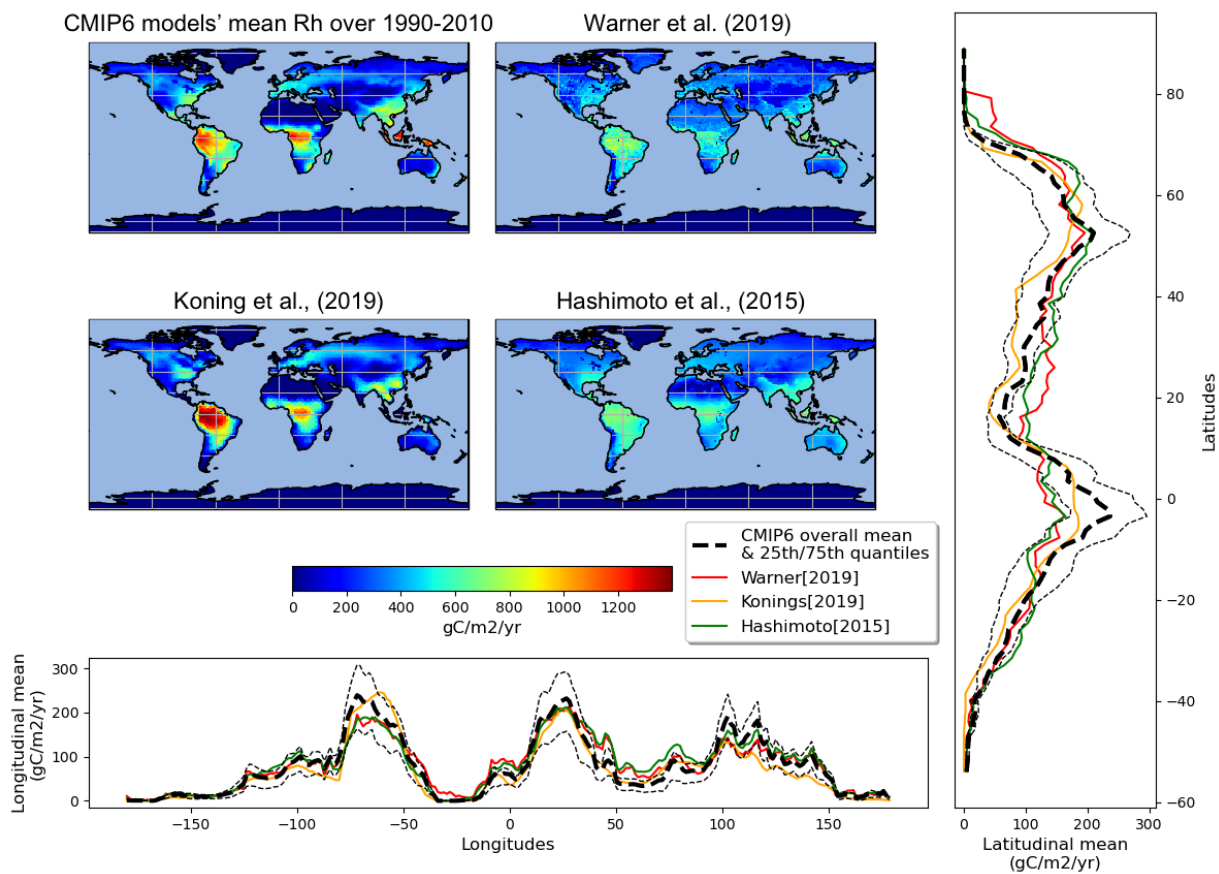
Fig. 2. Comparison of mean soil heterotrophic respiration spatial distribution among mean CMIP6 outputs and observation data.

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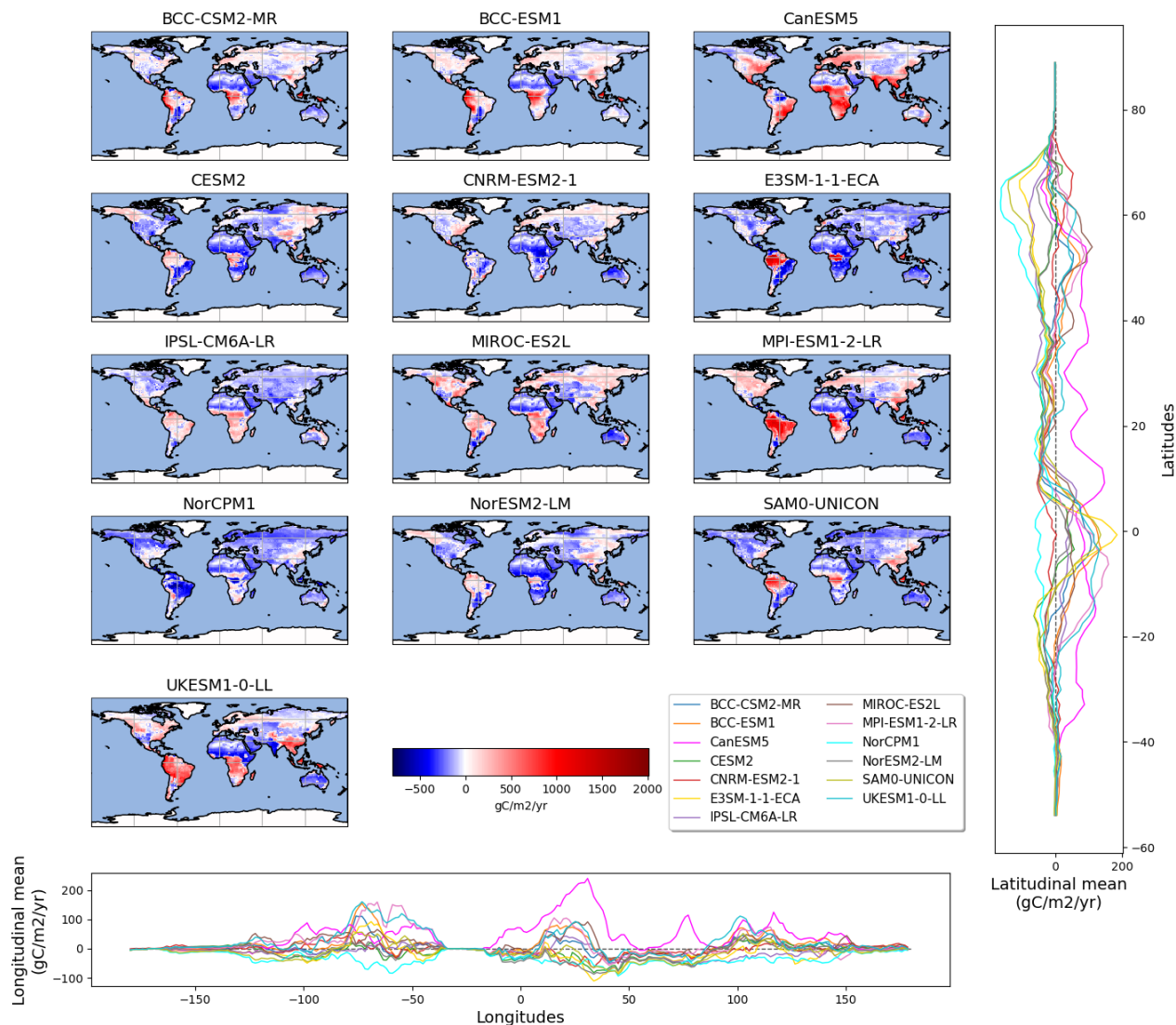
Fig. 3. Spatially distributed residuals of CMIP6 ESMs predictions over the period 1990-2010 with respect to median observation products.

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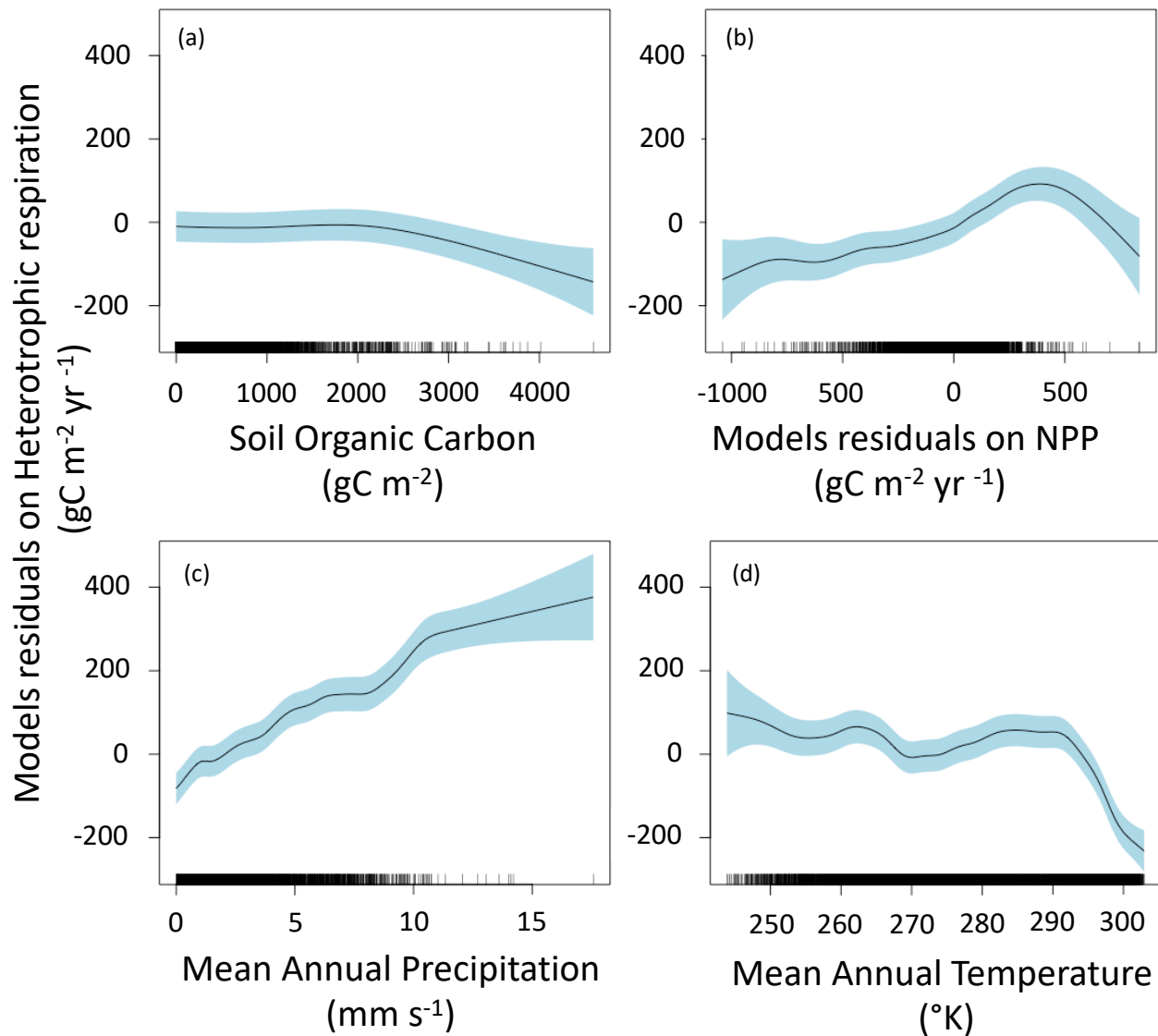
Fig. 4. Median of ESMs residuals on soil heterotrophic respiration. The residuals are explained by soil organic carbon (a), median of NPP residuals (b), mean annual precipitation (c) and mean annual temperature (d). Negative values mean model underestimation.

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