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► **To cite this version:**

Lucas Hardouin, Christine Delire, Bertrand Decharme, David M Lawrence, Julia E M S Nabel, et al.. Uncertainty in land carbon budget simulated by terrestrial biosphere models: the role of atmospheric forcing. Environmental Research Letters, 2022, 10.1088/1748-9326/ac888d . hal-03749645v1

HAL Id: hal-03749645

<https://hal.science/hal-03749645v1>

Submitted on 11 Aug 2022 (v1), last revised 15 Nov 2022 (v2)

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To cite this article before publication: Lucas Hardouin *et al* 2022 *Environ. Res. Lett.* in press <https://doi.org/10.1088/1748-9326/ac888d>

Manuscript version: Accepted Manuscript

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3 **Uncertainty in land carbon budget simulated by**
4 **terrestrial biosphere models: the role of atmospheric**
5 **forcing**
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Abstract

Global estimates of the land carbon sink are often based on simulations by terrestrial biosphere models. The use of a large number of models that differ in their underlying hypotheses, structure and parameters is one way to assess the uncertainty in the historical land carbon sink. Here we show that the atmospheric forcing datasets used to drive these terrestrial biosphere models represent a significant source of uncertainty that is currently not systematically accounted for in land carbon cycle evaluations. We present results from three terrestrial biosphere models each forced with three different historical atmospheric forcing reconstructions over the period 1850-2015. We perform an analysis of variance to quantify the relative uncertainty in carbon fluxes arising from the models themselves, atmospheric forcing, and model-forcing interactions. We find that atmospheric forcing in this set of simulations plays a dominant role on uncertainties in global gross primary productivity (75% of variability) and autotrophic respiration (90%), and a significant but reduced role on net primary productivity and heterotrophic respiration (30%). Atmospheric forcing is the dominant driver (52 %) of variability for the net ecosystem exchange flux, defined as the difference between gross primary productivity and respiration (both autotrophic and heterotrophic respiration). In contrast, for wildfire-driven carbon emissions model uncertainties dominate and, as a result, model uncertainties dominate for net ecosystem productivity. At regional scales, the contribution of atmospheric forcing to uncertainty shows a very heterogeneous pattern and is smaller on average than at the global scale. We find that this difference in the relative importance of forcing uncertainty between global and regional scales is related to large differences in regional model flux estimates, which partially offset each other when integrated globally, while the flux differences driven by forcing are mainly consistent across world and therefore which add up to a larger fractional contribution to global uncertainty.

1 Introduction

During the last decade, about 45% of anthropogenic carbon dioxide (CO₂) emissions remained and accumulated in the atmosphere. Model- and observation-based studies suggest that the remaining term was shared among ocean (24%) and land (32%) since 1960 (Friedlingstein et al., 2021). Together, the contribution of the ocean and terrestrial CO₂ uptake nearly halves the increase in atmospheric CO₂, damping the pace of climate change (Canadell et al., 2021). These sinks significantly increased since the middle of the

20th century, mainly due to the acceleration of the increase in CO_2 concentrations, caused by fossil fuel emissions. However, carbon uptake processes depend strongly on climate variability, especially for the terrestrial biosphere (Le Quéré et al., 2009; DeVries et al., 2019). While the ocean sink grew from $1.1 \pm 0.4 \text{ PgC}\cdot\text{yr}^{-1}$ in the 1960s to $2.8 \pm 0.4 \text{ PgC}\cdot\text{yr}^{-1}$ in 2011–2020, with an inter-annual variability of a few tenths of $\text{PgC}\cdot\text{yr}^{-1}$, the land sink rose from $1.2 \pm 0.5 \text{ PgC}\cdot\text{yr}^{-1}$ to $3.1 \pm 0.6 \text{ PgC}\cdot\text{yr}^{-1}$, but with inter-annual variations up to $2 \text{ PgC}\cdot\text{yr}^{-1}$ (Friedlingstein et al., 2021).

Accurate evaluations of anthropogenic emissions, atmospheric CO_2 levels and carbon cycle perturbation are necessary to monitor, understand and predict climate change. The Global Carbon Project (GCP) has published an annual report since 2013 (Le Quéré et al., 2013, 2014; Friedlingstein et al., 2020, 2021) that quantifies the magnitude and uncertainty of the five major components of the global carbon budget: fossil fuel emissions (E_{FOS}), emissions from land use change (E_{LUC}), the growth rate of atmospheric CO_2 (G_{ATM}), the ocean sink (S_{OCEAN}) and the land sink (S_{LAND}). In earlier analyses provided by the Global Carbon Project, the terrestrial carbon cycle simulated by the Terrestrial Biosphere Models (TBMs, called by the authors Land Biosphere Models or Dynamical Global Vegetation Models) was not considered reliable enough to be used in the report to estimate the land carbon sink (Le Quéré et al., 2009; Schaefer et al., 2012; Todd-Brown et al., 2013). The land sink S_{LAND} was hence diagnosed indirectly as the residual of the other terms. However, the methodology was updated in the 2017 global carbon budget (Le Quéré et al., 2017), partly due to improvements in carbon cycle representation (Collier et al., 2018; Lawrence et al., 2019; Arora et al., 2020; Davies-Barnard et al., 2020), but also because of evidence of underestimation and uncertainty in the ocean sink variability (Landschützer et al., 2015; DeVries et al., 2017). The global land sink is now estimated by the multi-model mean of the TBM simulations, with the budget imbalance term, B_{IM} , representing residual uncertainty and/or unexplained aspects of the actual global carbon cycle.

To account for model construction, structural, and parametric uncertainty, as many as 17 TBMs were used to estimate S_{LAND} by Friedlingstein et al. (2020). Simulations were run using a unified land use change data set (LUH2; Hurtt et al., 2020), global atmospheric CO_2 trend, and atmospheric climate forcing (CRUJRA; (Harris, 2019)). Use of a single forcing dataset for climatic forcing, however, means that any model spread due to climate forcing data uncertainty is not represented by the GCP ensemble. Yet,

several studies have identified historical climate forcing as a large source of uncertainty in terrestrial carbon cycle modelling (Hicke, 2005; Jung et al., 2007; Poulter et al., 2011; Bonan et al., 2019; Lawrence et al., 2019). Hicke (2005), for example, highlights important biases in net primary productivity (NPP) estimation while using different radiation datasets, and Poulter et al. (2011) conclude that atmospheric forcing results in a large uncertainty compared to land-cover datasets for NPP, heterotrophic respiration (Rh) and net ecosystem exchange (NEE). More recently, as part of the assessment and benchmarking of the Community Land Model version 5 (CLM5) (Lawrence et al., 2019), climate forcing uncertainty was compared to model structure uncertainty using two forcing datasets (Global Soil Wetness Project 3 and CRUNCEP) and three versions of CLM (CLM4, CLM4.5, and CLM5) that differ markedly in their carbon cycle representation (Bonan et al., 2019). The authors concluded that climate forcing is a large source of uncertainty in the global carbon cycle, especially for GPP, NPP and Rh, and to a lesser extent for Net Biome Productivity. However, this study was performed with different versions of a single model, and only two estimates of atmospheric climate forcing. Arguably therefore, the importance of atmospheric forcing on carbon cycle estimation by TBMs remain insufficiently explored, especially in the context of recent model structural improvements in the CMIP6 generation of models.

In this study, we used the output from the TBMs of three Earth System Models (ESMs) participating in the 6th Coupled Model Intercomparison Project (CMIP6). We performed an analysis of variance similar to (Hawkins & Sutton, 2009; Lovenduski & Bonan, 2017; Bonan et al., 2019) in order to quantify the relative uncertainty from atmospheric forcing, models and forcing-model interactions in carbon flux estimates made by TBMs. We used a combination of three TBMs from Earth System Models (ESM) and three atmospheric forcing datasets in our analysis. We present results for the major terrestrial carbon cycle fluxes; gross primary productivity (GPP), autotrophic respiration (Ra) and heterotrophic respiration (Rh), at global and regional scales. We also investigate estimates of CO₂ emissions from natural fires (fFire) and highlight their role in the calculation of the land carbon sink, before focusing on sources of uncertainty in the global net ecosystem productivity ($NEP = GPP - Ra - Rh - fFire$).

2 Methods

2.1 CMIP6 models and atmospheric forcings

We used the results of three TBMs of CMIP6 Earth System Models described in Table 1, from the Land Surface, Snow and Soil moisture Model Intercomparison Project (LS3MIP, (Van den Hurk et al., 2016)) of CMIP6. For the three models, land use transitions are forced by the Land Use Harmonization 2 (LUH2) time series (Hurtt et al., 2020). Those three models have been selected because they are the only ones that report output from three different atmospheric forcings and also share data for emissions from fire, on the Earth System Grid Federation (ESGF) archive.

Three climate forcing datasets were used to force the TBMs, according to the LS3MIP protocol. Atmospheric forcing consists of hourly- to 6-hourly data on precipitation, short and long wave solar radiation, near surface air temperature, specific humidity, and wind speed. The three forcings described in Table 2 have a $0.5^\circ \times 0.5^\circ$ spatial resolution.

For reference, results of analysis of this set of model simulations with the International Land Model Benchmarking (ILAMB, (Collier et al., 2018)) package are provided here: <https://www.ilamb.org/land-hist/>. ILAMB produces systematic evaluation (plots, summary tables, scoring) of model output against observations for a range of metrics including bias, RMSE, pattern correlation, annual cycle phase, and variable-to-variable comparisons. The version of ILAMB presented here assesses 22 land carbon, water, and energy cycle variables model variables against more than 50 observational datasets.

2.2 Analysis of variance

To statistically disaggregate the impacts of climate forcing, model choice and their interactions on relevant output variables, we performed an ANOVA. We analysed nine terrestrial carbon cycle simulations - three TBMs forced by three forcings - for the time period 1960 to 2012, chosen to coincide with the beginning of atmospheric carbon dioxide measurements in the 1960s, and the end of the Princeton dataset. We quantify relative uncertainty into three sources: models, atmospheric forcing differences and model-forcing interactions which measure the fact that models behave differently to different forcing product. Details can be found in the Supplementary Material.

Table 1. Model description

Terrestrial biosphere model	Community Land Model CLM5 (Lawrence et al., 2019)	ISBA-CTRIP (Delire et al., 2020; Decharme et al., 2019)	JSBACH3.2(Reick et al., 2021)
Parent climate model	Community Earth System Model CESM2 (Danabasoglu et al., 2020)	CNRM-ESM2-1 (S��ferian et al., 2019)	MPI-ESM1.2-LR (Mauritsen et al., 2019)
Simulation resolution	0.9� latitude by 1.25� longitude	T127 (~ 1.4�)	T63 (~ 1.9�)
Fire	process-based (Li et al., 2012; Li & Lawrence, 2017)	simple, based on GlobFirm (Thonicke et al., 2001)	mechanistic, SPIT-FIRE (Lasslop et al., 2014)
Natural vegetation dynamics	no	no	yes (Reick et al., 2013)
Nitrogen cycle	revised (Fisher et al., 2019)	no	new (Goll et al., 2017)
Plant hydrodynamics	(Kennedy et al., 2019)	no	no
Soil carbon decomposition	yes	yes	new (Goll et al., 2015)
Soil hydrology	multilayer	multilayer	multilayer (Hagemann & Stacke, 2015)
Other	numerous updates to hydrology, snow, gas exchange and crops	similar	similar

Table 2. Atmospheric forcing description

Name	Global Soil Wetness Project (GSWP3) version 1.09 (Kim et al., 2017)	CRUJRA ^a (Harris, 2019)	Princeton (Sheffield et al., 2006) v2.2
Time resolution	3-hourly	6-hourly	3-hourly
Covered period	1901-2014	1901-2018	1901-2012
Reanalysis used	20th Century Reanalysis version 2 (Compo et al., 2011)	Japanese Reanalysis (JRA) by the Japanese Meteorological Agency (JMA) ^b	National Centers for Environmental Prediction (NCEP) reanalysis
Corrected by			
Air Temperature	Climate Research Unit Timeseries (CRU TS) v3.21	CRU TS v4.03	CRU TS v3.2
Precipitation	Global Precipitation Climatology Center (GPCC) v7	CRU TS v4.03	CRU, Global Precipitation Climatology Project and TRMM Multi-satellite Precipitation Analysis
Radiation	Surface Radiation Budget (SRB) datasets (downwelling radiation fluxes)	CRU TS v4.03	SRB
Use	LS3MIP	GCP	hydrology

^aerroneously named CRUNCEP in CMIP6 simulations.

^b<http://hydro.iis.u-tokyo.ac.jp/GSWP3/>

3 Results

3.1 Global scale

We first investigated and compared the forcing data in order to highlight the main differences and similarities. The three forcings mostly agree on near surface air temperature, but they present large differences in specific humidity, incoming shortwave and longwave radiation, and windspeed (Figure 1). Princeton has much higher specific (and relative - not shown) humidity than CRUJRA or GSWP3 in most parts of the world, except in desert areas. Additionally, specific humidity is generally greater with GSWP3 than with CRUJRA in tropical regions. CRUJRA also has higher shortwave and lower longwave incoming radiation than GSWP3 and Princeton, both having almost identical values. The precipitation forcing differs also with higher values for GSWP3, especially within the Arctic circle related to snowfall uncertainties.

We performed the analysis of variance on the global estimates of GPP, Ra, Rh, GPP-Ra-Rh, fFire and NEP (Figure 2). The results illustrate a dominant role of the atmospheric forcing variation on global GPP estimates (Fig. 2(a)), with large differences between the multi-model mean values according to the forcings (about $15 \text{ PgC}\cdot\text{yr}^{-1}$), with GSWP3 resulting in lowest GPPs for all three models, Princeton the highest GPPs, and CRUJRA in between. The discrepancies between the models for a given forcing are smaller, especially for CRUJRA and Princeton. Global GPP estimates of the ISBA-CTRIIP and CLM5 models are very similar when forced with the CRUJRA forcing, and slightly differ when forced with GSWP3 or Princeton. The global GPP estimates of JSBACH are the largest with all 3 forcings and the difference with the 2 other models is the biggest with the GSWP3 forcing. However, the three models obtain very similar results with the Princeton atmospheric forcing. This suggests a general sensitivity of the models to an atmospheric variable that is different between Princeton's and the two other forcings, such as specific humidity (Figure 1). These nine simulation results indicate a strong sensitivity of modelled GPP to climate forcing.

Figure 2(b) confirms the dominant role of atmospheric forcing on global GPP uncertainty. It accounts for $\sim 75\%$ of the variability in the mean estimates, against $\sim 19\%$ for models and $\sim 6\%$ for interactions terms.

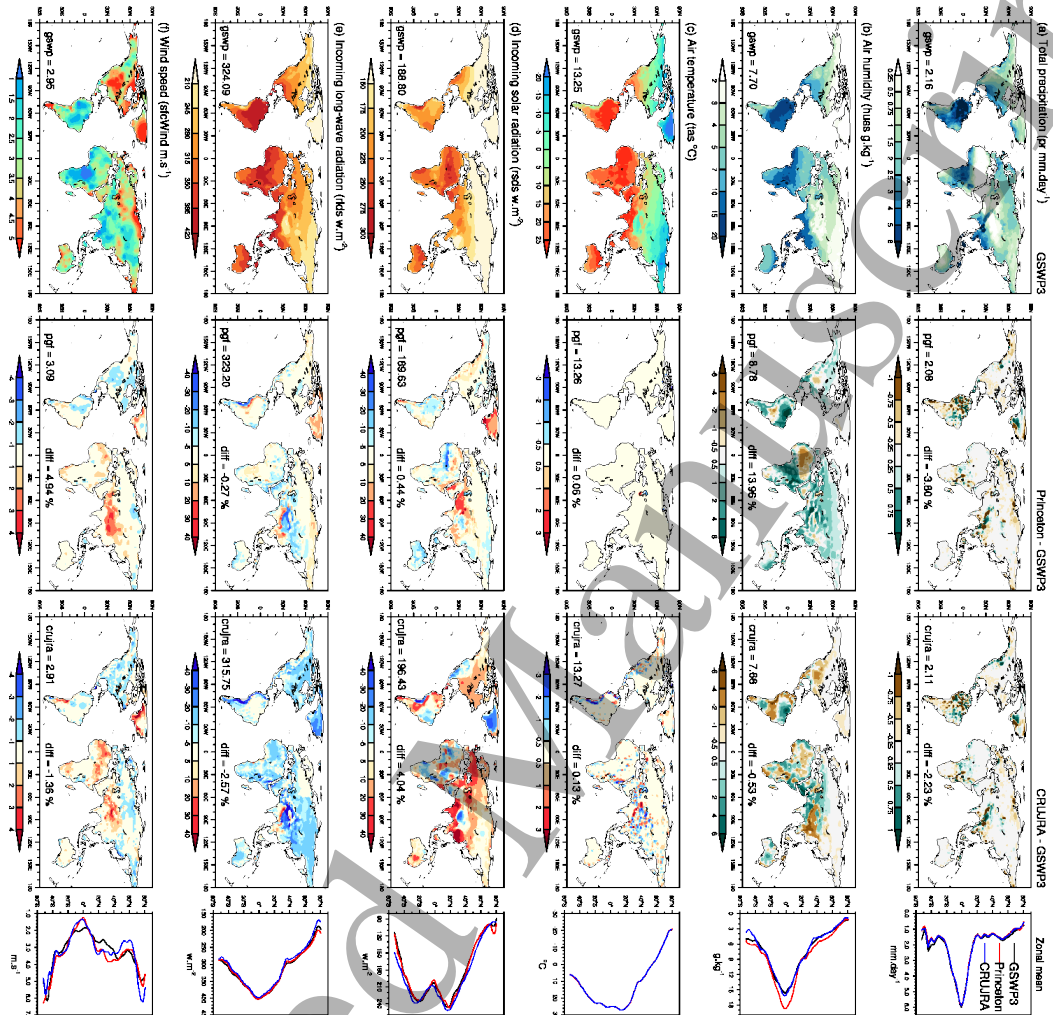


Figure 1. Annual mean of atmospheric variables used to drive terrestrial biosphere models: GSWP3 (*gswp*, left-most column), Princeton minus GSWP3 (*pgf-gswp*; center left column), CRUJRA minus GSWP3 (*crujra-gswp*; center right column), and zonal averages of each product (right-most column).

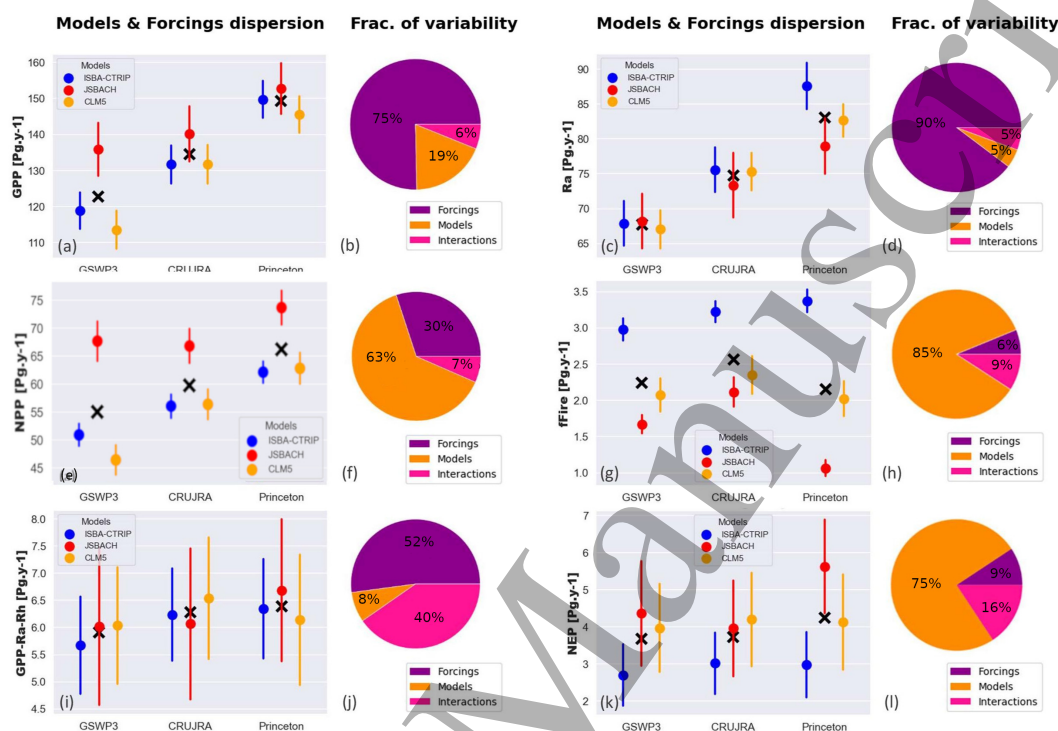


Figure 2. Model means and standard deviations (color dots and bars) and multi-model means (black crosses) of global carbon flux time series for each atmospheric forcing between 1960 and 2012 (pointplot) and fractional distribution of uncertainty (variability) obtained from the ratios of the sum of squared deviation from the mean (eq. 3 to 6 in Supplementary Material) (pieplot) for GPP (a, b), Ra (c, d), NPP (e, f), fFire (g, h), GPP-Ra-Rh (i, j) and NEP=GPP-Ra-Rh-fFire (k, l). Standard deviations are calculated from the yearly time series of the fluxes.

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3 The dominance of atmospheric forcing contribution over the uncertainty is even more
4 obvious for autotrophic respiration (figure 2(c)), again with similar model mean values
5 for a given forcing but large differences between forcings with no overlap. According to
6 our analysis of variance, $\sim 90\%$ of the uncertainty can be assigned to forcings, $\sim 5\%$ to
7 models and $\sim 5\%$ to the interactions terms (figure 2(d)). The Princeton forcing results
8 in a slightly larger spread between the average autotrophic respiration than the other
9 forcings.
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15 Global NPP (GPP-Ra) behaves differently. Despite differences in multi-model mean
16 values per atmospheric forcings (around $5 \text{ PgC}\cdot\text{yr}^{-1}$) attesting to the role of forcing in
17 uncertainty, we can see that JSBACH estimates are clearly higher than the two others
18 (more than $10 \text{ PgC}\cdot\text{yr}^{-1}$) in figure 2(e). This indicates greater model contribution to un-
19 certainty, confirmed by figure 2(f) where models are the dominant source ($\sim 63\%$) of un-
20 certainty for NPP, but atmospheric forcing remains important with $\sim 30\%$ of variabil-
21 ity explained and $\sim 7\%$ for model-forcing interactions. Contrary to ISBA-CTRIP and
22 CLM5 that simulate the lowest NPP with GSWP3 and the highest with Princeton (like
23 for GPP and Ra), JSBACH simulates a slightly smaller global NPP with the CRUJRA
24 forcing. Global Rh presents similar results to global NPP (not shown), both for atmo-
25 spheric contribution to uncertainty and for greater values obtained with GSWP3 than
26 CRUJRA for JSBACH.
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35 We show that atmospheric forcings have an important (NPP, Rh) and even dom-
36 inant (GPP, Ra) role in uncertainty distribution for the major fluxes of global carbon
37 cycle estimates. It seems that forcing contribution to uncertainty decreases when we con-
38 sider net flux such as NPP and Rh rather than direct products of photosynthesis (GPP
39 and Ra).
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45 Wildfires are a small contribution to the global land carbon loss fluxes ($\sim 2\text{-}3 \text{ PgC}\cdot\text{yr}^{-1}$)
46 (Van der Werf et al., 2010), especially when compared to plant and soil respiration. Nonethe-
47 less, fire carbon losses correspond to approximately one-third of the GPP-Ra-Rh net flux.
48 Moreover, this flux has particularly high seasonal and inter-annual variability, in response
49 to both land cover change, as well as climatic events like drought. Despite its importance,
50 anthropogenic biomass burning is not yet represented by all terrestrial biosphere mod-
51 els. Overall, high uncertainty remains in the carbon emissions associated with fire (fig-
52 ure 2(g,h)). ISBA-CTRIP tends to overestimate global fire emissions compared to the
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3 global fire emission database ($2.14 \text{ PgC}\cdot\text{yr}^{-1}$ for 1997-2015 van der Werf et al., 2017),
4 while JSBACH is slightly lower (especially with Princeton). Part of these differences may
5 be explained by the intermediate complexity fire module GlobFirm (Thonicke et al., 2001)
6 used in ISBA-CTRIP that is known to overestimate fire emissions (Li et al., 2012). Fig-
7 ure 2(g) shows a large discrepancy between model values for a given forcing, particularly
8 for the Princeton one, and figure 2(h) confirms a fractional contribution to uncertainty
9 of $\sim 85\%$ for the models, $\sim 6\%$ for forcings and $\sim 9\%$ for interactions. A closer look at
10 fire results shows indeed interesting interactions between the forcings and fire modules
11 that explain the bigger dispersion for Princeton. We saw that GPP and NPP (GPP-Ra)
12 is enhanced with the Princeton forcing, most probably because of the high level of air
13 humidity. For the GlobFirm module implemented in ISBA-CTRIP, this leads simply to
14 lower evapotranspiration rates, less moisture stress, higher productivity and litterfall (not
15 shown) resulting in more biomass burned and greater associated carbon emissions. How-
16 ever, with the more mechanistic fire module of CLM5, the higher air humidity results
17 directly in lower level of fuel flammability (see eq.8 (Li et al., 2012)). In JSBACH, fi-
18 nally, the three applied forcings cause very different fire-vegetation feedbacks, such that
19 the natural vegetation cover in the three simulations differs strongly, particularly in fire
20 prone regions such as Africa and Asia (not shown). Such strong fire-vegetation feedbacks
21 have already been observed for JSBACH in previous idealised model simulations (Lasslop
22 et al., 2016). Emissions from fire appear to be quite sensitive to atmospheric forcing when
23 we compare individually the relative dispersion for each model, but this dependency is
24 overshadowed in this analysis by the even larger uncertainty related to the model struc-
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42 Here, we first present results for GPP-Ra-Rh estimates. This flux takes into ac-
43 count the most important and probably best represented processes of the terrestrial bio-
44 sphere carbon sink, by excluding fire emissions. As expected, this net flux is smaller and
45 has larger interannual variability (standard deviation) relative to the mean than the gross
46 fluxes GPP, Ra and Rh. Figure 2(i) suggests a more important contribution to uncer-
47 tainty by forcing than models: model mean values are close to each other for a given forc-
48 ing and there is a small difference between forcings. The analysis of variance results shows
49 effectively a dominant role of forcings ($\sim 52\%$) over models ($\sim 8\%$) but also a substan-
50 tial contribution of the interaction terms ($\sim 40\%$) (figure 2(j)). Indeed, the models do
51 not show similar patterns with respect to the forcings. CLM5 results in greater values
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3 for CRUJRA ($6.53 \text{ PgC}\cdot\text{yr}^{-1}$) than Princeton ($6.14 \text{ PgC}\cdot\text{yr}^{-1}$), while ISBA-CTRIP sim-
4 ulates slightly bigger fluxes with Princeton ($6.33 \text{ PgC}\cdot\text{yr}^{-1}$) than with CRUJRA (6.23
5 $\text{PgC}\cdot\text{yr}^{-1}$), as does JSBACH with a greater difference (6.06 for CRUJRA against 6.68
6 $\text{PgC}\cdot\text{yr}^{-1}$ with Princeton). In addition, we observe only slightly bigger results for CRU-
7 JRA than GSWP3 for JSBACH, consistent with the results obtained from Rh and NPP,
8 while the difference is more pronounced for ISBA-CTRIP and CLM5. This highlights
9 differences in model sensitivity to atmospheric forcings, such as air humidity or down-
10 ward radiation flux, for the land sink calculation.

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17 Larger differences are obtained when we take into account fFire in the NEP cal-
18 culation (figure 2(k,l)). There is only a small difference between the multi-model mean
19 values per forcing, and a larger spread between the values of the different models, espe-
20 cially with the Princeton forcing (figure 2(k)). Moreover, global NEP is almost indepen-
21 dent of the forcing with CLM5 and ISBA-CTRIP, which is not the case with JSBACH.
22 The variance analysis results show that models contribute $\sim 75\%$ to uncertainty, forc-
23 ings account for $\sim 9\%$ and interactions for $\sim 16\%$. This contrasts with the significant
24 forcing contribution we obtained when not accounting for fFire, and indicates clearly a
25 high model uncertainty related to fire emission.

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33 To complete the global picture we analyze the contribution of atmospheric forc-
34 ing to uncertainty in carbon stocks (fig3). Atmospheric forcing plays a role in global car-
35 bon stock uncertainties but not a dominant one like for gross carbon fluxes. There are
36 large differences in live (cVeg) and dead biomass (cLitter) and soil organic carbon con-
37 tent (cSoil) between multi-model means per forcing but the differences between mod-
38 els are even larger. The analysis of variance for cVeg shows that $\sim 26\%$ of the uncertainty
39 can be assigned to forcings, $\sim 67\%$ to models and $\sim 7\%$ to the interactions terms (fig3(b)).
40 For cLitter and cSoil, these numbers are respectively $\sim 20\%$ and $\sim 9\%$ for forcing, $\sim 68\%$
41 and $\sim 81\%$ for models and $\sim 13\%$ and $\sim 10\%$ for interactions (fig3(d,f)). CLM5 and ISBA-
42 CTRIP both simulate the smallest live and dead stocks with GSWP3 while JSBACH
43 simulates the smallest stocks with CRUJRA(fig3(a,c,e)). Princeton results in the largest
44 stocks with every model. Live biomass from CLM5 and ISBA-CTRIP are fairly similar
45 while JSBACH's is lower. The litter reservoir is the highest with ISBA-CTRIP and the
46 lowest with CLM5 while the soil carbon is the largest with CLM5 especially for CRU-
47 JRA and Princeton. The higher soil carbon content with CLM5 can be explained by the
48 vertically discretized soil carbon module with deeper soils (down to a maximum of 8.5m).
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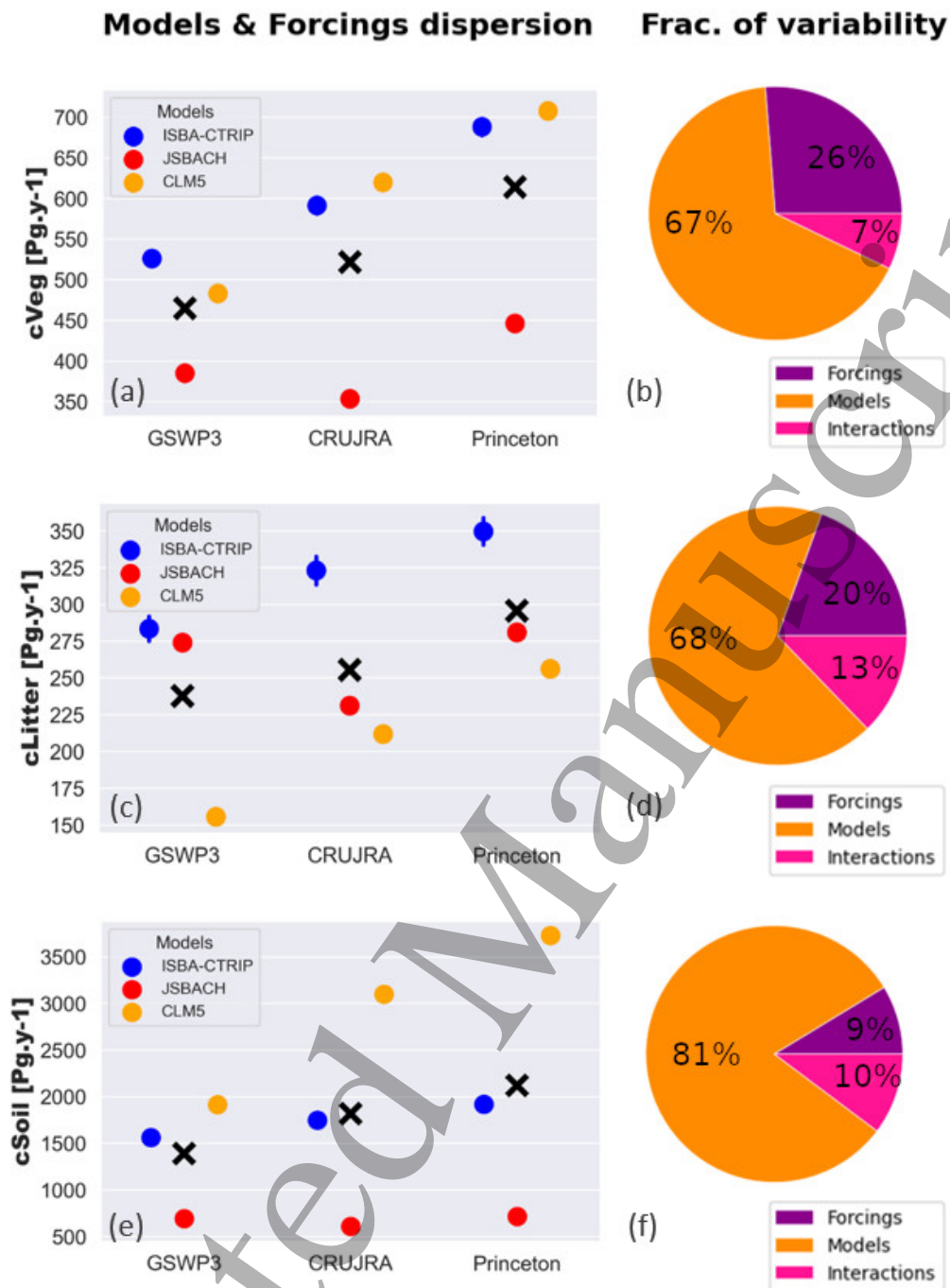


Figure 3. Model means and standard deviations (color dots and bars) and multi-model means (black crosses) of global carbon stocks time series for each atmospheric forcing between 1960 and 2012 (pointplot) and fractional distribution of uncertainty (variability) obtained from the ratios of the sum of squared deviation from the mean (eq. 3 to 6 in Supplementary Material) (pieplot) for cVeg (a, b), cLitter (including coarse woody debris) (c, d), and cSoil (e, f).

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3 In the case of ISBA-CTrip and JSBACH the soil carbon reservoir only represents the
4 carbon in the first meter.
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8 **3.2 Regional scale**

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10 We performed the same analysis of variance on the 30 sub-continental regions de-
11 fined in the Intergovernmental Panel on Climate Change (IPCC) Special Report on Man-
12 aging the Risks of Extreme Events and Disasters to Advance Climate Change Adapta-
13 tion (SREX; (SREX, 2012)). Figure 4 presents the results for GPP, Ra and Rh. The re-
14 gions that present the largest uncertainty (largest pies) for GPP (figure 4 (a) and Sup-
15 plementary Table S2-4) are North Asia (NAS), the Amazon forest (AMZ), and to a lesser
16 extent West Africa (WAF), South Asia (SAS), South East Asia (SEA), East Africa (EAF),
17 South Africa (SAF), and West North America (WNA) even if WNA contributes only 2
18 to 4 PgC·yr⁻¹ to global GPP. Atmospheric forcing is a dominant source of uncertainty
19 (more than half) in some regions that have fairly large contributions to the global to-
20 tal GPP flux, such as EAF and East Asia (EAS), but also in Central North America (CNA),
21 West Coast South America (WSA), and North East Brazil (NEB). Atmospheric forc-
22 ing is an important source of uncertainty (more than a third) in AMZ and WAF, trop-
23 ical forest regions, which contribute greatly to global GPP. Generally, it seems that at-
24 mospheric forcings play an important role in tropical regions. Less important contribu-
25 tion in SAS and SEA could be explained by monsoon regimes that prevail on atmospheric
26 forcing differences, but also by model resolution that could explain dominant model un-
27 certainty in island regions (SEA but also Caribbean and Pacific Island Regions). Model-
28 forcing interactions play a secondary but significant role in some regions such as NAS,
29 WAF and South East South America (SSA) for the ones that contribute the most to global
30 GPP.
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46 Slightly different results can be observed for Ra (figure 4(b)). Atmospheric forc-
47 ing contribution to uncertainty is lower in NAS and AMZ, as well as SEA and NEB. Gen-
48 erally, the forcing and interaction terms seem to play a less important role in Ra than
49 in GPP regional estimates. For Rh (figure 4(c)), forcing contribution is even more re-
50 duced in tropical regions, where the fractional distribution never exceeds one-third. How-
51 ever, atmospheric forcing plays an important role in heterotrophic respiration uncertainty
52 in the northern hemisphere's mid and high latitudes (about one-third). Interaction terms
53 become also important in numerous mid and northern regions, particularly in NAS, CNA
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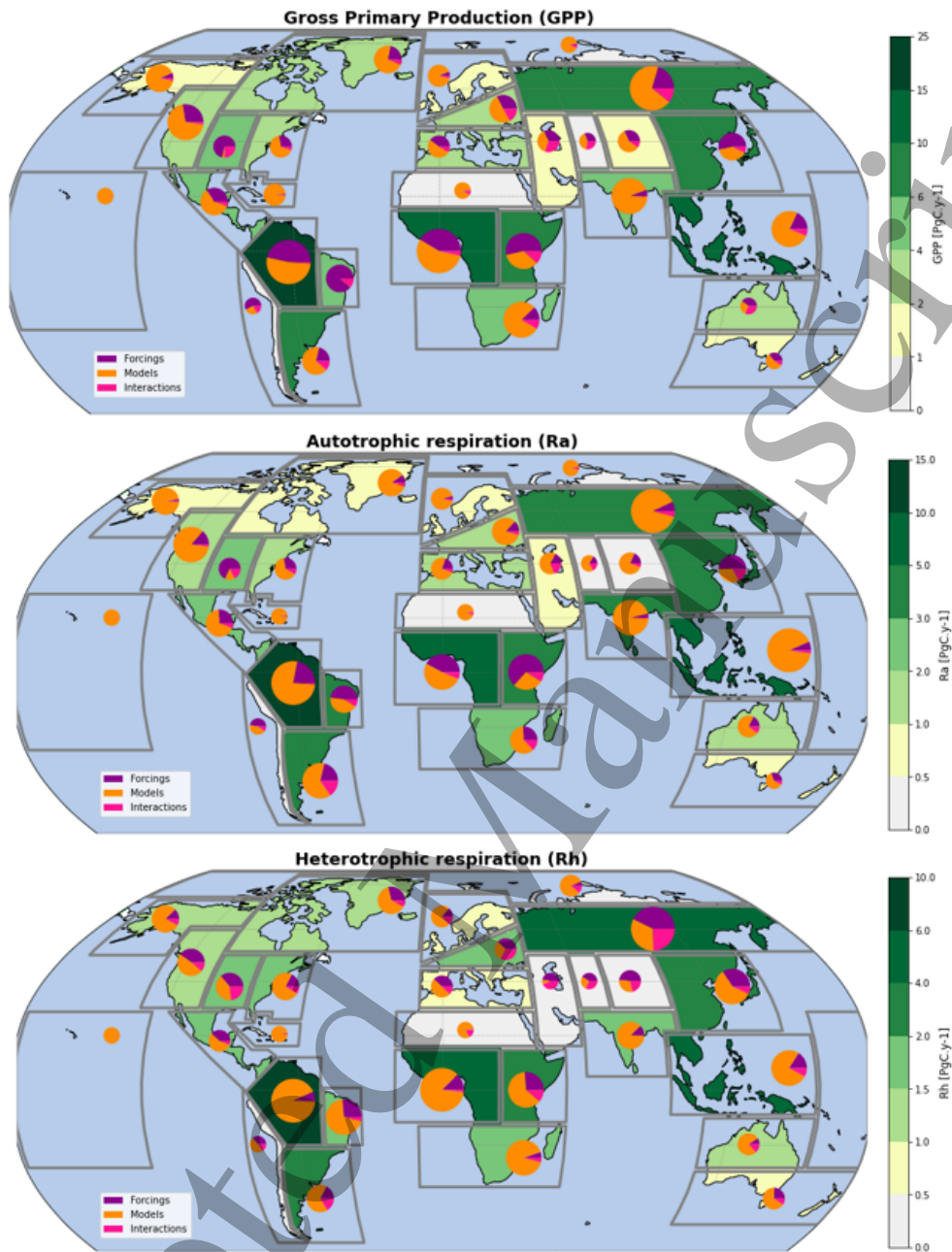


Figure 4. *Regional carbon fluxes for 1960-2012. Total flux value for each SREX region in background, distribution of uncertainty between forcings, models and interactions as overlaid pieplots with size of the pies proportional to the total uncertainty value (eq. 3 and Table S2-4 in Supplementary Material).*

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3 and Central Europe (CEU). An interpretation could be that models do not predict the
4 same evolution for Rh in the areas where atmospheric variables are changing faster.
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7 It is interesting to probe why atmospheric forcing accounts for more uncertainty
8 at global than regional scale. We found that some differences between the forcings have
9 the same impact on most of the world's area, while model differences induce strong re-
10 gional uncertainty but not in the same manner everywhere. As an example, GPP esti-
11 mates are slightly larger with Princeton than with CRUJRA or GSWP3 in all regions
12 (see Supplementary Material fig S1), regardless of the model and add up to a large dif-
13 ference at global scale. This is consistent with the idea that the higher humidity in the
14 Princeton dataset allows for higher photosynthetic rates for all models forced by it. Con-
15 versely, GPP estimates by ISBA-CTRIP and CLM5 appear to be similar at global scale,
16 yet the regional analysis highlights strong opposition between tropical regions with higher
17 GPP for ISBA-CTRIP compared to CLM5, and the northern hemisphere which has higher
18 GPP in CLM5 compared to ISBA-CTRIP (see Supplementary Material fig S2). This leads
19 to a strong model contribution to uncertainty at regional scale, but those differences com-
20 pensate each other globally.
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35 **4 Conclusion**

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37 The goal of this study was to evaluate the uncertainty related to the use of differ-
38 ent global atmospheric forcing datasets in terrestrial carbon cycle modelling. We used
39 nine CMIP6 simulations from three terrestrial biosphere models run with three differ-
40 ent forcings to perform our analysis. First, we focused on global averages and found that
41 atmospheric forcings are a dominant source of uncertainty compared to model choice for
42 GPP and Ra, and contribute significantly to the overall uncertainty for Rh and NPP.
43 The contribution of atmospheric forcing to the net fluxes uncertainty is reduced since
44 positive effects of atmospheric forcings on photosynthesis are partially offset by enhance-
45 ment in the respiration fluxes. We still found an important role of atmospheric forcing
46 on GPP-Ra-Rh temporal mean estimates, but with important interaction terms that trans-
47 late different model responses to climate variables. Important differences in fire mod-
48 elling lead to a dominant role of models in NEP uncertainty, even on a global scale, de-
49 spite a visible relationship and interactions between fire emission and climate forcings.
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3 Secondly, we looked at the partitioning of uncertainty at the regional scale, with
4 the purpose of identifying the regions where atmospheric forcings contribute the most
5 to the variability of GPP, Ra and Rh. We showed that generally, the model structure
6 is the dominant source of uncertainty regionally, in contrast to what we found globally.
7 Atmospheric forcing contribution remains significant and even slightly dominant in some
8 regions, notably in tropical forests for GPP and Ra and in mid and northern high lat-
9 itudes for Rh, but regional discrepancies among the models are stronger. However, and
10 in contrast with the forcings, it is not the same models that result in the biggest and low-
11 est values everywhere. Those differences add up and offset each other, leading to closer
12 results globally.
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20 While the purpose of the study was to investigate the contribution of forcing un-
21 certainty and to demonstrate the influence of choosing a specific forcing over another forc-
22 ing, this experimental design, using three distinct sets of forcing data fields is not ideal
23 for identifying the relative sensitivity to which drivers are most critical. While the large
24 difference in humidity between Princeton and the other two datasets points to that field
25 being particularly important in governing GPP and other fluxes, a more specific one-at-
26 a-time propagation of the uncertainty in each field may allow for a more specific attri-
27 bution of uncertainty to meteorologic variables. Likewise, perturbations to the distribu-
28 tions while holding mean values constant may allow attribution of carbon cycle sensi-
29 tivity to extremes. Nonetheless, these results point to a focus on constraining humid-
30 ity values as key to reducing forcing uncertainty. To the extent that humidity is a key
31 driver in GPP uncertainty, another question is whether this uncertainty is exacerbated
32 in offline simulations such as used here, GCP, and elsewhere, because of the inability for
33 surface moisture fluxes to attenuate humidity biases in the forcing fields due to the one-
34 way coupling.
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45 Additional work involving more terrestrial biosphere models and climate forcings
46 should be done in order to better quantify the role of forcings in carbon cycle uncertainty,
47 especially for the interactions between fire, land-cover dynamics and climate forcings.
48 Even so, we conclude that atmospheric forcings are a key source of uncertainty in car-
49 bon cycle modelling at the global scale and are a significant source of uncertainty in some
50 regions. Therefore, we suggest that where possible, it would be preferable for future MIPs
51 and assessments (e.g., TRENDY, GCP, CMIP) to run simulations with several alterna-
52 tive climate forcing datasets, and to more specifically generate datasets to allow attri-
53 bution of uncertainty to meteorologic variables. Likewise, perturbations to the distribu-
54 tions while holding mean values constant may allow attribution of carbon cycle sensi-
55 tivity to extremes. Nonetheless, these results point to a focus on constraining humid-
56 ity values as key to reducing forcing uncertainty. To the extent that humidity is a key
57 driver in GPP uncertainty, another question is whether this uncertainty is exacerbated
58 in offline simulations such as used here, GCP, and elsewhere, because of the inability for
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bution of carbon cycle sensitivity both to uncertainty in meteorologic fields and to uncertainty in mean versus extreme values of meteorologic fields, when estimating the terrestrial carbon sink in order to correctly represent the uncertainty associated.

Acknowledgments

LH, CD, BD, RS, TS and RF acknowledge funding by the European Union's Horizon 2020 (H2020) research and innovation program under Grant Agreement no. 641816 (CRESCENDO) for LH, BD, CD and TS, no. 101003536 (ESM2025 – Earth System Models for the Future) for RS and no. 821003 (4C) for RF. CD and BD are supported by the “Centre National de Recherches Météorologiques” (CNRM) of Météo-France and the “Centre National de la Recherche Scientifique” (CNRS) of the French research ministry. DML is supported by the National Center for Atmospheric Research, which is a major facility sponsored by the NSF under Cooperative Agreement 1852977 and by the U.S. Department of Energy, Office of Biological and Environmental Research Grant DE-FC03-97ER62402/A0101. JEMSN and TS would like to thank Veronika Gayler for conducting many of the CMIP6 MPI-ESM1.2-LR simulations. TS work was funded by the EU CRESCENDO project. CDK acknowledges support by the Director, Office of Science, Office of Biological and Environmental Research of the U.S. Department of Energy under Contract DE-AC02-05CH11231 through the Early Career Research Program and the Regional and Global Model Analysis Program (RUBISCO SFA).

References

- Arora, V. K., Katavouta, A., Williams, R. G., Jones, C. D., Brovkin, V., Friedlingstein, P., ... Ziehn, T. (2020). Carbon-concentration and carbon-climate feedbacks in cmip6 models and their comparison to cmip5 models. *Biogeosciences*, 17(16), 4173–4222. Retrieved from <https://bg.copernicus.org/articles/17/4173/2020/> doi: 10.5194/bg-17-4173-2020
- Bonan, G. B., Lombardozzi, D. L., Wieder, W. R., Oleson, K. W., Lawrence, D. M., Hoffman, F. M., & Collier, N. (2019). Model structure and climate data uncertainty in historical simulations of the terrestrial carbon cycle (1850–2014). *Global Biogeochemical Cycles*, 33(10), 1310–1326.
- Canadell, J., Monteiro, P., Costa, M., Cotrim da Cunha, L., Cox, P., Eliseev, A., ... Zickfeld, K. (2021). Global carbon and other biogeochemical cycles and

- 1
2
3 feedbacks. In V. Masson-Delmotte et al. (Eds.), *Climate change 2021: The*
4 *physical science basis. contribution of working group i to the sixth assessment*
5 *report of the intergovernmental panel on climate change*. Cambridge University
6 Press.
7
8
9
10 Collier, N., Hoffman, F. M., Lawrence, D. M., Keppel-Aleks, G., Koven, C. D., Riley,
11 W. J., ... Randerson, J. T. (2018). The international land model benchmark-
12 ing (ilamb) system: Design, theory, and implementation. *Journal of Advances*
13 *in Modeling Earth Systems*, 10(11), 2731-2754.
14
15
16 Compo, G. P., Whitaker, J. S., Sardeshmukh, P. D., Matsui, N., Allan, R. J., Yin,
17 X., ... others (2011). The twentieth century reanalysis project. *Quarterly*
18 *Journal of the Royal Meteorological Society*, 137(654), 1-28.
19
20
21 Danabasoglu, G., Lamarque, J.-F., Bacmeister, J., Bailey, D., DuVivier, A., Ed-
22 wards, J., ... others (2020). The community earth system model version 2
23 (cesm2). *Journal of Advances in Modeling Earth Systems*, 12(2).
24
25
26 Davies-Barnard, T., Meyerholt, J., Zaehle, S., Friedlingstein, P., Brovkin, V., Fan,
27 Y., ... Wiltshire, A. J. (2020). Nitrogen cycling in cmip6 land surface
28 models: progress and limitations. *Biogeosciences*, 17(20), 5129-5148. Re-
29 trieved from <https://bg.copernicus.org/articles/17/5129/2020/> doi:
30 10.5194/bg-17-5129-2020
31
32
33
34
35 Decharme, B., Delire, C., Minvielle, M., Colin, J., Vergnes, J.-P., Alias, A., ...
36 Voldoire, A. (2019). Recent changes in the isba-ctrip land surface system for
37 use in the cnrm-cm6 climate model and in global off-line hydrological applica-
38 tions. *Journal of Advances in Modeling Earth Systems*, 11(5), 1207-1252.
39
40
41
42 Delire, C., Séférian, R., Decharme, B., Alkama, R., Calvet, J.-C., Carrer, D., et al.
43 (2020). The global land carbon cycle simulated with isba-ctrip: Improvements
44 over the last decade. *Journal of Advances in Modeling Earth Systems*, 12.
45
46
47 DeVries, T., Holzer, M., & Primeau, F. (2017). Recent increase in oceanic car-
48 bon uptake driven by weaker upper-ocean overturning. *Nature*, 542(7640),
49 215-218.
50
51
52
53 DeVries, T., Le Quéré, C., Andrews, O., Berthet, S., Hauck, J., Ilyina, T., ...
54 Séférian, R. (2019). Decadal trends in the ocean carbon sink. *Proceed-*
55 *ings of the National Academy of Sciences*, 116(24), 11646-11651. Re-
56 trieved from <https://www.pnas.org/content/116/24/11646> doi:
57
58
59
60

- 1
2
3 10.1073/pnas.19003711116
4
5 Fisher, R. A., Wieder, W. R., Sanderson, B. M., Koven, C. D., Oleson, K. W., Xu,
6 C., ... Lawrence, D. M. (2019). Parametric controls on vegetation responses
7 to biogeochemical forcing in the clm5. *Journal of Advances in Modeling Earth*
8 *Systems*, 11(9), 2879–2895.
9
10
11 Friedlingstein, P., Jones, M. W., O’Sullivan, M., Andrew, R. M., Bakker, D. C.,
12 Hauck, J., ... others (2021). Global carbon budget 2021. *Earth System*
13 *Science Data Discussions*, 1–191.
14
15 Friedlingstein, P., O’Sullivan, M., Jones, M. W., Andrew, R. M., Hauck, J., Olsen,
16 A., ... others (2020). Global carbon budget 2020. *Earth System Science Data*,
17 12(4), 3269–3340.
18
19
20
21 Goll, D. S., Brovkin, V., Liski, J., Raddatz, T., Thum, T., & Todd-Brown, K. E.
22 (2015). Strong dependence of co2 emissions from anthropogenic land cover
23 change on initial land cover and soil carbon parametrization. *Global Biogeo-*
24 *chemical Cycles*, 29(9), 1511–1523.
25
26
27
28 Goll, D. S., Winkler, A. J., Raddatz, T., Dong, N., Prentice, I. C., Ciais, P., &
29 Brovkin, V. (2017). Carbon–nitrogen interactions in idealized simulations with
30 jsbach (version 3.10). *Geoscientific Model Development*, 10(5), 2009–2030.
31
32
33 Hagemann, S., & Stacke, T. (2015). Impact of the soil hydrology scheme on simu-
34 lated soil moisture memory. *Climate Dynamics*, 44, 1731–1750. doi: <https://doi.org/10.1007/s00382-014-2221-6>
35
36
37
38 Harris, I. (2019). *Cru jra v1. 1: A forcings dataset of gridded land surface blend*
39 *of climatic research unit (cru) and japanese reanalysis (jra) data, january*
40 *1901–december 2017, university of east anglia climatic research unit, centre for*
41 *environmental data analysis*.
42
43
44
45 Hawkins, E., & Sutton, R. (2009). The potential to narrow uncertainty in regional
46 climate predictions. *Bulletin of the American Meteorological Society*, 90(8),
47 1095–1108.
48
49
50 Hicke, J. A. (2005). Ncep and giss solar radiation data sets available for ecosystem
51 modeling: Description, differences, and impacts on net primary production.
52 *Global Biogeochemical Cycles*, 19(2).
53
54
55 Hurrst, G. C., Chini, L., Sahajpal, R., Frohling, S., Bodirsky, B. L., Calvin, K., ...
56 others (2020). Harmonization of global land use change and management
57
58
59
60

- 1
2
3 for the period 850–2100 (luh2) for cmip6. *Geoscientific Model Development*,
4 13(11), 5425–5464.
5
6 Jung, M., Vetter, M., Herold, M., Churkina, G., Reichstein, M., Zaehle, S., ... oth-
7 ers (2007). Uncertainties of modeling gross primary productivity over europe:
8 A systematic study on the effects of using different drivers and terrestrial
9 biosphere models. *Global Biogeochemical Cycles*, 21(4).
10
11 Kennedy, D., Swenson, S., Oleson, K. W., Lawrence, D. M., Fisher, R., Lola da
12 Costa, A. C., & Gentine, P. (2019). Implementing plant hydraulics in the com-
13 munity land model, version 5. *Journal of Advances in Modeling Earth Systems*,
14 11(2), 485–513.
15
16 Kim, H., Watanabe, S., Chang, E., Yoshimura, K., Hirabayashi, J., Famiglietti, J.,
17 & Oki, T. (2017). *Global soil wetness project phase 3 atmospheric bound-*
18 *ary conditions (experiment 1)[data set], data integration and analysis system*
19 *(dias)*.
20
21 Landschützer, P., Gruber, N., Haumann, F. A., Rödenbeck, C., Bakker, D. C.,
22 Van Heuven, S., ... others (2015). The reinvigoration of the southern ocean
23 carbon sink. *Science*, 349(6253), 1221–1224.
24
25 Lasslop, G., Brovkin, V., Reick, C. H., Bathiany, S., & Kloster, S. (2016). Mul-
26 tiple stable states of tree cover in a global land surface model due to a fire-
27 vegetation feedback. *Geophysical Research Letters*, 43(12), 6324–6331.
28
29 Lasslop, G., Thonicke, K., & Kloster, S. (2014). Spitfire within the mpi earth system
30 model: Model development and evaluation. *Journal of Advances in Modeling*
31 *Earth Systems*, 6(3), 740–755. doi: <https://doi.org/10.1002/2013MS000284>
32
33 Lawrence, D. M., Fisher, R. A., Koven, C. D., Oleson, K. W., Swenson, S. C., Bo-
34 nan, G., ... others (2019). The community land model version 5: Description
35 of new features, benchmarking, and impact of forcing uncertainty. *Journal of*
36 *Advances in Modeling Earth Systems*, 11(12), 4245–4287.
37
38 Le Quéré, C., Andres, R. J., Boden, T. A., Conway, T., Houghton, R. A., House,
39 J. I., ... others (2013). The global carbon budget 1959–2011.
40
41 Le Quéré, C., Andrew, R. M., Friedlingstein, P., Sitch, S., Pongratz, J., Manning,
42 A. C., ... others (2017). Global carbon budget 2017. *Earth System Science*
43 *Data Discussions*, 1–79.
44
45 Le Quéré, C., Peters, G. P., Andres, R. J., Andrew, R. M., Boden, T. A., Ciais, P.,
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

- 1
2
3 ... others (2014). Global carbon budget 2013. *Earth System Science Data*,
4 6(1), 235–263.
5
6 Le Quéré, C., Raupach, M. R., Canadell, J. G., Marland, G., Bopp, L., Ciais, P.,
7 ... others (2009). Trends in the sources and sinks of carbon dioxide. *Nature*
8 *geoscience*, 2(12), 831–836.
9
10 Li, F., & Lawrence, D. M. (2017). Role of fire in the global land water budget dur-
11 ing the twentieth century due to changing ecosystems. *Journal of Climate*,
12 30(6), 1893–1908.
13
14 Li, F., Zeng, X., & Levis, S. (2012). A process-based fire parameterization of in-
15 termediate complexity in a dynamic global vegetation model. *Biogeosciences*,
16 9(7), 2761–2780.
17
18 Lovenduski, N. S., & Bonan, G. B. (2017). Reducing uncertainty in projections of
19 terrestrial carbon uptake. *Environmental Research Letters*, 12(4), 044020.
20
21 Mauritsen, T., Bader, J., Becker, T., Behrens, J., Bittner, M., Brokopf, R., ... oth-
22 ers (2019). Developments in the mpi-m earth system model version 1.2 (mpi-
23 esm1.2) and its response to increasing co2. *Journal of Advances in Modeling*
24 *Earth Systems*, 11(4), 998–1038.
25
26 Poulter, B., Frank, D., Hodson, E., & Zimmermann, N. (2011). Impacts of land
27 cover and climate data selection on understanding terrestrial carbon dynamics
28 and the co₂ airborne fraction. *Biogeosciences*, 8(8), 2027–2036.
29
30 Reick, C. H., Gayler, V., Goll, D., Hagemann, S., Heidkamp, M., Nabel, J. E., ...
31 Wilkenskeld, S. (2021). Jsbach 3-the land component of the mpi earth system
32 model: documentation of version 3.2.
33
34 Reick, C. H., Raddatz, T., Brovkin, V., & Gayler, V. (2013). Representation of
35 natural and anthropogenic land cover change in mpi-esm. *Journal of Advances*
36 *in Modeling Earth Systems*, 5(3), 459-482. doi: <https://doi.org/10.1002/jame>
37 .20022
38
39 Schaefer, K., Schwalm, C. R., Williams, C., Arain, M. A., Barr, A., Chen, J. M.,
40 ... others (2012). A model-data comparison of gross primary productivity:
41 Results from the north american carbon program site synthesis. *Journal of*
42 *Geophysical Research: Biogeosciences*, 117(G3).
43
44 Séférian, R., Nabat, P., Michou, M., Saint-Martin, D., Voldoire, A., Colin, J., ...
45 others (2019). Evaluation of cnrm earth system model, cnrm-esm2-1: Role of
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

- 1
2
3 earth system processes in present-day and future climate. *Journal of Advances*
4 *in Modeling Earth Systems*, 11(12), 4182–4227.
- 5
6 Sheffield, J., Goteti, G., & Wood, E. F. (2006). Development of a 50-year high-
7 resolution global dataset of meteorological forcings for land surface modeling.
8 *Journal of climate*, 19(13), 3088–3111.
- 9
10
11 SREX, I. (2012). Managing the risks of extreme events and disasters to advance
12 climate change adaptation. *A Special Report of Working Groups I and II of*
13 *the Intergovernmental Panel on Climate Change*, edited by: Field, CB, Barros,
14 V., Stocker, TF, Qin, D., Dokken, DJ, Ebi, KL, Mastrandrea, MD, Mach,
15 KJ, Plattner, G.-K., Allen, SK, Tignor, M., and Midgley, PM, Cambridge
16 University Press, Cambridge, UK, and New York, NY, USA.
- 17
18
19 Thonicke, K., Venevsky, S., Sitch, S., & Cramer, W. (2001). The role of fire dis-
20 turbance for global vegetation dynamics: coupling fire into a dynamic global
21 vegetation model. *Global Ecology and Biogeography*, 10(6), 661–677.
- 22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
- Todd-Brown, K., Randerson, J., Post, W., Hoffman, F., Tarnocai, C., Schuur, E., &
Allison, S. (2013). Causes of variation in soil carbon simulations from cmip5
earth system models and comparison with observations. *Biogeosciences*, 10(3),
1717–1736.
- Van den Hurk, B., Kim, H., Krinner, G., Seneviratne, S. I., Derksen, C., Oki, T., ...
others (2016). Ls3mip (v1.0) contribution to cmip6: the land surface, snow
and soil moisture model intercomparison project—aims, setup and expected
outcome. *Geoscientific Model Development*, 9(8), 2809–2832.
- Van der Werf, G. R., Randerson, J. T., Giglio, L., Collatz, G., Mu, M., Kasibhatla,
P. S., ... van Leeuwen, T. T. (2010). Global fire emissions and the contribu-
tion of deforestation, savanna, forest, agricultural, and peat fires (1997–2009).
Atmospheric chemistry and physics, 10(23), 11707–11735.