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1 **Evaluation of terrestrial carbon cycle models for their response**
2 **to climate variability and to CO₂ trends**

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18

1 **Abstract**

2 The purpose of this study is to evaluate 10 process-based terrestrial biosphere models that
3 were used for the IPCC 5th Assessment Report. The simulated distribution of gross primary
4 productivity (GPP) is compared with gridded estimates established from a data-driven model
5 based upon flux-tower measurements by Jung et al. (2011) (JU11). The net primary
6 productivity (NPP) apparent sensitivity to climate variability and atmospheric CO₂ trends is
7 diagnosed from each model output, using statistical functions. The temperature sensitivity is
8 compared against independent ecosystem field warming experiments results. The CO₂
9 sensitivity of NPP is compared to the results from four Free Air CO₂ Enrichment (FACE)
10 experiments. The simulated global net biome productivity (NBP) is compared with the
11 residual land sink (RLS) of the global carbon budget from Friedlingstein et al. (2010) (FR10).
12 We found that models produce a higher GPP (133 ± 15 Pg C yr⁻¹) than JU11 (118 ± 6 Pg C yr⁻¹).
13 In response to rising atmospheric CO₂ concentration, modelled NPP increases on average by
14 16% (5-20%) per 100 ppm, a slightly larger apparent sensitivity of NPP to CO₂ than that
15 measured at the FACE experiment locations (13 % per 100 ppm). Global NBP differs
16 markedly among individual models, although the mean value of 2.0 ± 0.8 Pg C yr⁻¹ is
17 remarkably close to the mean value of RLS (2.1 ± 1.2 Pg C yr⁻¹). The interannual variability of
18 modelled NBP is significantly correlated with that of RLS for the period 1980-2009. The
19 average linear regression slope of global NBP vs. Mean Annual Temperature (MAT) across
20 the 10 models is -3.0 ± 1.5 Pg C yr⁻¹ °C⁻¹. Yet, 9 of 10 models overestimate the regression slope
21 of NBP vs. precipitation, compared to the slope of the observed RLS vs. precipitation. With
22 most models lacking processes that control GPP and NBP in addition to CO₂ and climate,
23 such as N-deposition, forest regrowth, changes in the diffuse component of radiation, the
24 agreement between modelled and observation-based GPP and NBP can be fortuitous.
25 Carbon-nitrogen interactions (only separable in one model) significantly influence the
26 simulated response of GPP and NBP to temperature and atmospheric CO₂ concentration,
27 suggesting that nutrients limitations should be included in the next generation of terrestrial
28 biosphere models.

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30

1 **1. Introduction**

2 The human caused perturbation of the carbon cycle controls climate change, directly
3 through emissions but also via climate feedbacks on natural carbon sources and sinks. The
4 terrestrial carbon cycle has been modeled to be particularly sensitive to current and future
5 climate and atmospheric CO₂ changes, but regional patterns and mechanisms of terrestrial
6 carbon sources and sinks remain uncertain (Schimel et al., 2001; Houghton, 2007). During the
7 past decades, considerable efforts have been made to develop process-based carbon cycle
8 models, as tools to understand terrestrial carbon mechanisms and fluxes at local, regional,
9 continental and global scales (Moorcroft et al., 2006; Huntingford et al., 2011). Models were
10 applied to hindcast historical changes (Cramer et al., 2001; Piao et al. 2009), and to forecast
11 future changes (Friedlingstein et al., 2006; Sitch et al; 2008). Although carbon cycle models
12 have been tested against CO₂ fluxes measured by eddy-covariance technique at sites around
13 the world (Sitch et al., 2003; Krinner et al., 2005; Jung et al., 2007; Stockli et al. 2008; Wang
14 et al. 2012; Keenan et al. 2012), satellite based leaf area index (LAI) retrieval products (Lucht
15 et al., 2002; Piao et al., 2006, 2008), and observed vegetation productivity and carbon storage
16 (Randerson et al., 2009), it is difficult to draw a clear picture of model performance and
17 shortcomings from the current model-benchmarking literature dealing with the global
18 terrestrial carbon cycle. The reasons for this are several: 1) *in situ* high-quality measurements
19 are very sparse, and often cannot be extrapolated readily to larger spatial scales, 2) satellite
20 measurements provide only indirect proxies of carbon variables, 3) atmospheric CO₂
21 evaluates the combination of a terrestrial carbon model, atmospheric transport model and
22 potentially ocean carbon models, and as such the results thus depend on the choice of the
23 atmospheric transport model and its bias (Stephens et al. 2007), 4) uncertainties associated
24 with measurements are often not reported, which generates type-1 error (a model is estimated
25 to be realistic but the benchmark measurement is not accurate enough to say this) and type-2
26 error (a model is estimated to be erroneous, whereas the benchmark data is biased), and 5)
27 several recent studies have documented prototype benchmark schemes for the carbon cycle
28 (Randerson et al., 2009, Cadule et al., 2010; Blyth et al., 2011), however, a community-wide
29 set of agreed benchmark tests and performance indicators is currently still under development.

30

1 Current coupled-climate-carbon models used in the 4th and 5th Assessment Reports of
2 IPCC generally project a positive feedback between global warming and the reduction of
3 terrestrial carbon sinks in the 21st century (Denman et al., 2007). In some instances, these
4 feedbacks become stronger over time than the CO₂-induced fertilization and hence the land
5 surface has the potential to eventually become an overall source (Cox et al., 2000).
6 Characterizing this feedback has important implications for mitigation policies designed to
7 stabilize greenhouse gas levels (Matthews, 2005). The magnitude of this positive feedback
8 varies markedly among models (Friedlingstein et al., 2006). For the SRES-A2 CO₂ emission
9 scenario, by 2100 the modelled climate-carbon cycle feedback is estimated to cause an
10 additional increase in CO₂ content of between 20 ppmv to 200 ppmv, which corresponds to an
11 additional global temperature increase of 0.1°C–1.5°C (Friedlingstein et al., 2006). This large
12 uncertainty in carbon-climate feedbacks is associated with the different sensitivities of
13 simulated terrestrial carbon cycle processes to changes in climate and atmospheric CO₂
14 (Friedlingstein et al., 2006; Huntingford et al., 2009). Other important processes, such as
15 nutrient constraints, may further affect terrestrial carbon climate interactions (Arneeth et al.
16 2010, Zaehle & Dalmonech, 2011).

17
18 In this study, a set of ten process-based models is tested for their ability to predict current
19 global carbon fluxes (GPP, NPP & NBP) and their sensitivity to climate variability and rising
20 atmospheric CO₂ concentration. The model ensemble includes: HyLand (Levy et al., 2004),
21 Lund-Potsdam-Jena DGVM (Sitch et al., 2003), ORCHIDEE (Krinner et al., 2005),
22 Sheffield–DGVM (Woodward et al., 1995; Woodward and Lomas, 2004), TRIFFID (Cox,
23 2001), LPJ-GUESS (Smith et al., 2001), NCAR_CLM4C (Oleson et al., 2010; Lawrence et al.,
24 2011), NCAR_CLM4CN (Oleson et al., 2010; Lawrence et al., 2011), OCN (Zaehle & Friend,
25 2010), and VEGAS (Zeng et al., 2005). We compare the model output of NBP with the RLS
26 from Friedlingstein et al. (2010) (hereafter FR10). For global climatological GPP we compare
27 model results with those from Jung et al. (2011) (hereafter JU11), which is based on the
28 global interpolation of flux tower observations using a model tree ensemble (MTE) regression
29 approach trained with satellite FAPAR and climate fields. Finally, ecosystem controlled
30 warming experiments (six sites) and Free Air CO₂ Enrichment (FACE) experiments (four

1 sites) are used to test the models' sensitivity of NPP to individual changes in temperature and
2 CO₂.

4 **2. Methods**

5 **2.1 Terrestrial carbon cycle models**

6 The 10 carbon cycle models used in this study are briefly described in the Table S1. All
7 models describe surface fluxes of CO₂, water and the dynamics of water and carbon pools in
8 response to change in climate and atmospheric composition. However, the formulation and
9 number of processes primarily responsible for carbon and water exchange differs among
10 models.

11 Two simulations, S1 and S2, were performed over the period 1860-2009. In S1, models
12 were forced with rising atmospheric CO₂ concentration, while climate was held constant
13 (recycling climate mean and variability from the early decades of the 20th century, e.g.
14 1901-1920). In S2, models were forced with reconstructed historical climate fields and rising
15 atmospheric CO₂ concentration. All models used the same forcing files, of which historical
16 climate fields were from CRU-NCEP v4 dataset
17 (<http://dods.extra.cea.fr/data/p529viov/cruncep/>) and global atmospheric CO₂ concentration
18 were from the combination of ice core records and atmospheric observations (Keeling &
19 Whorf, 2005 and update). Details of the simulation settings are described in Sitch et al.
20 (*submitted*). It should be noted that land use change was not taken into account in S1 and S2.

22 **2.2 Data-oriented global estimation of GPP**

23 Direct observation of Gross Primary Production (GPP) at the global scale does not exist.
24 Thus, we used a GPP gridded data product from a Multiple Tree Ensemble (MTE) model-data
25 fusion scheme involving eddy covariance flux tower data, climate, and satellite FAPAR fields
26 (Jung et al., 2011 for description of the method), available during 1982-2008, to compare with
27 model output. In the MTE method employed by JU11, a set of regression trees were trained
28 with local GPP estimation from eddy flux NEE measurements with the Lasslop et al. (2010)
29 method used to separate GPP, and 29 candidate predictor climate and biophysical variables,
30 including vegetation types, observed temperature, precipitation and radiation, and satellite

1 derived fraction of absorbed photosynthetic active radiation (FAPAR). The ensemble of the
2 trained regression trees was driven by global fields of predictor variables to derive gridded
3 GPP estimates (Beer et al., 2010). Uncertainty of the GPP estimated from MTE is relatively
4 small, at about $\pm 6 \text{ Pg C yr}^{-1}$ (Jung et al., 2011). However, this does not consider other sources
5 of uncertainty such as measurement uncertainties of eddy covariance fluxes, of global
6 predictor variables as well as sampling bias driven by unevenly distributed eddy covariance
7 flux sites, with many sites in temperate regions and very few sites in the tropics. As described
8 further below, this dataset should also be used with extreme caution for assessment of
9 interannual variability of GPP.

11 **2.3 The ‘residual’ land sink (RLS)**

12 The RLS of anthropogenic CO₂ during the period 1980-2009 is taken from the Global
13 Carbon Project carbon budget from Friedlingstein et al. (2010) and Le Quéré et al.(2009). It is
14 estimated as a residual of all other terms that compose the global carbon budget, since no
15 direct global observation of land carbon balance is otherwise available, except for the global
16 forest sink (Pan et al., 2011). The RLS is the sum of fossil fuel and cement emissions and land
17 use change emissions minus the sum of observed atmospheric CO₂ growth rate and modeled
18 ocean sink. The CO₂ emissions from fossil fuel and cement are estimated based on statistics
19 provided by United Nations Energy Statistics (Marland et al., 2005), British Petroleum
20 statistic review of world energy
21 (<http://www.bp.com/productlanding.do?categoryId=6929&contentId=7044622>), and USGS
22 statistics on cement production (Van Oss, 2006). Emissions from land use change (Houghton,
23 1999) are based on statistics published by the United Nations Food and Agriculture
24 Organization and a book-keeping model (Houghton, 2010). Atmospheric annual CO₂ growth
25 rate is derived from the NOAA/ESRL global cooperative air-sampling network (Conway et al.,
26 1994). The ocean sink of anthropogenic CO₂ is calculated from the average of four ocean
27 carbon cycle models (Le Quéré et al., 2009). It is important to note that the net land use
28 source estimate in FR10 is 0.3 Pg C yr^{-1} lower over 2000-2009 than the previous LUC
29 emission estimate (Le Quéré et al., 2009). This lower estimate uses the same Houghton et al.
30 model, but takes as input data updated information on forest area change from (FAO, TBRFA

1 2010) instead of the TBFRA 2005. A lower LUC emission estimate results in a lower RLS
2 mean value.

4 **2.4 Field ecosystem warming experiment**

5 Data from a harmonized field warming experiment dataset compiled from 124 published
6 papers (Lu et al., submitted) was used to evaluate model performance. In order to compare
7 with model outputs, available observations of Net Primary Production (NPP) in experimental
8 sites with warming only treatments and the control experiment were used in our study. The six
9 available sites were located over the temperate and boreal northern hemisphere between 30°N
10 - 70°N with mean annual temperature spanning from -7 °C to 16 °C and mean annual
11 precipitation spanning from 320 mm to 818 mm (Table S2). The magnitude of experimental
12 warming ranges from 1°C to 3.5 °C among different treatments and different sites. These
13 levels of warming are of a magnitude equal or higher than inter-annual variability of
14 temperature, and so complement comparison of simulations S2 and their testing against data,
15 where for the latter an emphasis might be placed on anomalously warm years. It should be
16 noted that total NPP (both aboveground and belowground NPP) were measured in four of the
17 sites, while the other two sites (HARS and Toolik Lake) only measured aboveground NPP.

19 **2.5 Free Air Carbon Dioxide Enrichment (FACE) experiments**

20 Free Air Carbon Dioxide Enrichment (FACE) experiment provided field experimental
21 data on the response of NPP to elevated CO₂. Four FACE experiments in temperate forest
22 stands provided data for our evaluation (Table S3). NPP was calculated as annual carbon
23 increments in all plant parts plus the major inputs to detritus, litterfall, and fine root turnover.
24 We used data from Norby et al. (2005), however data from the ORNL FACE site was
25 corrected and extended to 2008 (Iversen et al., 2008). Data from young stands in the early
26 stage of sapling development with expanding canopies, and some plots with increasing O₃ at
27 the ASPEN FACE were not included in the dataset, as described by Norby et al. (2005). There
28 were in total 21 site-year NPP observations available for our study. Site characteristics and
29 experiment settings in each stand can be found in Table S3, with a more detailed description
30 given in Norby et al. (2005). There are no FACE experiments for tropical ecosystems.

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2.6 Analysis

2.6.1 Response of carbon fluxes to climate variations

We estimate empirically the response of GPP, NPP and NBP to climate variability (MAT and annual precipitation) over the last three decades by using a multiple regression approach (Eq. 1):

$$y = \gamma^{\text{int}} x_T + \delta^{\text{int}} x_P + \varepsilon \quad (\text{Eq. 1})$$

where y is the detrended anomaly of the carbon fluxes GPP, NPP and NBP from the S2 simulations (i.e. simulations considering change in both climate and atmospheric CO₂ concentration, see section 2.1) estimated by each model. Equation (1) is also fitted to the data-oriented model of GPP (JU11 GPP) and to the RLS values from FR10. The variable x_T is the detrended MAT anomaly, and x_P is the detrended annual precipitation anomaly. The fitted regression coefficients γ^{int} and δ^{int} define an *apparent* carbon flux sensitivity to interannual variations in temperature and precipitation, and ε the residual error term. Note that γ^{int} (or δ^{int}) reflect the contributive effect of temperature (or precipitation) variations on carbon fluxes, but not the ‘true’ sensitivities of these fluxes, given that: (1) temperature and precipitation co-vary over the time, and (2) other climate drivers discarded in Eq.1, such as solar radiation, humidity, and wind speed may also contribute to the variability of detrended carbon fluxes. The regression coefficients are calculated using maximum likelihood estimates (MLE). The uncertainty in γ^{int} and δ^{int} was estimated using the standard error of the corresponding regression coefficients. Data from 1980 to 2009 were used to quantify the response of carbon fluxes to climate variations, except for GPP where instead the period 1982-2008 was considered in order to be consistent with the period covered by the JU11 data-oriented estimate. In order to be consistent with RLS, we first aggregate each grid cell carbon flux into a global mean flux (see SI) and then remove the trend using a least squares linear fitting method.

2.6.2 Response of carbon fluxes to CO₂ trended over the past 30 years

Two approaches were applied to estimate the response of carbon fluxes to CO₂ (β). In the

1 first approach, β was estimated based on S1 simulations (i.e. the simulations that only
2 consider change in atmospheric CO₂ concentration) using Eq. (2):

$$3 \quad \beta = \frac{\Delta F}{\Delta CO_2} \quad (\text{Eq. 2})$$

4 where, ΔF is the difference of average carbon fluxes between the last and the first five
5 years of the S1 simulation, while ΔCO_2 is the corresponding change in atmospheric CO₂
6 concentration. In order to estimate the uncertainty of β , we also calculated the change in
7 carbon fluxes and CO₂ over the study period by randomly selecting a different year over the
8 first and last five year period.

9

10 In the second approach, we used a multiple regression approach (Eq. 3) to estimate β for
11 RLS, or for JU11's GPP, and for each model's carbon flux from simulation S2 (both climate
12 and CO₂ change).

$$y = \beta CO_2 + a Tmp + b Prcp + c + \varepsilon \quad (\text{Eq. 3})$$

13

14 where, y is the carbon flux of each model from S2, or RLS from FR10, and CO₂, Tmp,
15 and Prcp are the atmospheric CO₂ concentration, MAT and annual precipitation respectively.
16 Quantities β , a , b , and c are regression coefficients, while ε is the residual error term. The
17 regression coefficients are calculated using maximum likelihood estimates (MLE). Our Eq. 3
18 attributes the time series of the y flux to what we consider as the dominant drivers of change
19 i.e. temperature, precipitation, and CO₂. However we do recognize that other land surface
20 changes or meteorological forcing might influence too, and these become implicit in our
21 regression co-efficients. Such effects are for example land use, forest demography, nitrogen
22 deposition, solar radiation, humidity, and wind speed, which influence the trend of RLS time
23 series. Therefore, although we believe rising CO₂ to be strongly influencing the RLS trend the
24 precise values of our regression co-efficients should be treated with caution. Generally, a and
25 b indicate the contributive effect of temperature (resp. precipitation) variations on the carbon
26 fluxes variations (Fig. S1). The period 1980-2009 is used to estimate the carbon fluxes
27 sensitivities to climate and CO₂, except for GPP where the period considered is 1982-2008.

28

2.6.3 Temperature sensitivities of vegetation productivity derived warming experiment

For warming experiments, the sensitivity of NPP to an (generally stepwise) applied change in temperature, is estimated as the ratio of the relative difference between NPP in warmed minus control plots to the applied warming magnitude. The estimated temperature sensitivity at each experimental site is then compared with the ratio of γ_{NPP}^{int} estimated from model simulations and with the multiple regression method (Eq. 1). This corresponds to the 30-year average NPP (hereafter $R\gamma_{NPP}^{int}$), and with models being sampled at the grid point containing the experimental site. In addition, we also extract modeled sensitivities in ‘climate neighbours’ grid points where the mean annual temperature differs by less than 1°C and mean annual precipitation by less than 50 mm from the conditions at each experimental site. Only neighbouring grid points with the same dominant vegetation cover as observed at each experimental site are retained, e.g. for grassland warming sites; all grid points with grassland cover of less than 50% are excluded. Since models do not explicitly represent wetland processes, we grouped wetland with grasslands. Using a similar approach, we estimated the sensitivities of NPP to rising atmospheric CO₂ concentration from the FACE sites and the relative response of NPP to CO₂ ($R\beta_{NPP}$, the ratio of β_{NPP} estimated by Eq. 2 to the 30-year average NPP in each model).

We note that due to this set-up, we cannot make quantitative statements about the nature of the model-data agreement. Both, the step-wise nature of the experiment and the magnitude of the perturbation may induce non-linear effects in the ecosystems that cannot (and should not) be reproduced by ecosystem models simulating the consequences of a gradual and less pronounced perturbation over the last three decades. In particular, because of the saturating effect of CO₂ on leaf level photosynthesis, we expect to see a larger relative effect of CO₂ on photosynthesis when evaluating the increase from 338 to 386 ppm than the response from field experiments elevating CO₂ concentration from about 360 to 550 ppm.

3. Vegetation productivity

3.1 GPP estimation

Global terrestrial GPP averaged across 10 models is 133 ± 15 Pg C yr⁻¹, ranging from

1 111±4 Pg C yr⁻¹ (±s.d. of GPP over the three decades) in SDGVM to 151±4 Pg C yr⁻¹ in
2 ORCHIDEE and CLM4C. The higher estimates are consistent with the inferred estimate from
3 ¹⁸OCO in the atmosphere (Welp et al., 2011), although this high value is also uncertain and in
4 contrast to earlier studies (Ciais et al., 1995, Beer et al. 2010). The JU11 GPP product derived
5 from eddy-covariance flux towers, generally gives a lower estimate of GPP than the majority
6 of the processed-based models (Fig. 1), particularly in temperate regions (Fig. S2b). At the
7 global scale, the magnitude of GPP (113±3 Pg C yr⁻¹) in LPJ-GUESS is close to JU11 (118±1
8 Pg C yr⁻¹). However, this result should be viewed with caution, since a similar global
9 magnitude can mask compensation of biases between tropical and non-tropical regions. As
10 shown in Fig. S2 and S3, the LPJ-GUESS simulation has a low bias of GPP in tropical
11 regions compared to JU11 (68% of JU11), compensated by a high bias in non-tropical
12 regions.

13

14 At the global scale, the correlation of interannual GPP variations among the different
15 models is much higher than that with JU11 as shown by Fig. 2a. JU11 GPP is estimated from
16 satellite and eddy covariance flux tower measurements, and flux tower sites are mainly
17 distributed in northern temperate regions (mainly forest). Hence a larger sampling uncertainty
18 is associated with JU11 for GPP outside this northern region. This is of importance as tropical
19 ecosystems are largely driving the interannual variability of the carbon cycle (Denman et al.,
20 2007). Interestingly, the lowest correlation between GPP from models and JU11 is found in
21 tropical regions (Fig. S4c) perhaps due to fewer eddy-covariance flux sites available to create
22 the interpolated global product. Furthermore, the standard deviation of GPP is found to be
23 substantially higher in the 10 process models than in JU11 (compare error bars in Fig. 1a), and
24 particularly over tropical regions (Fig. S2c). This leads us to make the hypothesis that the
25 GPP interannual variability is under-sampled in JU11 and hence systematically lower than the
26 interannual variability simulated by the DGVMs. This hypothesis is further discussed in the
27 next section.

28

29 **3.2 Response of GPP to temperature variations (γ_{GPP}^{int})**

1 At the global scale, the models suggest that interannual variation in global GPP is not
2 significantly correlated with temperature (all variables detrended), as can be seen from the
3 large differences in the magnitude and even in the sign of the γ_{GPP}^{int} (Fig. 3a) due to the
4 different sensitivity values over different regions (Fig. S6). In the tropical regions, all models
5 have a negative apparent sensitivity γ_{GPP}^{int} (-2.2 ± 1.2 Pg C yr⁻¹ °C⁻¹ or -2.9 ± 1.4 % °C⁻¹;
6 significant for 7 out of 10 models), while JU11 has a positive γ_{GPP}^{int} (0.4 ± 0.7 Pg C yr⁻¹ °C⁻¹ or
7 0.6 ± 1.0 % °C⁻¹, $P > 0.05$) (Fig. S6c). JU11's GPP response to temperature variability over
8 tropical regions, however, may be considered as more uncertain than models, since satellite
9 FAPAR used by JU11 for spatial-temporal interpolation of GPP distribution between flux
10 tower locations is often contaminated by cloudiness (Myneni et al., 1997). Furthermore, JU11
11 trained their MTE using *spatial gradients* among different sites (there are few long series) and
12 then used the derived relationship to extrapolate to *temporal* interannual gradients. This
13 assumes that spatial and interannual sensitivity of GPP to climate are the same, which may be
14 not correct. Measurements of tree growth in tropical forests have shown negative correlation
15 with temperature (Clark et al., 2003; Clark et al., 2008). This result is also supported by
16 short-term leaf level measurements in tropical forests which indicate a decrease in net carbon
17 assimilation at higher temperature (Tribuzy, 2005; Doughty and Goulden, 2008). This
18 negative response of vegetation productivity to MAT variability may arise from the fact that
19 tropical forests already operate near to a high temperature optimum threshold above which
20 vegetation photosynthesis declines sharply (Corlett et al., 2011).

21
22 In boreal regions, vegetation growth is limited by temperature which controls the length
23 of the growing-season, implying that rising MAT causes an extension of the growing season,
24 and induces an increase in GPP (Piao et al. 2007; Richardson et al., 2010). It has been
25 suggested that rising temperature is enhancing vegetation growth in boreal regions (Lucht et
26 al., 2002; Piao et al., 2006; Piao et al., 2009; Wang et al., 2011) except in regions affected by
27 summer drought, during the analysis period, such as parts of Alaska (Beck et al., 2011). All
28 the models show significant positive relationship ($P < 0.05$) between boreal GPP and MAT with

1 an average γ_{GPP}^{int} of $0.8 \pm 0.3 \text{ Pg C yr}^{-1} \text{ } ^\circ\text{C}^{-1}$ (or $4.5 \pm 1.5 \text{ \% } ^\circ\text{C}^{-1}$), which is close to the γ_{GPP}^{int}
2 derived from the GPP of JU11 ($0.9 \pm 0.3 \text{ Pg C yr}^{-1} \text{ } ^\circ\text{C}^{-1}$ or $4.7 \pm 1.5 \text{ \% } ^\circ\text{C}^{-1}$) (Fig. S6a).

3

4 In temperate regions, the response of GPP to MAT depends partly on the balance
5 between the positive effect of warming through extending the growing season in spring and
6 possibly in autumn (although recent work suggest that the photoperiod may limit GPP,
7 Bauerle et al., 2012), reaching more optimal growing temperature, and the negative effect of
8 warming through enhanced soil moisture stress in summer. At the regional scale, most models
9 (except CLM4CN and HYLAND) and JU11 data-product show a non-significant interannual
10 correlation between MAT and GPP (Fig. S6b).

11

12 **3.3 Comparison with the field warming experiments**

13 Fig. 4 shows the spatial distribution of the $R\gamma_{NPP}^{int}$ (the ratio of γ_{NPP}^{int} to the 30-years
14 average NPP of each model) averaged across the 10 models. Similar to the regional scale
15 analyses of γ_{GPP}^{int} above, we checked for a positive (resp. negative) interannual correlation
16 between MAT and NPP in boreal (resp. tropical) regions. We then compared the simulated
17 $R\gamma_{NPP}^{int}$ against the relative sensitivity derived from field warming experiments, which are
18 only distributed over the northern hemisphere. Field warming experiments show that rising
19 temperature generally increases NPP (after 4 years of warming on average) across most sites,
20 except at the Haibei Alpine Research Station (in the Tibet Plateau) where rising temperature
21 significantly decreased aboveground NPP by $-8 \text{ \% } ^\circ\text{C}^{-1}$ (Fig. 4). The sign of this sensitivity in
22 Haibei Alpine Research Station is correctly captured by six of ten models (Fig. 4). One can
23 also see in Fig. 4 that models tend to predict smaller $R\gamma_{NPP}^{int}$ values than observed at the
24 warming experiment temperate sites, particularly at Jasper Ridge Global Change Experiment
25 (JRGCE), Kessler's Farm Field Laboratory (KFFL), Toivola and Alborn (Minnesota 2), and
26 Duolun. One can assume that this may be because in the grid points containing these sites,
27 annual precipitation used in model forcing is less than actual precipitation at field sites (by
28 15% at Jasper Ridge Global Change Experiment, 8% at Kessler's Farm Field Laboratory, 46%

1 at Toivola and Alborn, and 17% at Duolun). The results of two field warming experiment sites
2 in Minnesota, USA (47°N, 92°W) have shown that the wetter site (annual precipitation of 762
3 mm) has a much higher NPP sensitivity to warming (12 - 22 % °C⁻¹ yr⁻¹) than the drier site
4 (annual precipitation of 497 mm, -3 - 6 % °C⁻¹ yr⁻¹) (Fig. 4), implying that average climatic
5 conditions (in particular through soil moisture availability) regulate the response of NPP to
6 temperature. To mini minimize the effect of biases in the climate drivers, we also extract
7 modeled sensitivities in ‘climate neighbours’ grid points where the mean annual temperature
8 differs by less than 1°C and mean annual precipitation by less than 50 mm from the conditions
9 at each experimental site. As shown in Fig. 4, however, the model estimated at JRGCE,
10 KFFL, Minnesota 2, and Duolun, is still systematically lower than observation, implying that
11 the different forcing may be not the primary reason the mismatch between models and
12 observations. A recent study comparing model simulations driven by site-level climate forcing
13 and by gridded climate forcing suggested that model structure, rather than climate forcing,
14 remained the main limitation for improving model-site data comparison (Rackza et al.,
15 submitted).

16
17 In addition, it should be noted that the methods we used to quantify the response of NPP
18 to temperature change in models (interannual variability) and in field warming experiments
19 (multi-years treatments have a higher amplitude of stepwise warming than the inter-annual
20 range of natural variability, and no covariate precipitation change) are different, which may
21 cause inconsistencies in evaluating models. Even at the same site, the magnitude of the
22 temperature sensitivity of NPP depends upon the magnitude of warming. For example, field
23 warming experiments at the drier site in Minnesota, USA (47°N, 92°W), show that
24 temperature sensitivity of NPP for a step 2 °C warming (1 - 6% yr⁻¹) is larger than that for a
25 step 3 °C warming (-3 - 2% yr⁻¹). Furthermore, $R\gamma_{NPP}^{int}$ of processed-based models does not
26 consider local heterogeneity of environmental conditions and land cover, and local
27 biogeophysical feedbacks (e.g., Long et al. 2006). This spatial scale mismatch adds
28 uncertainty to model evaluation using warming experiment sites. For instance, the
29 temperature sensitivity of NPP derived from the warming experiment at the two Minnesota

1 sites (47°N, 92°W) that are located in the same grid point of models, varies from -3% °C⁻¹ to
2 22% °C⁻¹, which is a larger range than that predicted by the models over the corresponding
3 grid point (from -2.7% °C⁻¹ to 6.1% °C⁻¹). In addition, the models may not fully represent
4 ecosystem-level mechanisms underlying NPP responses to warming in experiments, such as
5 warming-induced changes in nutrient availability, soil moisture, phenology, and species
6 composition (Luo, 2007). Overall, the inconsistency of the response of NPP to temperature
7 change between models and field warming experiments should be addressed by further
8 studies, for instance running the same models with site observed forcing data and vegetation,
9 soil parameters.

11 **3.4 Response of GPP to precipitation variations (δ_{GPP}^{int})**

12 Over the past few decades, many regions have experienced drought, which has a
13 negative effect on vegetation productivity (Zhao et al., 2010 for the globe; Angert et al., 2005
14 and Zeng et al., 2005 for the Northern Hemisphere; Ciais et al., 2005 for Europe; Zhang et al.,
15 2010 for North America; Potter et al., 2011 for Amazonia, McGrath et al., 2012 for Australia,
16 Wang et al., 2010 for China). Droughts that occurred from 1998 to 2002 in the northern
17 hemisphere mid-latitudes, for example, led to an estimated reduction of vegetation NPP by
18 5% compared to the average of the previous two decades (Zeng et al., 2005). Although
19 individual drought events cannot be attributed to anthropogenically-induced climate change,
20 there is a concern that a general situation of more extreme weather events is emerging,
21 including the potential for alteration to the global hydrological cycle. Over the northern
22 hemisphere, all models have a positive δ_{GPP}^{int} . However the interannual correlation between
23 GPP and precipitation was found not significant for JU11, HYLAND, LPJ-GUESS, and
24 VEGAS in boreal regions (Fig. S7a), and JU11, HYLAND in northern temperate regions (Fig.
25 S7b).

26
27 There has been much discussion in the literature about the impact of drought on
28 vegetation growth and mortality in tropical regions (Nepstad et al., 2004; Da Costa et al.,
29 2010; Phillips et al., 2009 and 2010). A rainfall exclusion experiment in an east-central

1 Amazonian rainforest at Tapajos showed that a 50% reduction in precipitation led to a 25%
2 reduction in vegetation NPP over the first two years of the experiment (Nepstad et al., 2002).
3 It has been suggested that spatial GPP variability in 30% of tropical forest and in 55% of
4 tropical savannahs and grasslands is primary correlated with the precipitation (Beer et al.,
5 2010). Indeed, at the continental scale, all models show a positive correlation of GPP with
6 annual precipitation over tropical regions (not significant in JU11 and HYLAND), but the
7 magnitude of δ_{GPP}^{int} differs among models with TRIFFID and LPJ having the largest δ_{GPP}^{int}
8 (about 2.2 ± 0.4 Pg C yr⁻¹ per 100 mm or 2.8 ± 0.5 % per 100 mm for TRIFFID, and 1.8 ± 0.4 Pg
9 C yr⁻¹ per 100 mm or 2.7 ± 0.5 % per 100 mm for LPJ) (Fig. S7c). The average of tropical
10 δ_{GPP}^{int} across the 10 models is 1.4 ± 0.5 Pg C yr⁻¹ per 100 mm (or $1.8\pm 0.7\%$ per 100 mm),
11 which is three times larger than δ_{GPP}^{int} of the JU11 data-oriented GPP (0.5 ± 0.3 Pg C yr⁻¹ per
12 100 mm or 0.6 ± 0.4 % per 100 mm).

13

14 Overall, at the global scale, δ_{GPP}^{int} averaged across the 10 models is 4.1 ± 2.0 Pg C yr⁻¹ per
15 100 mm (or $3.1\pm 1.5\%$ per 100 mm) (Fig. 3b). Among the 10 models, 8 exhibit significant
16 correlations between global GPP and annual precipitation (all variables detrended).
17 Considering that global GPP was not correlated with MAT in any of the models (see section
18 3.2.1), we conclude that interannual variation of GPP is more closely controlled by
19 precipitation rather than by temperature (Piao et al., 2009; Jung et al., 2011). The TRIFFID
20 model has the highest δ_{GPP}^{int} (7.6 ± 1.5 Pg C yr⁻¹ per 100 mm or $5.5\pm 1.1\%$ per 100 mm) as seen
21 in Fig. 3b. Differences in simulated land cover between models, in addition to structural
22 sensitivities (i.e., sensitivity of stomata to soil moisture) may also explain the variability
23 among models, particularly in arid and temperate regions (Poulter et al. 2011).

24

25 **3.5 Response of vegetation productivity to CO₂**

26 According to the results of simulation S1 driven by atmospheric CO₂ only, model results
27 consistently indicate that rising atmospheric CO₂ concentration increased NPP by 3-10% with
28 an average of 7% over the past three decades (for a 48 ppm CO₂ increase) (or 0.05-0.2 %

1 ppm⁻¹ with the average of 0.16 % ppm⁻¹). This relative response of NPP to CO₂ ($R\beta_{NPP}$) is
2 slightly larger than the sensitivity derived from FACE elevated CO₂ experiments, which
3 might be expected because of the saturating effect of CO₂ on photosynthesis. Norby et al.
4 (2005) analyzed the response of NPP to elevated CO₂ in four FACE experiments in temperate
5 forest stands and concluded that the enhancement of NPP due to elevated CO₂ (about 180
6 ppmv) was of about 23% (or 0.13% ppm⁻¹). When comparing the results from the four FACE
7 experiments with model simulations at the corresponding sites and climatic condition,
8 however, we found that the models underestimated CO₂ fertilization effect on NPP at the
9 ASPEN FACE site, but overestimated it at the Duke and ORNL FACE sites (Fig. 6). The
10 study of Hickler et al. (2008) suggested that these currently available FACE results are not
11 applicable to vegetation globally since there may be large spatial heterogeneity of the positive
12 effect of CO₂ on vegetation productivity across the global land surface. Hence we do not
13 present the FACE values in global plot Fig 5a. As shown in Fig. 6, the modeled response of
14 NPP to CO₂ is generally larger in dryer regions. Among the four FACE experimental sites, a
15 largest CO₂ fertilization effect of NPP was also found in the driest (ASPEN FACE) site (Fig.
16 6 and Table S3). This NPP enhancement could be due to the additional saving of soil moisture
17 induced by elevated CO₂ on stomatal closure (i.e. increased water use efficiency of plants in
18 water limited regions).

19

20 It has been suggested that the CO₂ fertilization effect on vegetation productivity may be
21 overestimated by not considering N limitations (Hungate et al., 2003; Bonan and Levis, 2010;
22 Zaehle et al., 2010). As in Bonan and Levis 2010, we find that for CLM4, β_{GPP} in the
23 CLM4CN that considers C-N interaction and N limitations is lower than that estimated in the
24 CLM4C without C-N interaction (Fig 5a). In boreal regions, β_{GPP} of CLM4CN (2.2±1.4Pg
25 C yr⁻¹ per 100 ppm or 12±8% per 100 ppm) is only about half of CLM4C estimated β_{GPP}
26 (4.4±1.5Pg C yr⁻¹ per 100 ppm 21±7% per 100 ppm). As noted previously (Zaehle &
27 Dalmonech 2011), there is a difference in the extend of N limitation on global carbon cycling
28 between CLM4C-N and OCN, although both of them have N limitations on GPP. OCN

1 predicts a relatively high β_{GPP} , particularly in tropical regions (12.7 ± 1.6 Pg C yr⁻¹ per
2 100ppm or $18 \pm 2\%$ per 100ppm), which is two times larger than that estimated by CLM4CN
3 (6.6 ± 1.2 Pg C yr⁻¹ per 100ppm or $7 \pm 1\%$ per 100ppm) (Fig. S9c).

4
5 According to equation (3), the GPP data-driven product of JU11 shows weak sensitivity
6 to CO₂ at the global scale (Fig. 5a), although satellite data used to drive the empirical model
7 of Jung et al. (2011) includes a greening trend whose spatial pattern can be partly accounted
8 for by rising CO₂ (Piao et al., 2006). Furthermore, the model results show that β_{GPP} derived
9 from simulations S2 (i.e. consider both climate change and rising atmospheric CO₂
10 concentration and equation (3)) are generally larger than β_{GPP} from simulation S1 that only
11 consider rising atmospheric CO₂ concentration (Fig. 5a). This is particularly true in the
12 tropical regions (Fig. S9c). This may be partly because the mean climate in the early decades
13 of the 20th century for S1 simulation is wetter than that in end decades of the 20th century for
14 S2 simulation in the tropical regions (IPCC, 2007), or indicate that the linear regression
15 approach does not replicate the intricate non-linear complexity of the global carbon cycle.

16 17 **4 Net Biome Productivity**

18 **4.1 NBP estimation**

19 Global NBP is not significantly correlated with the global GPP across 10 models
20 ($R=0.48$, $P=0.16$) (Fig. 1), suggesting that models predicting larger GPP does not necessarily
21 translate into larger NBP. The ensembles model average NBP (all without land use change)
22 during the period 1980-2009 is 2.0 ± 0.8 Pg C yr⁻¹, which is very close to the RLS of 2.1 ± 1.2
23 Pg C yr⁻¹. However, there are large differences among different models, with NBP ranging
24 from 0.24 ± 1.03 Pg C yr⁻¹ (VEGAS) to 3.04 ± 0.98 Pg C yr⁻¹ (HYLAND) (Fig. 1). The smaller
25 NBP of VEGAS is related to the net tropical carbon source produced by this model (-0.12 ± 0.9
26 Pg C yr⁻¹). In contrast, the other 9 models (in absence of land-use) produce a net sink of
27 1.13 ± 0.44 Pg C yr⁻¹ on average (Fig. S2c), explaining 54% of global RLS.

28
29 In addition, for analysis of the interannual variability in modeled global NBP from 1980

1 to 2009, all models show generally good agreement with the observed variability of the RLS
2 ($P < 0.05$) (Fig. 2b). Interestingly, for NBP variability, CLM4CN has a lower correlation with
3 RLS than CLM4C (Fig. 2b), implying that in this particular model, incorporation of the
4 nitrogen cycle does not improve the performance for interannual variability, which may
5 reflect model structural problems in describing processes controlling C-N interactions (Bonan
6 and Levis, 2010). Note, however, that a strong dampening of the interannual variability in the
7 carbon cycle is not a general feature of nitrogen dynamics (Zaehle et al. 2010). In addition, at
8 the regional scale, the correlation of interannual NBP among different models is higher in the
9 tropical regions than that in non-tropical regions (Fig. S5).

11 **4.2 Response of NBP to temperature variations (γ_{NBP}^{int})**

12 Direct observational evidence for a positive feedback of the terrestrial carbon cycle to
13 climate warming is limited (Scheffer et al., 2006; Cox and Jones, 2008; Frank et al., 2010).
14 Applying the regression of Equation (1) to RLS timeseries defines an ‘observed’ contributive
15 effect of temperature variations on the RLS variations (γ_{RLS}^{int}) of -3.9 ± 1.1 Pg C yr⁻¹ °C⁻¹ (Fig.
16 3a), which is larger than, but within the uncertainty range of γ_{NBP}^{int} in the 10 models (-3.0 ± 1.5
17 Pg C yr⁻¹ °C⁻¹). Except for HYLAND and SDGVM, 8 out of 10 models show significant
18 negative correlation between NBP and MAT, but γ_{NBP}^{int} varies among models from -1.0 ± 0.6
19 Pg C yr⁻¹ °C⁻¹ in HYLAND to -5.1 ± 0.9 Pg C yr⁻¹ °C⁻¹ in LPJ-GUESS. Such difference in
20 across 10 models mainly depends on model differences in the response of GPP to temperature
21 ($R=0.63$, $P=0.05$), rather than response of respiration to temperature ($R=0.44$, $P>0.05$).
22 Furthermore, the contribution of fire to the is also limited (Fig. S8a). The value of γ_{NBP}^{int} in
23 CLM4CN (-2.1 ± 0.5 Pg C yr⁻¹ °C⁻¹) is only half of that in CLM4C (-4.3 ± 0.8 Pg C yr⁻¹ °C⁻¹),
24 which may be partly because during warmer years, increased soil nitrogen mineralization and
25 availability may promote vegetation growth (Melillo et al., 2002). However, γ_{NBP}^{int} from
26 CLM4C is closer to the observed γ_{RLS}^{int} than that for CLM4CN.

1 The negative value of global γ_{NBP}^{int} is mainly due to negative NBP anomalies (abnormal
2 CO₂ source to the atmosphere) occurring during warm years over tropical regions (Fig. S6c).
3 All models show statistically significant interannual correlation of NBP with MAT in the
4 tropical regions ($R < 0.05$), and an average γ_{NBP}^{int} of -3.0 ± 1.2 Pg C yr⁻¹ °C⁻¹. Compared with
5 tropical regions, other regions have a relatively smaller γ_{NBP}^{int} (Fig. S6). In the boreal zone,
6 there are large differences in the magnitude and even in the sign of γ_{NBP}^{int} among models. For
7 example, LPJ, LPJ-GUESS, and TRIFFID have a γ_{NBP}^{int} of -0.37 ± 0.13 Pg C yr⁻¹ °C⁻¹, -0.53
8 ± 0.19 Pg C yr⁻¹ °C⁻¹, and -0.29 ± 0.1 Pg C yr⁻¹ °C⁻¹, respectively, but VEGAS has a positive
9 γ_{NBP}^{int} of 0.23 ± 0.08 Pg C yr⁻¹ °C⁻¹ (Fig. S6a) due to its highest γ_{GPP}^{int} (Fig. S6a). Such model
10 divergence on over boreal zone and the consistency in the sign of over tropical zone can
11 explain why models agree more on the interannual variation of tropical NBP than on the
12 interannual variations of boreal NBP (Fig. S5a and c). In the northern temperate regions, all
13 models (except CLM4CN) show negative γ_{NBP}^{int} with average of -0.44 ± 0.45 Pg C yr⁻¹ °C⁻¹
14 (Fig. S6b).

15

16 **4.3 Response of NBP to precipitation variations (δ_{NBP}^{int})**

17 The RLS is not significantly correlated with the precipitation (after statistically removing
18 the contributive effect of temperature using partial correlation) at the global scale, but in
19 contrast, 8 of 10 models still have a significant positive correlation between NBP and
20 precipitation (all variables detrended) (Fig. 3b). Furthermore, 9 models (except LPJ-GUESS)
21 estimate a higher δ_{NBP}^{int} (average of 2.3 ± 1.6 Pg C yr⁻¹ per 100 mm of interannual precipitation
22 change) compared to the observed RLS (0.8 ± 1.1 Pg C yr⁻¹ per 100 mm of interannual
23 precipitation change) (Fig. 3b). These results indicate that current state-of-the-art carbon cycle
24 models are likely to be too sensitive to precipitation variability. TRIFFID has the highest δ_{NBP}^{int}
25 sensitivity (6.0 ± 0.9 Pg C yr⁻¹ per 100 mm) due to highest. At the global scale, is
26 significantly increased with the increase in by the slope of 0.61 across 10 models ($R=0.81$,

1 P<0.01). In addition, the model estimated response fire emission to precipitation is much
2 smaller than the inter-model differences in (Fig. S8).

3
4 It has been suggested that decreased CO₂ sinks in the next century over tropical regions,
5 in response to soil drying, was one of the principal mechanisms explaining the positive carbon
6 cycle-climate feedback diagnosed from the C4MIP coupled models (Friedlingstein et al.,
7 2006; Sitch et al., 2008). In the tropics indeed, all models (nine of ten models significant)
8 consistently produce a positive interannual covariance between precipitation and NBP.
9 TRIFFID has the highest tropical δ_{NBP}^{int} (1.5 ± 0.2 Pg C yr⁻¹ per 100 mm), while ORCHIDEE
10 shows the smallest tropical δ_{NBP}^{int} (0.3 ± 0.3 Pg C yr⁻¹ per 100 mm). In the extra-tropical
11 regions however, several models predict a negative response of NBP to wetter years, but the
12 NBP-precipitation relationship is generally not significant (HYLAND, CLM4CN, and
13 SDGVM only exhibit a significant relationship in the boreal region, and TRIFFID, LPJ, OCN
14 in the northern temperate regions as shown by Fig. S7). In both boreal and temperate regions,
15 the highest δ_{NBP}^{int} was also simulated by the TRIFFID model due to its highest δ_{GPP}^{int} (Fig.
16 S7a and b).

18 **4.4 Response of NBP to rising atmospheric CO₂ concentration (β_{NBP})**

19 From the average of the 10 models, we estimated β_{NBP} using simulation S1 to be 2.39
20 ± 1.52 Pg C yr⁻¹ per 100 ppm at the global scale. CLM4CN shows the smallest β_{NBP} of 0.54
21 ± 2.79 Pg C yr⁻¹ per 100 ppm, which is only 23% of β_{NBP} in CLM4C. This supports results
22 from previous studies that the nutrient limitation of vegetation productivity and carbon
23 sequestration could decrease the land carbon sensitivity to atmosphere CO₂ concentration
24 (Sokolov et al., 2008; Thornton et al., 2009; Zaehle et al., 2010). ORCHIDEE has the largest
25 β_{NBP} of 5.86 ± 2.02 Pg C yr⁻¹ per 100 ppm (Fig. 5b), probably due to its highest β_{GPP}
26 compared to other models (Fig. 5a). Indeed, there is a significant correlation between β_{NBP}

1 and β_{GPP} across 10 models ($P < 0.05$), suggesting that models have different β_{NBP} partly
2 because of the different CO₂ fertilization effect on the vegetation growth (Ciais et al., 2005).
3 Among the 10 models, CLM4CN simulates the lowest carbon sequestration efficiency under
4 rising atmospheric CO₂ concentration (4%), defined as the ratio of β_{NBP} to β_{GPP} , while
5 ORCHIDEE has the highest carbon sequestration efficiency under rising atmospheric CO₂
6 concentration (20%). The ratio of β_{NBP} to β_{GPP} for the ensemble model average is about 12
7 $\pm 4\%$.

8
9 Similar to β_{GPP} (Fig. 5a), β_{NBP} derived from simulation S2 and equation (3) is
10 generally larger than β_{NBP} from simulation S1 (Fig. 5b), particularly in tropical regions (Fig.
11 S10c). As shown in Fig. 5b, CLM4CN, OCN, SDGVM, and VEGAS estimated global β_{NBP}
12 from the simulation S2 with equation (3) is smaller than the diagnosed sensitivity of RLS to
13 atmospheric CO₂ (β_{RLS} , 8.12 ± 2.38 Pg C yr⁻¹ per 100 ppm) based on equation (3). However,
14 it should be noted that since other factors such as ecosystem management and nitrogen
15 deposition could also explain the trend of RLS over the last three decades (Zaehle et al., 2006;
16 Ciais et al., 2008; Bellassen et al., 2010; Magnani et al., 2007, Zaehle & Dalmonech 2011),
17 the sensitivity of RLS to CO₂ from the equation (3) may be overestimated.

18

19 **5. From model testing to directions for future research**

20 To overcome the inevitable spread of curves resulting from a comparison of complex
21 models with poorly constrained processes, we compared in this study the *contributive*
22 *response* of models to climate variability, with available ‘observations’ (in fact other
23 data-driven models). The main contributive responses to interannual climate drivers are γ –
24 the response to temperature anomalies in units of PgC yr⁻¹ °C⁻¹, δ – the response to rainfall
25 anomalies in units of PgC yr⁻¹ 100 mm⁻¹, and β – the response to CO₂ trend, in units of PgC
26 yr⁻¹ 100 ppm⁻¹. Four key datasets are used to estimate these contributive responses, a
27 data-oriented gridded GPP field (JU11), imposed warming experiments, imposed raised

1 atmospheric CO₂ experiments (FACE) and the global residual land sink modeled to close the
2 anthropogenic CO₂ budget (RLS). These four datasets provide information on different
3 contributive responses, JU11 constrains γ , δ and β of GPP, experimental warming site data
4 constrain γ of NPP, the (scarce) FACE site data constrain β of NPP, and the RLS over 30 years
5 constrains γ , δ and β of NBP. We report the following new findings.

6 1. The 10 carbon cycle models give a higher mean GPP and a higher year to year GPP
7 variability than JU11, particularly in tropical regions. In tropical regions, the GPP interannual
8 variance in JU11 may however be considered as too uncertain to falsify the process models.
9 JU11 trained their MTE using *spatial gradients* among different sites (there are few long
10 series) and extrapolated *temporal gradients*, confounding spatial and interannual sensitivity of
11 GPP to climate. To overcome this limitations of comparing the uncertain process-models with
12 another uncertain data-driven model, we recommend future work to models at site scale at
13 which the measurements are made (in particular the long term FLUXNET sites) to investigate
14 their response to climate drivers for different time scales, and different ecosystems (Schwalm
15 et al. 2010). This will also require better protocols with site-history to account for site specific
16 disequilibrium of biomass and soil carbon pools (Carvillhais et al. 2007, 2008).

17 2. The process models generally capture the interannual variation of the data-driven
18 residual land carbon sink (RLS) estimation over the last three decades. But the models's
19 contributive response to precipitation is too high, particularly in tropical forests and savannas
20 (Wang et al., 2012). It is not clear, however, if this too high contributive response of NBP to
21 rainfall is induced by a bias of GPP or ecosystem respiration to soil moisture, or to an
22 inaccurate representation of soil moisture by models. We recommend future work to compare
23 the contributive response of net and gross CO₂ fluxes between models with independent
24 large-scale flux estimations, such as from data-driven upscaling of fluxes and top down
25 inversions.

26 3. In response to interannual variation in temperature, all the models are found to
27 simulate a stronger negative response of NBP than GPP, implying that respiration responds
28 positively to temperature. To investigate this effect, we evaluated for the first time the global
29 process models against site-data from a collection of ecosystem warming experiments. We
30 find that models tend to under-predict the response of NPP to temperature change at the

1 temperate sites. However it is difficult to tell from the warming experiments for NPP, which
2 have significant between-site variation, whether this results predominantly from plant or soil
3 respiration, or possibly both, where the balance varies strongly depending on geographical
4 variation. The different approaches to derive the NPP response to temperature between global
5 models forced offline by gridded climate data, and local field warming experiments that are
6 coupled to the atmosphere, bias as well as the fact that process models do not consider
7 sub-grid scale heterogeneity in environmental conditions and vegetation distribution. We
8 recommend to design a global benchmarking of carbon cycle models against ecosystem
9 warming and drought experiments, and to compile a database of experiments results and
10 forcing data that would be open-access.

11 4. Despite the fact that carbon cycle models are often suspected to overestimate CO₂
12 fertilization as a driver of net land uptake, we found that the ensemble mean global NPP
13 enhancement is comparable with FACE experiments observation. The CLM4CN model that
14 have nitrogen limitations do show a sensitivity of NPP to CO₂ that is 50% lower than the
15 same models versions (CLM4C) but without nitrogen. The strength of the CO₂ fertilization on
16 the NBP is poorly quantified. The magnitude of NBP response to CO₂ is not merely dependent
17 on the NPP response. NPP increases could create higher litterfall enhancing soil carbon stores
18 also available to respire. We recommend all carbon cycle models to include nutrients, and
19 pursue the evaluation of C-N interactions using both global and local observations (e.g.,
20 Zaehle et al. 2010).

21 Overall, reducing these uncertainties of climate sensitivities of carbon fluxes is essential
22 to more accurately predict future dynamics of the global carbon cycle and its feedbacks to
23 climate system, and thus it is a priority for the carbon cycle modeling community. We
24 recommend carbon cycle models to be run both "free running" with their default parameters
25 values used in global simulations, and "adjusted" with parameters calibrated or optimized
26 against site observations (e.g, warming, precipitation, and elevated CO₂ experiments, fluxnet
27 data) so that the " portability" of improvements gained from small scale can be assessed at
28 larger, regional or global scale.

29

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- 12

1 **Figure Legends**

2

3 **Figure 1.** The magnitude of global Gross Primary Production (GPP) and global Net Biome
4 Productivity (NBP) estimated by the 10 carbon cycle models. x-axis indicates mean annual
5 global GPP during 1982-2008 with error bars showing standard deviation of the inter-annual
6 variations. y-axis indicate mean annual global NBP during 1980-2009 with error bars showing
7 standard deviation of the inter-annual variations. The red line shows global GPP estimated by
8 a data driven model tree ensemble approach (JU11, Jung et al., 2011), while black lines shows
9 global Residual Land Sink (RLS) (Friedlingstein et al., 2010). Global RLS is estimated as the
10 difference between CO₂ emissions (from fossil fuel combustion and land use change) and
11 carbon storage change in the atmosphere (atmospheric CO₂ growth rate) and in the oceans
12 (model simulated ocean carbon sink) (Friedlingstein et al., 2010). The 10 carbon cycle models
13 include Community Land Model 4C (CLM4C), Community Land Model 4CN (CLM4CN),
14 HYLAND, Lund-Potsdam-Jena (LPJ), LPJ-GUESS, O-CN (OCN), ORCHIDEE,
15 Sheffield-DGVM (SDGVM), TRIFFID and VEGAS.

16

17 **Figure 2.** Color-coded correlation matrixes for global GPP estimated by the 10 carbon cycle
18 models and a data driven model tree ensemble approach (JU11, Jung et al., 2011) and global
19 NBP estimated by the 10 carbon cycle models and global Residual Land Sink (RLS)
20 (Friedlingstein et al., 2010). The correlation matrixes display (a) correlation coefficient in
21 pairs among detrended GPP anomalies estimated by the different approaches during
22 1982-2008. (b) correlation coefficient in pairs among detrended NBP anomalies estimated by
23 different models and RLS during 1980-2009. Model abbreviations are the same as in Figure 1.

24

25 **Figure 3.** The response of global Gross Primary Production (GPP), global Net Biome
26 Production (NBP) and global Residual Land Sink (RLS) to (a) interannual variation in
27 temperature (γ_{GPP}^{int} , γ_{NBP}^{int} and γ_{RLS}^{int} , respectively) and (b) interannual variation in
28 precipitation (δ_{GPP}^{int} , δ_{NBP}^{int} and δ_{RLS}^{int} , respectively). γ_{GPP}^{int} and δ_{GPP}^{int} are estimated using
29 Eq.1 with data during 1982-2008. γ_{NBP}^{int} , δ_{NBP}^{int} , γ_{RLS}^{int} , and δ_{RLS}^{int} estimated using Eq.1 with data

1 during 1980-2009. Grey area indicates the standard error of γ_{RLS}^{int} and δ_{RLS}^{int} . Error bars show
2 standard error of the sensitivity estimates. Dashed error bars in both (a) and (b) indicate the
3 estimated sensitivity from the regression approaches are statistically insignificant ($P>0.05$).
4 The red line shows the 1σ range of β_{GPP} estimated by JU11's GPP products using Eq. 3.
5 Model abbreviations are the same as in Figure 1.

6
7 **Figure 4.** Comparisons of observed relative response of Net Primary Production (NPP) to
8 temperature change in warming experiments (Lu et al., in preparation, Table S1) and
9 estimated relative response of NPP to interannual variation in temperature ($R\gamma_{NPP}^{int}$, the ratio of
10 γ_{NPP}^{int} to 30 year average NPP) by 10 models for the period of 1980-2009. The gray histogram
11 at each site shows the frequency distribution of $R\gamma_{NPP}^{int}$ according to the ensemble of 10
12 model simulations at the grid containing the experiment site and at model grids with grassland
13 dominant land cover (grassland vegetation more than 50% according to GLC land cover map,
14 changing the threshold of grassland percentage from 50% to 70% only induce small change in
15 the frequency distribution of $R\gamma_{NPP}^{int}$ (Figure S11)) and with similar climate to the experiment
16 site (the difference in mean annual temperature less than 1°C and difference in mean annual
17 precipitation less than 50 mm). The mean of model estimated $R\gamma_{NPP}^{int}$ is shown in dashed
18 black line. Model estimates at the gridcell of the experiment site are shown using
19 model-specific mark and color with horizontal error bars showing standard error of $R\gamma_{NPP}^{int}$
20 estimated by the same model in the ensemble of this grid and grids with grassland dominant
21 land cover and showing similar climate. The position of model-specific mark in the vertical
22 axis only represents alphabetical order of model abbreviations. Observed relative temperature
23 sensitivities of NPP in different plots or different time period in the same site, if reported, are
24 shown separately in red circles. Since belowground NPP was not measured in HARS and
25 Toolik Lake, experiment observed temperature sensitivities of NPP at the two sites were based
26 on aboveground NPP measurements. The background color map shows spatial distribution of
27 average of $R\gamma_{NPP}^{int}$ from 10 carbon cycle models. Pentagrams in the color map show locations

1 of experiment sites. Model abbreviations are the same as in Figure 1.

2
3 **Figure 5.** The response of global Gross Primary Production (GPP), global Net Biome
4 Productivity (NBP) and global Residual Land Sink (RLS) to rising atmospheric CO₂
5 concentration (β_{GPP} , β_{NBP} and β_{RLS} , respectively). (a) β_{GPP} estimated by the two
6 approaches. x-axis indicates β_{GPP} estimated by Eq. 2 using simulation S1, while y-axis
7 indicates β_{GPP} estimated by Eq. 3 using simulation S2 with data during 1982-2008. (b)
8 β_{NBP} estimated by two approaches. x-axis indicates β_{NBP} estimated by Eq. 2 using
9 simulation S1, while y-axis indicates β_{NBP} estimated by Eq. 3 using simulation S2 with data
10 during 1980-2009. Error bars show standard error of the sensitivity estimates. The solid black
11 line shows β_{RLS} estimated by Eq. 3. Grey area shows the standard error of the β_{RLS} . Dashed
12 error bars in both (a) and (b) indicate the estimated sensitivity from the regression approaches
13 are statistically insignificant ($P>0.05$). Model abbreviations are the same as in Figure 1.

14
15 **Figure 6.** Comparison of the observed relative response of Net Primary Production (NPP) to
16 rising atmospheric CO₂ concentration in the Free Atmospheric CO₂ Enrichment (FACE)
17 experiment sites (Table S2) and estimated relative response of NPP to rising atmospheric CO₂
18 ($R\beta_{NPP}$, the ratio of β_{NPP} estimated by the Eq. 2 to 30 year average NPP) by 10 models for
19 the period 1980-2009. The gray histogram at each site shows the frequency distribution of
20 $R\beta_{NPP}$ according to the ensemble of 10 model simulations at the grid containing the
21 experiment site and at model grids with forest dominant land cover (forest vegetation more
22 than 50% according to GLC2000 land cover map, changing the threshold of forest percentage
23 from 50% to 70% only induce small change in the frequency distribution of $R\beta_{NPP}$ (Figure
24 S12)) and with similar climate to the experiment site (the difference in mean annual
25 temperature less than 1°C and difference in mean annual precipitation less than 50 mm). The
26 mean of the model estimated $R\beta_{NPP}$ is shown in dashed black line. Model estimates at the

1 grid containing the experiment site are shown using model-specific symbol and color with
2 horizontal error bars showing standard error of the $R\beta_{NPP}$ estimated by the same model in
3 the ensemble of this grid and grids with forest as the dominant land cover having similar
4 climate. The position of model-specific mark in the vertical axis only represent alphabetical
5 order of model abbreviations. Observed NPP response to rising atmospheric CO₂ at different
6 year at the same site are shown separately in red circles. The background color map shows
7 spatial distribution of $R\beta_{NPP}$ estimated from the average NPP of the 10 carbon cycle models.
8 Solid pentagrams in the map show locations of the FACE forest sites. Model abbreviations are
9 the same to Figure 1.

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1 **Figure 1**

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1 **Figure 2**

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1 **Figure 3**

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1 **Figure Legends**

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3 **Figure 1.** The magnitude of global Gross Primary Production (GPP) and color-coded
4 correlation matrix for global GPP estimated by the 10 carbon cycle models and a data driven
5 model tree ensemble approach (JU11, Jung et al., 2011). **(a)** Mean annual global GPP during
6 1982-2008 with error bars showing standard deviation of the inter-annual variations. **(b)** The
7 correlation matrix displays correlation coefficient in pairs among detrended GPP anomalies
8 estimated by the different approaches during 1982-2008. The 10 carbon cycle models include
9 Community Land Model 4C (CLM4C), Community Land Model 4CN (CLM4CN),
10 HYLAND, Lund-Potsdam-Jena (LPJ), LPJ-GUESS, O-CN (OCN), ORCHIDEE,
11 Sheffield-DGVM (SDGVM), TRIFFID and VEGAS.

12

13 **Figure 2.** The response of global Gross Primary Production (GPP) to interannual variation in
14 temperature (γ_{GPP}^{int}), interannual variation in precipitation (δ_{GPP}^{int}), and rising atmospheric CO₂
15 concentration (β_{GPP}) during 1982-2008. **(a)** γ_{GPP}^{int} and $\delta_{GPP}^{int} \cdot \gamma_{GPP}^{int}$ and δ_{GPP}^{int} are estimated
16 using Eq.1 and simulation S2. Error bars show standard error of the sensitivity estimates. **(b)**
17 β_{GPP} estimated by two approaches. x-axis indicates β_{GPP} estimated by Eq. 2 using
18 simulation S1, while y-axis indicates β_{GPP} estimated by Eq. 3 using simulation S2. Error
19 bars show standard error of the sensitivity estimates. The solid black line shows β_{GPP}
20 estimated by JU11's GPP products using Eq. 3. The red line shows the 1σ range of β_{GPP}
21 estimated by JU09's GPP products using Eq. 3. Dashed error bars in both (a) and (b) indicate
22 the estimated sensitivity from the regression approaches are statistically insignificant
23 ($P>0.05$).

24

25 **Figure 3.** Comparisons of observed relative response of Net Primary Production (NPP) to
26 temperature change in warming experiments (Lu et al., in preparation, Table S1) and
27 estimated relative response of NPP to interannual variation in temperature (γ , the ratio of to 30
28 year average NPP) by 10 models for the period of 1980-2009. The gray histogram at each site

1 shows the frequency distribution of ΔNPP according to the ensemble of 10 model simulations at
2 the grid containing the experiment site and at model grids with grassland dominant land cover
3 (grassland vegetation more than 50% according to GLC land cover map) and with similar
4 climate to the experiment site (the difference in mean annual temperature less than 1°C and
5 difference in mean annual precipitation less than 50 mm). The mean of model estimated ΔNPP is
6 shown in dashed black line. Model estimates at the gridcell of the experiment site are shown
7 using model-specific mark and color with horizontal error bars showing standard error of
8 estimated by the same model in the ensemble of this grid and grids with grassland dominant
9 land cover and showing similar climate. The position of model-specific mark in the vertical
10 axis only represents alphabetical order of model abbreviations. Observed relative temperature
11 sensitivities of NPP in different plots or different time period in the same site, if reported, are
12 shown separately in red circles. Since belowground NPP was not measured in HARS and
13 Toolik Lake, experiment observed temperature sensitivities of NPP at the two sites were based
14 on aboveground NPP measurements. The background color map shows spatial distribution of
15 average of ΔNPP from 10 carbon cycle models. Pentagrams in the color map show locations of
16 experiment sites. Model abbreviations are the same as in Figure 1..

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18 **Figure 4.** Comparison of the observed relative response of Net Primary Production (NPP) to
19 rising atmospheric CO₂ concentration in the Free Atmospheric CO₂ Enrichment (FACE)
20 experiment sites (Table S2) and estimated relative response of NPP to rising atmospheric CO₂
21 (ΔNPP , the ratio of ΔNPP estimated by the Eq. 2 to 30 year average NPP) by 10 models for the period
22 1980-2009. The gray histogram at each site shows the frequency distribution of ΔNPP according to
23 the ensemble of 10 model simulations at the grid containing the experiment site and at model
24 grids with forest dominant land cover (forest vegetation more than 50% according to
25 GLC2000 land cover map) and with similar climate to the experiment site (the difference in
26 mean annual temperature less than 1°C and difference in mean annual precipitation less than
27 50 mm). The mean of the model estimated ΔNPP is shown in dashed black line. Model estimates at
28 the grid containing the experiment site are shown using model-specific symbol and color with
29 horizontal error bars showing standard error of the ΔNPP estimated by the same model in the
30 ensemble of this grid and grids with forest as the dominant land cover having similar climate.

1 The position of model-specific mark in the vertical axis only represent alphabetical order of
2 model abbreviations. Observed NPP response to rising atmospheric CO₂ at different year at
3 the same site are shown separately in red circles. The background color map shows spatial
4 distribution of β_{NBP} estimated from the average NPP of the 10 carbon cycle models. Solid
5 pentagrams in the map show locations of the FACE forest sites. Model abbreviations are the
6 same to Figure 1.

7

8 **Figure 5.** The magnitude of global Net Biome Productivity (NBP) and color-coded
9 correlation matrix for global NBP estimated by the 10 carbon cycle models and global
10 Residual Land Sink (RLS) (Friedlingstein et al., 2010). (a) Mean annual global NBP during
11 1980-2009 with error bars showing standard deviation of the inter-annual variations. (b) The
12 correlation matrix displays correlation coefficient in pairs among detrended NBP anomalies
13 estimated by different models and RLS during 1980-2009. Global RLS is estimated as the
14 difference between CO₂ emissions (from fossil fuel combustion and land use change) and
15 carbon storage change in the atmosphere (atmospheric CO₂ growth rate) and in the oceans
16 (model simulated ocean carbon sink) (Friedlingstein et al., 2010). Model abbreviations are the
17 same as in Figure 1.

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19 **Figure 6.** The response of global Net Biome Productivity (NBP) and global Residual Land
20 Sink (RLS) to interannual variation in temperature (γ_{NBP}^{int} and γ_{RLS}^{int} , respectively), interannual
21 variation in precipitation (δ_{NBP}^{int} and δ_{RLS}^{int} , respectively), and rising atmospheric CO₂
22 concentration (β_{NBP} and β_{RLS} , respectively) during 1980-2009. (a) γ_{NBP}^{int} , δ_{NBP}^{int} , γ_{RLS}^{int} , and δ_{RLS}^{int}
23 estimated using Eq.1. Error bars show standard error of the sensitivity estimates. Grey area
24 indicates the standard error of γ_{RLS}^{int} and δ_{RLS}^{int} . (b) β_{NBP} estimated by two approaches.
25 x-axis indicates β_{NBP} estimated by Eq. 2 using simulation S1, while y-axis indicates β_{NBP}
26 estimated by Eq. 3 using simulation S2. Error bars show standard error of the sensitivity
27 estimates. The solid black line shows β_{RLS} estimated by Eq. 3. Grey area shows the standard

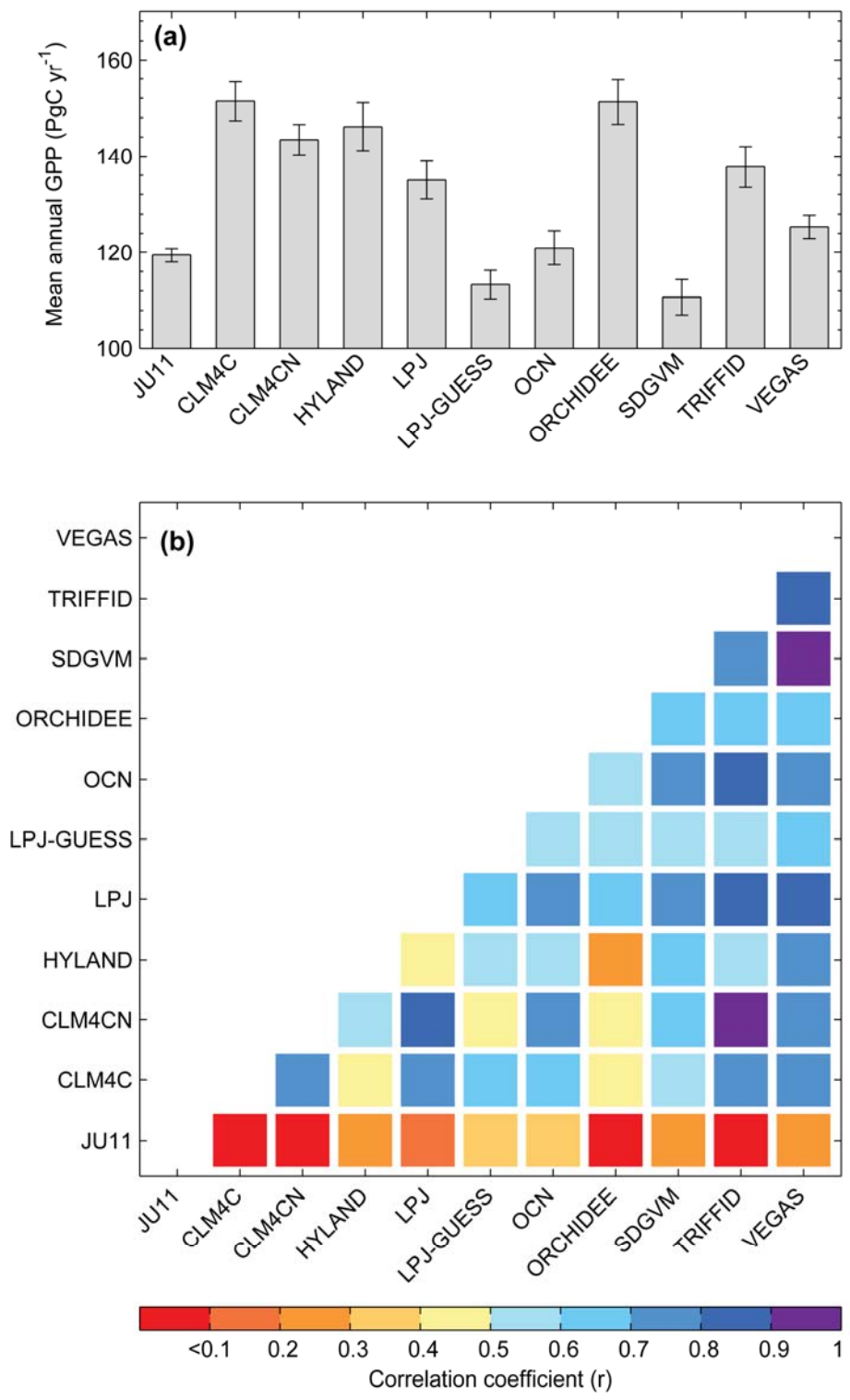
1 error of the β_{RLS} . Dashed error bars in both (a) and (b) indicate the estimated sensitivity from
2 the regression approaches are statistically insignificant ($P>0.05$). Model abbreviations are the
3 same as in Figure 1.

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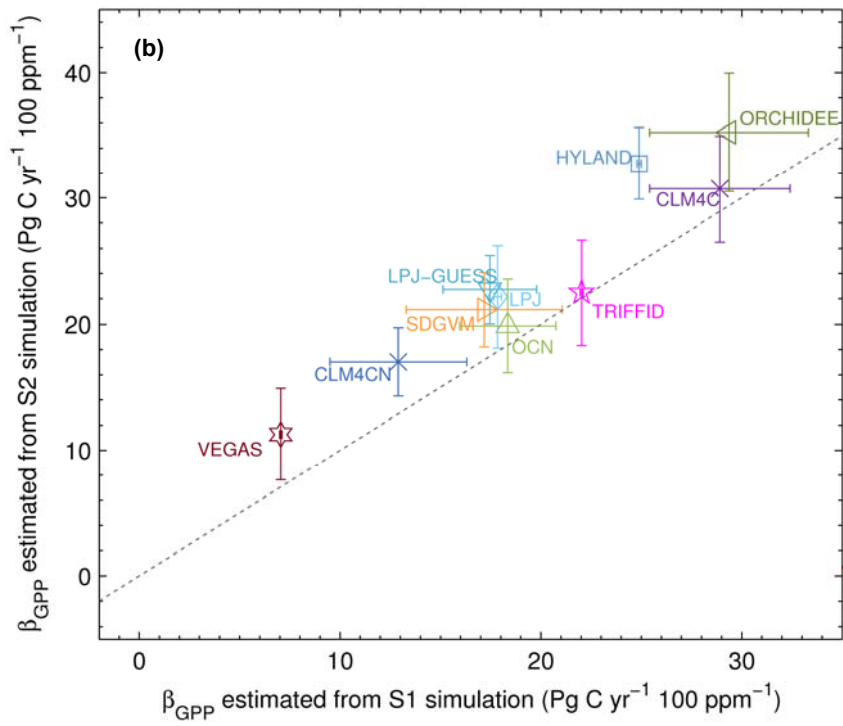
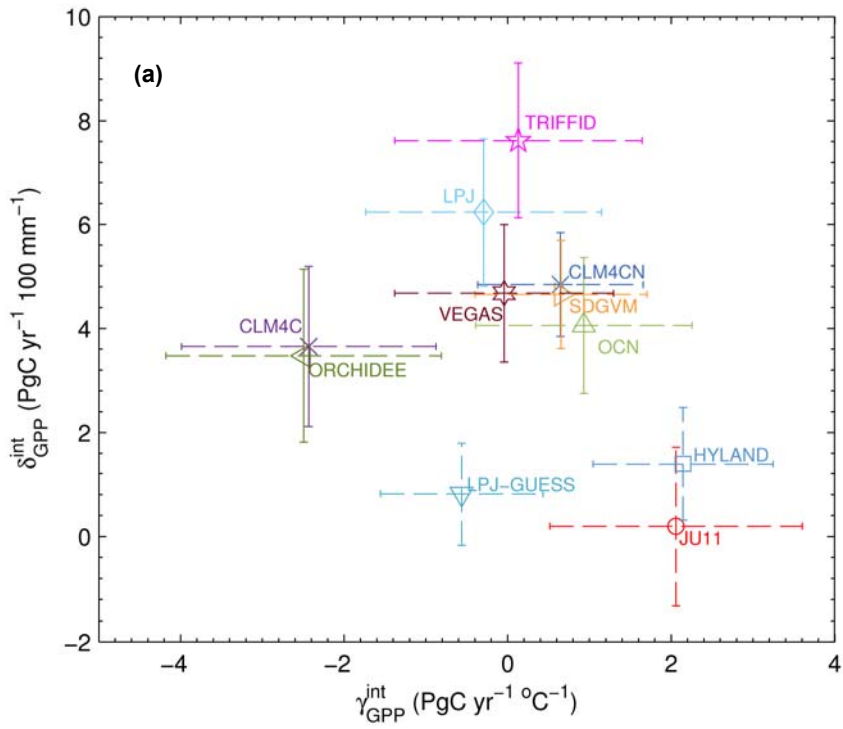
1 **Figure 1.**

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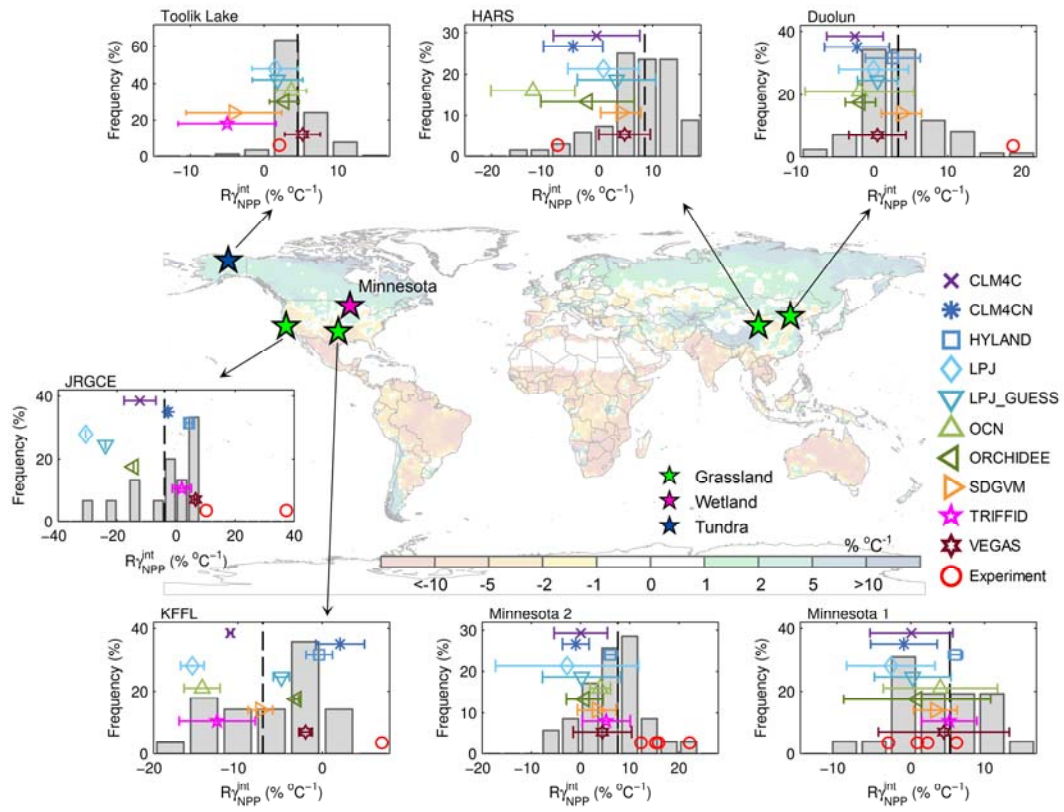
1 **Figure 2.**

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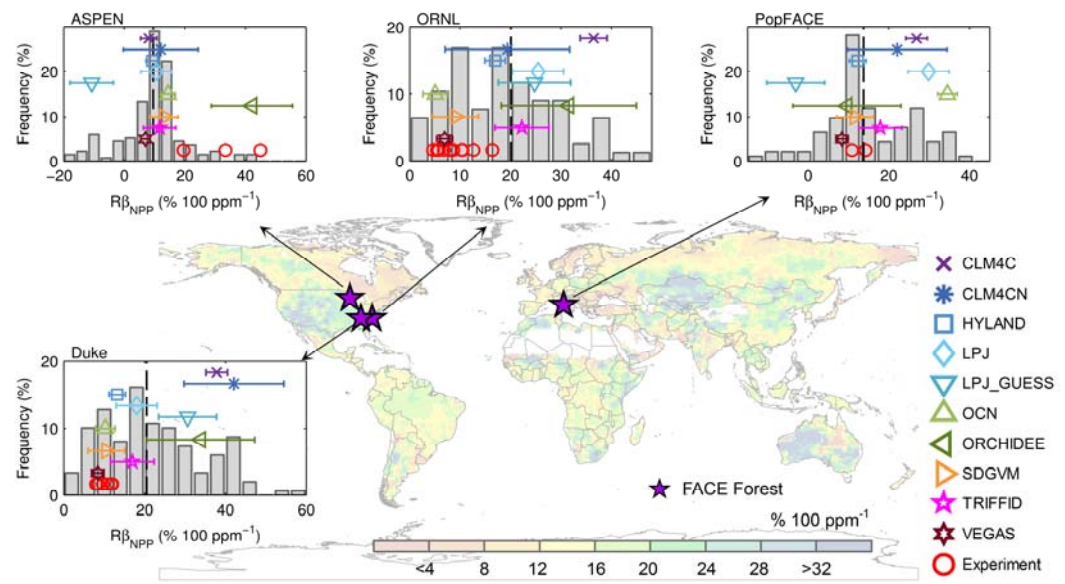
1 **Figure 3.**

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1 **Figure 4**

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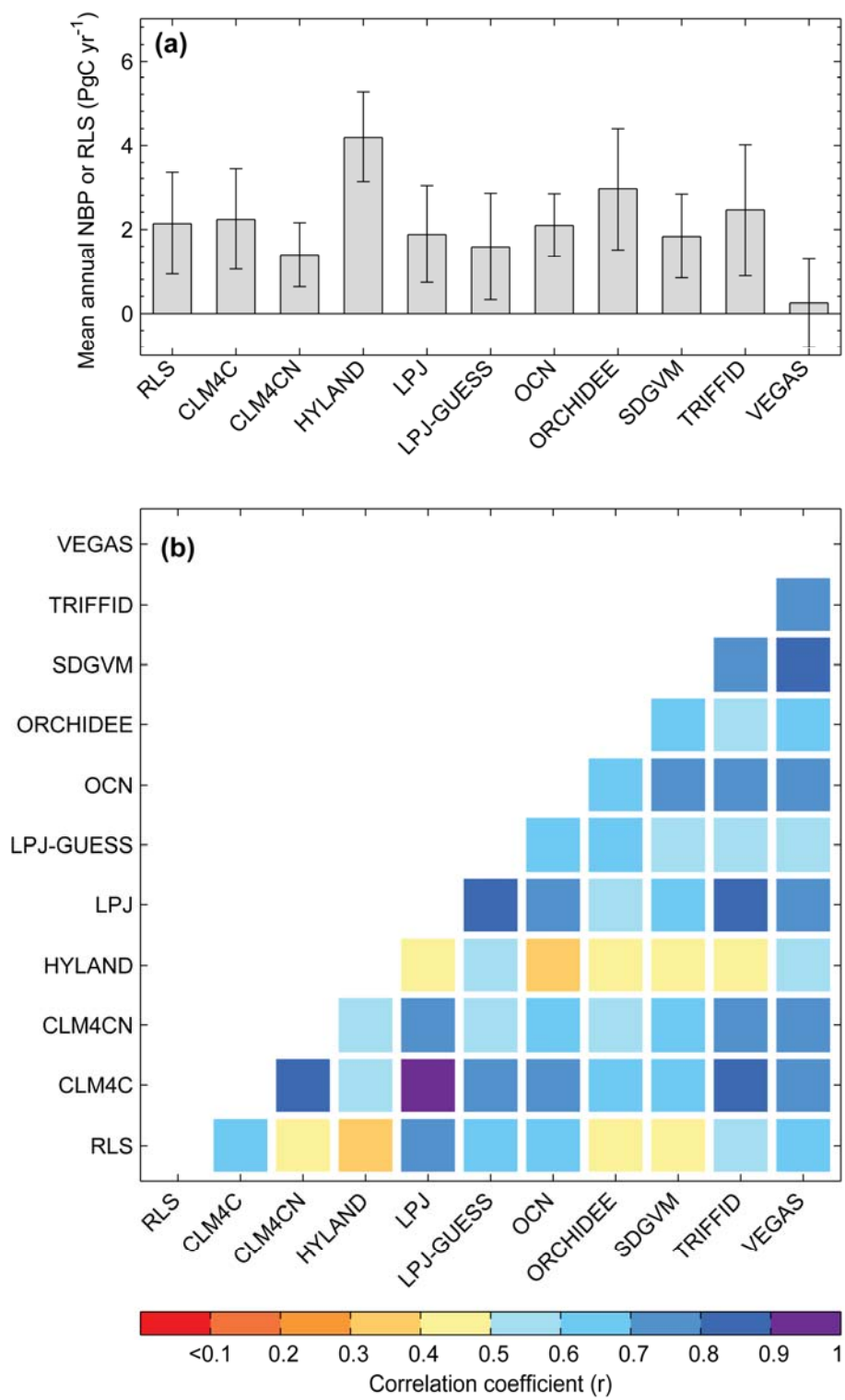


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1 **Figure 6**

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