



Supplement of

Impacts of land use change and elevated CO₂ on the interannual variations and seasonal cycles of gross primary productivity in China

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1 S1 Models and data

2 In this study, we used twelve terrestrial biosphere models (TBMs) that participated in the Multiscale Synthesis and Terrestrial Model Intercomparison Project (MsTMIP) (Huntzinger et al., 2013; 3 Wei et al., 2014a, 2014b) to investigate the effects of climate change, land use and land cover change 4 (LULCC), and rising CO2 concentration on the temporal changes in GPP. These models are 5 Community Land Model version 4 (CLM4; Shi et al., 2011; Mao et al., 2012), CLM4 with Variable 6 Infiltration Capacity Runoff Parameterization (CLM4VIC; Lei et al., 2014), Dynamic Land Ecosystem 7 8 Model (DLEM; Tian et al., 2011, 2012), Global Terrestrial Ecosystem Carbon model (GTEC; Ricciuto et al., 2011), Integrated Science Assessment Model (ISAM; Jain et al., 2013), Lund-Potsdam-Jena 9 10 Dynamic Global Vegetation Model, Swiss Federal Research Institute WSL modification (LPJ-wsl; Sitch et al., 2003), Organizing Carbon and Hydrology in Dynamic Ecosystems (ORCHIDEE-LSCE; 11 Krinner et al., 2005), Simple Biosphere version 3 by Jet Propulsion Laboratory (SiB3-JPL; Baker et 12 al., 2008), SiB3 with Carnegie-Ames-Stanford Approach (SiBCASA; Schaefer et al., 2008), 13 Terrestrial Ecosystem Model version 6 (TEM6; Hayes et al., 2011), Vegetation Global Atmosphere 14 and Soil version 2.1 (VEGAS2.1; Zeng et al., 2005), and Vegetation Integrative SImulator for Trace 15 gases (VISIT; Ito and Inatomi, 2012), respectively. They were all forced by the same climate drivers, 16 LULCC, and CO2 data. The climate forcing data set was generated by combining the Climate Research 17 Unit (CRU) data and the National Center for Environmental Prediction and National Center for 18 Atmospheric Research (NCEP/NCAR) Reanalysis product (hereafter CRU-NCEP). Time-series data 19 20 for atmospheric CO2 concentration derived from observations were applied to SG3, and other 21 simulations used constant CO2. A merged product derived from a static satellite-based land cover product, SYNergetic land cover MAP (SYNMAP) (Jung et al., 2006) and the time-varying land use 22 23 harmonization version 1 (LUH1) data (Hurtt et al., 2011) from the fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) were used to describe historical LULCC. 24

25 S2 Analysis methods

The nonparametric Mann-Kendall method was used to determine the statistical significance of trends in Chinese and regional GPP (area-weighted), where the Sen median slope (Sen, 1968) was considered as the trend value in this paper. Trend analysis was based on annual values averaged from monthly values. The first step was to test for statistical significance of trends by computing the Mann-Kendall statistic *S*. Each data value was compared with all subsequent data values as follows:

31 $S = \sum_{k=1}^{n-1} \sum_{i=k+1}^{n} sgn(GPP_i - GPP_k),$ (S1)

32
$$sgn(GPP_j - GPP_k) = \begin{cases} 1, GPP_j > GPP_k \\ 0, GPP_j = GPP_k \\ -1, GPP_j < GPP_k \end{cases}$$
 (S2)

where *n* is the length of the record for a given grid cell or region. The variance of S (Eq. (S3)) was then calculated to test for the presence of a statistically significant trend using the *Z*-value (Eq. (S4)):

35
$$var(S) = \frac{1}{18} [n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p-1)(2t_p+5)],$$
 (S3)
36 $Z = \begin{cases} \frac{S-1}{\sqrt{var(S)}}, S > 0\\ 0, S = 0\\ \frac{S+1}{\sqrt{var(S)}}, S < 0 \end{cases}$ (S4)

where *q* is the number of tied groups and t_p is the number of data values in the p^{th} group. The statistic Z was compared with a tolerable probability (the default significance level was set to 0.05 in this study). If a linear trend was statistically significant, then the change per unit time was estimated using a simple nonparametric procedure developed by Sen (1968):

41
$$b_{sen} = Median\left(\frac{GPP_j - GPP_k}{j-k}\right), j > k$$
 (S5)

42 If there were *n* values of GPP_j in the time series, as many as n(n-1)/2 slope estimates could be obtained, 43 and b_{sen} was taken as their median.

Each region's relative contribution to the interannual variation (IAV) and seasonal cycle amplitude (SCA) of China's GPP was also calculated based on the method proposed by Ahlström *et al.* (2015) and Chen *et al.* (2017). The regional contribution R_j (*j*=1,2, ...,9) to the IAV of China's GPP was calculated using the following equations:

$$f_i = \frac{\sum_t \frac{A_i x_{i,t} |X_t|}{X_t}}{\sum_t |X_t|},\tag{S6}$$

$$49 X_t = \sum_i A_i x_{i,t}, (S7)$$

48

where $x_{i,t}$ is the GPP anomaly for region *i* in year *t*, A_i is the area of region *i*, and X_t is the area-weighted 50 total GPP anomaly in the whole of China in year t. By this definition, f_i is the average relative area-51 weighted anomaly $A_{ix_{i,t}}/X_t$ for region *i*, weighted by the absolute regional area-weighted anomaly $|X_t|$. 52 f_i ranges from -1 to 1. Higher positive f_i indicates that IAV in the region varies in phase with integral 53 IAV and makes a larger contribution towards the IAV of China's GPP, whereas a smaller or negative 54 f_i represents the opposite. In the same way, the regional contribution to the seasonality of China's GPP 55 was calculated using Eq. (S6), in which $x_{i,t}$ is the monthly GPP departure from the annual mean 56 (seasonal anomaly) for region *i* in month *t* and X_t is the area-weighted total seasonal GPP anomaly for 57 all China in month *t*. 58



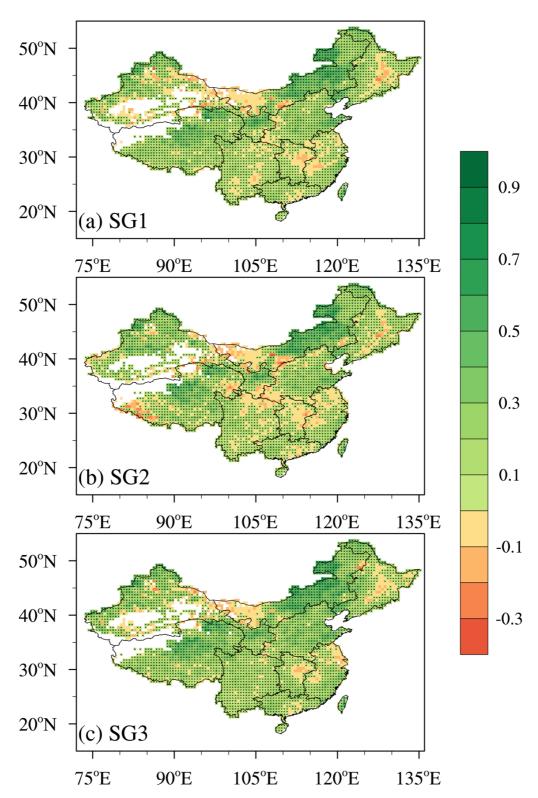


Figure S1. Spatial patterns of temporal correlation coefficients between annual GPP from MTE and that from ensemble mean of MsTMIP simulations for the period of 1982–2010, including: (a) SG1, (b)
5 SG2, and (c) SG3. Stippling highlights regions with significant correlations (p < 0.05).

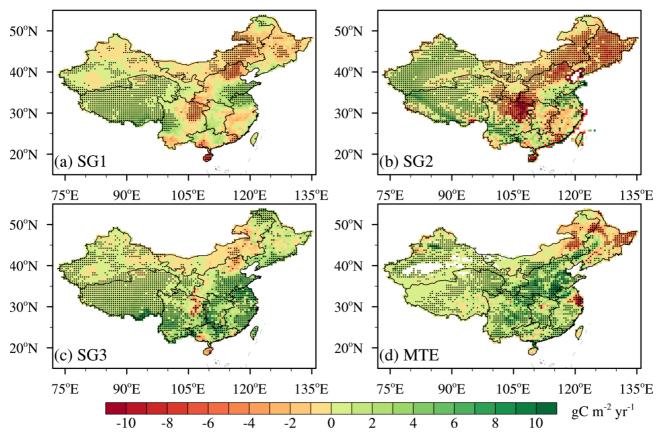


Figure S2. Trends in annual GPP between 1982 and 2010 from the ensemble mean of MsTMIP simulations: (a) SG1, (b) SG2, (c) SG3 and (d) MTE. Stippling highlights regions with significant trend (p < 0.05).

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