**Supplementary Information**

**Large Differences in Terrestrial Vegetation Production Derived from Satellite-Based Light Use Efficiency Models.**

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Wenwen Cai 1, Wenping Yuan 1,*, Shunlin Liang 2,3, Shuguang Liu 4, Wenjie Dong 1, Yang Chen 1, Dan Liu 1 and Haicheng Zhang 1

1 State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing 100875, China; E-Mails: caiwenwen@mail.bnu.edu.cn (W.C.); dongwj@bnu.edu.cn (W.D.); cheny0323@163.com (Y.C.); liu.dan@mail.bnu.edu.cn (D.L.); sysuzhaicheng@163.com (H.Z.)

2 State Key Laboratory of Remote Sensing Science, College of Global Change and Earth System Science, Beijing Normal University, Beijing 100875, China; E-Mail: sliang@umd.edu

3 Department of Geographical Sciences, University of Maryland, College Park, MD 20742, USA

4 Geospatial Science Center of Excellence, South Dakota State University, 1021 Medary Ave, Wecota Hall 115, Box 506B, Brookings, SD 57007, USA; E-Mail: shuguang.liu@yahoo.com

* Author to whom correspondence should be addressed; E-Mail: yuanwpcn@126.com; Tel.: +86-10-58-807-715; Fax: +86-10-58-803-002.

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**1. Abbreviations**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full name</th>
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<tbody>
<tr>
<td>LUE</td>
<td>Light Use Efficiency</td>
</tr>
<tr>
<td>GPP</td>
<td>Gross Primary Productivity</td>
</tr>
<tr>
<td>PAR</td>
<td>Photosynthetically Active Radiation</td>
</tr>
<tr>
<td>Rn</td>
<td>Net radiation</td>
</tr>
<tr>
<td>Ta</td>
<td>Average air temperature</td>
</tr>
<tr>
<td>T_{\text{min}}</td>
<td>Minimum air temperature</td>
</tr>
<tr>
<td>ET</td>
<td>Evapotranspiration</td>
</tr>
<tr>
<td>PET</td>
<td>Potential Evapotranspiration</td>
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Table S1. Cont.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full name</th>
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<tbody>
<tr>
<td>VPD</td>
<td>Vapor Pressure Deficit</td>
</tr>
<tr>
<td>LSWI</td>
<td>Land Surface Water Index</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>EVI</td>
<td>Enhanced Vegetation Index</td>
</tr>
<tr>
<td>FPAR</td>
<td>the Fraction of absorbed Photosynthetically Active Radiation</td>
</tr>
<tr>
<td>CASA</td>
<td>Carnegie–Ames–Stanford Approach [S1]</td>
</tr>
<tr>
<td>CFix</td>
<td>Carbon Fixation model [S2]</td>
</tr>
<tr>
<td>CFlux</td>
<td>Carbon Flux model [S3,S4]</td>
</tr>
<tr>
<td>EC-LUE</td>
<td>Eddy Covariance-Light Use Efficiency model [S5,S6]</td>
</tr>
<tr>
<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer GPP algorithm [S7]</td>
</tr>
<tr>
<td>VPM</td>
<td>Vegetation Photosynthesis Model [S8]</td>
</tr>
<tr>
<td>VPRM</td>
<td>Vegetation Photosynthesis and Respiration Model [S9]</td>
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</table>

2. LUE Models

2.1. Model Description and Equations

We used seven LUE models in the present study, including CASA, CFix, CFlux, EC-LUE, MODIS, VPM and VPRM models. The relative abbreviations were shown in the above Table S1. These models (Table S2) were briefly described below.

Table S2. Summary of the seven LUE models and input variables at global scale.

<table>
<thead>
<tr>
<th>LUE Models</th>
<th>Meteorology Data and Vegetation Indices Used in Each Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASA</td>
<td>PAR, Ta, ET, PET, NDVI</td>
</tr>
<tr>
<td>CFix</td>
<td>PAR, Ta, ET, PET, NDVI</td>
</tr>
<tr>
<td>CFlux</td>
<td>PAR, T\text{min}, VPD, ET, PET, Cloudiness, FPAR</td>
</tr>
<tr>
<td>EC-LUE</td>
<td>PAR, T\text{min}, ET, Rn, NDVI</td>
</tr>
<tr>
<td>MODIS</td>
<td>PAR, Ta, VPD, FPAR</td>
</tr>
<tr>
<td>VPRM</td>
<td>PAR, Ta, LSWI, EVI</td>
</tr>
</tbody>
</table>

3. CASA Model

CASA model runs on a monthly step to directly simulate vegetation net primary production, and GPP was obtained through an average ratio 0.5 of net primary production to GPP in this study [S10]. CASA converts the absorbed radiation to organic carbon through a globally universal potential LUE (LUE\text{max}) which is constrained by spatial- and temporally varied temperature and water. The complete expression of GPP estimation by CASA therefore is:

$$GPP = PAR \times FPAR \times LUE_{\text{max}} \times T_{s1} \times T_{s2} \times W_s \times 2$$  \hspace{1cm} (S1)

where T_{s1} and T_{s2} are two scalars for the effects of temperature on potential LUE, respectively. W_s is the scalar for the effect of moisture on LUE\text{max}. CASA utilizes remotely-sensed NDVI to quantify FPAR according to the linear relationship between FPAR and Simple Ratio (SR) vegetation index:
The temperature scalars $T_{s1}$ and $T_{s2}$ consider the limitation of extreme and sub-optimal temperature on vegetation photosynthesis, respectively. Potential LUE declines under very high or very low temperatures and also decreases when temperature is above or below the optimum temperature $T_{opt}$. $T_{opt}$ is defined as the air temperature in the month when NDVI reaches its maximum value for the whole year. The moisture scalar $W_s$ quantifies the limitation of soil water on vegetation photosynthesis. ET and PET are a practical choice used to calculate $W_s$. The three environmental stress scalars are formulated as:

$$T_{s1} = 0.8 + 0.02 \times T_{opt} - 0.0005 \times T_{opt}$$

$$T_{s2} = 1.1919 \left( \left( 1 + e^{0.2 \times (T_{opt} - 10 - T_a)} \right) / \left( 1 + e^{0.3 \times (T_{opt} + 10 + T_a)} \right) \right)$$

$$W_s = 0.5 + 0.5 \times \left( \frac{ET}{PET} \right)$$

4. CFix Model

CFix model is a daily Monteith type parametric model driven by air temperature, radiation, moisture and FPAR:

$$GPP = PAR \times FPAR \times \text{LUE}_w \times \rho(T_a) \times CO_{2} \text{fert}$$

where LUE$_w$ is the light use efficiency considering the effect of water on photosynthesis. The scalars $\rho(T_a)$ and CO$_2$fert models the dependency of GPP on air temperature and atmospheric CO$_2$ fertilization, respectively. Both are normalized to the range 0 and 1. The FPAR is quantified by a linear relationship which is insensitive to the pixel heterogeneity [S11]:

$$\text{FPAR} = 0.8642 \times \text{NDVI} - 0.0814$$

The temperature scalar $\rho(T_a)$ simulates the thermodynamic properties of the carboxylation/oxygenation reactions of Rubisco (photosynthesis) [S12]. The CO$_2$fert quantifies the increase in the proportion of carbon uptake by vegetation when CO$_2$ concentration rises above its atmospheric background level.

$$\rho(T_a) = e^{\left( C_i - \Delta H_a,p \right) / \left( R_g \times T_a \right)} \left( 1 + e^{\left( \Delta S \times T - \Delta H_d,p \right) / \left( R_g \times T_a \right)} \right)$$

$$CO_{2} \text{fert} = \frac{[CO_2] - \left( \frac{[O_2]}{2s} \right) K_m \times (1 + \frac{[O_2]}{K_0}) + [CO_2]^{ref}}{[CO_2]^{ref} - \left( \frac{[O_2]}{2s} \right) K_m \times (1 + \frac{[O_2]}{K_0}) + [CO_2]}$$

where $C_i$, $\Delta S$, $\Delta H_a,p$, $\Delta H_d,p$, $R_g$ at the temperature response equation $\rho(T_a)$ are 21.77, 704.98 J·K$^{-1}$·mol$^{-1}$, 52,750 J·mol$^{-1}$, 211,000 J·mol$^{-1}$, 8.31 J·K$^{-1}$·mol$^{-1}$ according to Verooustraete et al. [S2]; the parameter values of $s$, $K_m$, $K_0$, $[CO_2]^{ref}$ are 2550, 948, 30 and 281 ppm respectively. In this study, $[O_2]$ was set to 209,000 ppm, and $[CO_2]$ was set to be annual mean global carbon dioxide concentration using
measurements of weekly air samples from the Cooperative Global Air Sampling network (http://www.esrl.noaa.gov/gmd/ccgg/trends/global.html).

The \( LUE_w \) considers the effect of water availability especially water limitation on the process of photosynthesis [S13]. In the original CFix model, the water limited light use efficiency \( LUE_w \) is formulated based on soil and atmospheric moisture, since both affect water availability for photosynthesis. Considering the difficulty and large uncertainty in simulating soil moisture at large scale, we only adapted the impacts of atmospheric moisture on \( LUE_{\text{max}} \) in this study, and simplified the GPP dependency on water limitation as following:

\[
LUE_w = LUE_{\text{min}} + F_a \times (LUE_{\text{max}} - LUE_{\text{min}})
\]

where \( LUE_{\text{min}} \) and \( LUE_{\text{max}} \) are the minimum and maximum LUE, respectively. \( F_a \) is a coefficient adjusting the strength of water limitation.

5. CFix Model

The input variables of CFix model include daily meteorological data and satellite-derived information on land cover, stand age and FPAR [S3,S4]. The process of GPP estimation at a daily time step is realized by integrating the effects of daily minimum temperature, daytime average VPD, cloudiness, soil water status, and stand age on potential LUE, which are expressed as:

\[
GPP = \text{PAR} \times FPAR \times LUE_r
\]

\[
LUE_r = LUE_{\text{base}} \times S_{T_{\text{min}}} \times \min\{S_{\text{vpd}}, S_{\text{sw}}\} \times S_{\text{age}}
\]

\[
LUE_{\text{base}} = (LUE_{\text{max}} - LUE_{\text{cs}}) \times S_{\text{CI}} + LUE_{\text{cs}}
\]

where \( LUE_r \) is the realized light use efficiency, \( LUE_{\text{cs}} \) is the light use efficiency under clear sky condition. \( S_{\text{CI}} \) is the cloudiness scalar and cloudiness is determined by the ratio of incident PAR to potential PAR [S3]. The minimum temperature scalar \( S_{T_{\text{min}}} \) and daytime average VPD scalar \( S_{\text{vpd}} \) are adopted from the MODIS GPP algorithm. The scalar for the influence of soil water \( S_{\text{sw}} \) is based on the ratio of current soil water content to soil water holding capacity. When the ratio is above 0.5, \( S_{\text{sw}} \) is set to 1. When the ratio is below 0.5 there is a linear ramp from \( S_{\text{sw}} \) of 1 to \( S_{\text{sw}} \) of 0 as the ratio hits 0. We simplified the simulations of soil moisture and used evaporative fraction (EF) to indicate \( S_{\text{SW}} \). \( S_{\text{age}} \) is the stand age scalar, which is a unique feature of CFix model for forests, due to the reduced productivity observed in older stands. However, it is difficult to derive stand age information over large scale. The \( S_{\text{age}} \) scalar is therefore simplified to 1 when estimating GPP at global scale in our study.

6. EC-LUE Model

EC-LUE model is a light-use-efficiency daily GPP model based on eddy covariance measurements [S5]. It is driven by only four variables: NDVI, PAR, air temperature, and the Bowen ratio of sensible to latent heat flux. At large scale, Bowen ratio is substituted by the ratio of latent heat to net radiation [S6].

\[
GPP = \text{PAR} \times FPAR \times LUE_{\text{max}} \times \min(T_s, W_s)
\]

\[
FPAR = 1.24 \times NDVI - 0.618
\]
\[ T_s = \frac{(T_a - T_{\min}) \times (T_a - T_{\max})}{(T_a - T_{\min}) \times (T_a - T_{\max}) - (T_a - T_{\text{opt}})}^2 \]  

\[ W_s = \frac{LE}{R_n} \]

where \( T_s \) is the temperature scalar, quantified by daily air temperature combined with the minimum \( (T_{\min}) \), maximum \( (T_{\max}) \) and optimum \( (T_{\text{opt}}) \) air temperatures for photosynthesis. The calibrated values for \( T_{\min}, T_{\max}, \) and \( T_{\text{opt}} \) are 0, 40, 20.33 °C, respectively [S5]. If air temperature falls below \( T_{\min} \) or rises beyond \( T_{\max} \), \( T_s \) is set to 0. \( R_n \) is net radiation and the latent heat flux \( LE \) is estimated by the revised Remote Sensing–Penman Monteith model (the revised RS-PM) [S6]. The minimum value of \( T_s \) and \( W_s \) is employed to decline potential LUE, given the assumption that light use efficiency is only affected by the most limiting factor at any given time at location (Liebig’s Law).

7. MODIS GPP Algorithm

MODIS GPP algorithm integrates MODIS remote sensing products and DAO (NASA Data Assimilation Office) meteorological data to estimate global GPP based on Monteith’s LUE theory [S7]:

\[ GPP = PAR \times FPAR \times LUE_{\text{max}} \times T_s \times W_s \]  

\[ T_s = \begin{cases} 
0 & TMIN < TMIN_{\min} \\
\frac{TMIN - TMIN_{\min}}{TMIN_{\max} - TMIN_{\min}} & TMIN_{\min} < TMIN < TMIN_{\max} \\
1 & TMIN > TMIN_{\max} 
\end{cases} \]  

\[ W_s = \begin{cases} 
0 & VPD > VPD_{\max} \\
\frac{VPD_{\max} - VPD}{VPD_{\max} - VPD_{\min}} & VPD_{\min} < VPD < VPD_{\max} \\
1 & VPD < VPD_{\min} 
\end{cases} \]

where \( FPAR \) is the fraction of PAR absorbed by vegetation canopy, provided by MODIS land product MOD15A2. \( T_s \) is the attenuation scalar of daily minimum air temperature and it considers the reduction in the potential LUE due to stomata closure at cold night temperature. \( W_s \) is the attenuation scalar of the daytime average VPD which declines LUE_{\text{max}} through close stomata at very high VPD. \( LUE_{\text{max}} \) is used biome dependent values, which implies different photosynthetic ability among plant functional types.

8. VPM Model

VPM model is a satellite-based light use efficiency approach to estimate GPP based on conceptual partition of non-photosynthetically active vegetation and photosynthetically active vegetation within a canopy [S8]. The VPM model is realized as:

\[ GPP = PAR \times FPAR \times LUE_{\text{max}} \times T_s \times W_s \times P_s \]
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temperature, water, and leaf phenology. The temperature scalar $T_s$ is estimated at each time step, using the equation developed for the Terrestrial Ecosystem Model (Equation (18)) [S14]. The effect of water on plant photosynthesis $W_s$ uses a satellite-derived water index LSWI to estimate the seasonal dynamics of water availability:

$$W_s = \frac{1 + LSWI}{1 + LSWI_{\text{max}}}$$

(S23)

$$LSWI_{\text{max}} = \frac{\rho_{\text{NIR}} - \rho_{\text{SWIR}}}{\rho_{\text{NIR}} + \rho_{\text{SWIR}}}$$

(S24)

where $\rho_{\text{NIR}}$ and $\rho_{\text{SWIR}}$ is the surface reflectance at the near-infrared and shortwave band, respectively. MODIS surface reflectance product (MOD09A1) can be used to derive LSWI. $LSWI_{\text{max}}$ is the maximum LSWI within the plant growing season. When multi-year LSWI data are available, the mean LSWI values over multiple years at individual temporal points (daily, weekly or 10-day) are calculated, and then the maximum LSWI value within the photosynthetically active period is selected as $LSWI_{\text{max}}$.

In the VPM model, $P_s$ is used to account for the effect of leaf age on photosynthesis at canopy level, but it is set to be dependent only on life expectancy of leaves. The calculation of $P_s$ is therefor only for a canopy that is dominated by leaves with a life expectancy of 1 year (one growing season). During the period of bud burst to leaf full expansion and during the time of leaf full expansion to senescence, $P_s$ is formulated as:

$$P_s = \frac{1 + LSWI}{2}$$

(S25)

The dates for the three phases of phenology (bud burst, full canopy, and senescence) were obtained using an EVI seasonal threshold similar to that of the MODIS phenology product (MOD12Q2) [S15]. Thus for large-scale application of VPM model, MODIS phenology can be used directly.

9. VPRM Model

VPRM model is a satellite-based carbon assimilation LUE model to estimate GPP using meteorological data and satellite-derived EVI and LSWI data [S9]. The VPRM is developed from VPM model by adding a nonlinear radiation dependency of the potential LUE:

$$GPP = PAR \times FPAR \times \frac{1}{(1 + PAR/\text{PAR}_0)} \times LUE_{\text{max}} \times T_s \times W_s \times P_s$$

(S26)

where $\text{PAR}_0$ is the half-saturation value.

10. Model Parameterization

Fifty percent of the 157 FLUXNET sites were randomly selected to calibrate model parameters and the remaining sites were used to validate models. This parameterization process was repeated until all possible combinations of the 50% sites were achieved. We then simulated global terrestrial GPP using the seven LUE models each with the mean values of the calibrated parameters and global input variables described in Section 2.2 in the main text. The sites information was listed in Yuan et al. [S16].
**Figure S1.** Distribution of climatic constraints to GPP estimated by CASA model (a). Spatial patterns of correlation of annual PAR (b); annual mean temperature (c); and annual ET (d) with annual GPP; (a) is transformed from (b) to (d). The later three data are linearly stretched between 0 and 255, and assigned to Green (radiation (b)), Blue (temperature (c)) and Red (water (d)) for RGB display in (a). The interactions of the three primary color produce: Cyan (temperature and radiation), Magenta (water and temperature) and Yellow (water and radiation).

![Figure S1](image1.png)

**Figure S2.** Distribution of climatic constraints to GPP estimated by CFix model (a). Spatial patterns of correlation of annual PAR (b); annual mean temperature (c); and annual ET (d) with annual GPP; (a) is transformed from (b) to (d). The later three data are linearly stretched between 0 and 255, and assigned to Green (radiation (b)), Blue (temperature (c)) and Red (water (d)) for RGB display in (a). The interactions of the three primary color produce: Cyan (temperature and radiation), Magenta (water and temperature) and Yellow (water and radiation).

![Figure S2](image2.png)
**Figure S3.** Distribution of climatic constraints to GPP estimated by CFlux model (a). Spatial patterns of correlation of annual PAR (b); annual mean temperature (c); and annual ET (d) with annual GPP. (a) is transformed from (b) to (d). The later three data are linearly stretched between 0 and 255, and assigned to Green (radiation (b)), Blue (temperature (c)) and Red (water (d)) for RGB display in (a). The interactions of the three primary color produce: Cyan (temperature and radiation), Magenta (water and temperature) and Yellow (water and radiation).

**Figure S4.** Distribution of climatic constraints to GPP estimated by EC-LUE model (a). Spatial patterns of correlation of annual PAR (b); annual mean temperature (c); and annual ET (d) with annual GPP. (a) is transformed from (b) to (d). The later three data are linearly stretched between 0 and 255, and assigned to Green (radiation (b)), Blue (temperature (c)) and Red (water (d)) for RGB display in (a). The interactions of the three primary color produce: Cyan (temperature and radiation), Magenta (water and temperature) and Yellow (water and radiation).
Figure S5. Distribution of climatic constraints to GPP estimated by MODIS model (a). Spatial patterns of correlation of annual PAR (b), annual mean temperature (c); and annual ET (d) with annual GPP. (a) is transformed from (b) to (d). The latter three data are linearly stretched between 0 and 255, and assigned to Green (radiation (b)), Blue (temperature (c)) and Red (water (d)) for RGB display in (a). The interactions of the three primary color produce: Cyan (temperature and radiation), Magenta (water and temperature) and Yellow (water and radiation).

Figure S6. Distribution of climatic constraints to GPP estimated by VPM model (a). Spatial patterns of correlation of annual PAR (b), annual mean temperature (c), and annual ET (d) with annual GPP. (a) is transformed from (b) to (d). The latter three data are linearly stretched between 0 and 255, and assigned to Green (radiation (b)), Blue (temperature (c)) and Red (water (d)) for RGB display in (a). The interactions of the three primary color produce: Cyan (temperature and radiation), Magenta (water and temperature) and Yellow (water and radiation).
Figure S7. Distribution of climatic constraints to GPP estimated by VPRM model (a). Spatial patterns of correlation of annual PAR (b), annual mean temperature (c), and annual ET (d) with annual GPP. (a) is transformed from (b) to (d). The later three data are linearly stretched between 0 and 255, and assigned to Green (radiation (b)), Blue (temperature (c)) and Red (water (d)) for RGB display in (a). The interactions of the three primary color produce: Cyan (temperature and radiation), Magenta (water and temperature) and Yellow (water and radiation).

Figure S8. Biomes distribution derived from MODIS land cover product (MCD12Q1). ENF: evergreen needleleaf forest, EBF: evergreen broadleaf forest, DNF: deciduous needleleaf forest, DBF: deciduous broadleaf forest, MIF: mixed forest, SHR: shrubland, SAV: savanna, GRA: grassland, CRO: cropland, DES is no vegetation area.
References


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