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Title: Improved estimate of global gross primary production for reproducing its long-term variation, 1982–2017

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MS Type: Data description paper

Dear editor and reviewer,

We are very grateful to your great efforts and constructive comments on our manuscript "Improved estimate of global gross primary production for reproducing its long-term variation, 1982–2017" (**MS No.:** essd-2019-126). The comments have helped improve the paper quite tremendously. We have carefully studied these comments and substantially revised our manuscript accordingly.

Here are our detailed responses to the comments point by point. Please note that the comments from the reviewer are in **bold** followed by our responses in regular text. The changes in our manuscript are underlined with red.

Please contact us if further materials or information are required. We deeply appreciate your consideration of our manuscript.

Sincerely,

Yi Zheng, Wenping Yuan, on behalf of all co-authors

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Response to Reviewer #1:

1. LUE model is an important empirical model for estimating GPP. The authors added the impacts of CO_2 concentration, diffuse/direct PAR, and VPD to the traditional LUE model, which showed improvement.

Response: Thanks for your positive comments. We have revised the manuscript according to your comments point by point below.

2. Line 18-35 In the abstract section, it is necessary to present some quantitative results that can directly prove the improvement of the revised EC-LUE model over other currently popular models.

Response: As your suggestion, we adjusted and added more quantitative results to show the improvement of the revised EC-LUE model in the abstract section. The following is the revised abstract and the newly added sentences are underlined with red.

"Abstract. Satellite-based models have been widely used to simulate vegetation gross primary production (GPP) at the site, regional, or global scales in recent years. However, accurately reproducing the interannual variations in GPP remains a major challenge, and the long-term changes in GPP remain highly uncertain. In this study, we generated a long-term global GPP dataset at 0.05° latitude by 0.05° longitude and 8-day interval by revising a light use efficiency model (i.e. EC-LUE model). In the revised EC-LUE model, we integrated the regulations of several major environmental variables: atmospheric CO_2 concentration, radiation components, and atmospheric vapor pressure deficit (VPD). These environmental variables showed substantial long-term changes, which could greatly impact the global vegetation productivity. Eddy covariance (EC) measurements at 95 towers from the FLUXNET2015 dataset, covering nine major ecosystem types around the globe, were used to calibrate and validate the model. In general, the revised EC-LUE model could effectively reproduce the spatial, seasonal, and annual variations in the tower estimated GPP at most sites. The revised EC-LUE model could explain 71% of the spatial variations in annual GPP over 95 sites. At more than 95% of the sites, the correlation coefficients (R^2) of seasonal changes between tower estimated and model simulated GPP are larger than 0.5. Particularly, the revised EC-LUE model improved the model performance in reproducing the interannual variations in GPP, and the averaged R^2 between annual mean tower estimated and model simulated GPP is 0.44 over all 55 sites with observations longer than 5-years, which is significantly higher than those of original EC-LUE model (R^2 = 0.36) and other LUE models (R^2 ranged from 0.06 to 0.30 with an average value of 0.16). At the global scale, GPP derived from light use efficiency models, machine learning models, and process-based biophysical models exist substantial differences in magnitude and interannual variations. The revised EC-LUE model quantified the mean global GPP from 1982 to 2017 as 106.2 ± 2.9 Pg C yr^{-1} with the trend 0.15 Pg C yr^{-1}. Sensitivity analysis indicated that GPP simulated by the revised EC-LUE model was sensitive to VPD, radiation, and CO_2 concentration. Over the period of 1982–2017, the CO_2 fertilization effect on the global GPP (0.14 ± 0.001 Pg C yr^{-1}) could be offset by the effect of increased VPD (−0.16 ± 0.02 Pg C yr^{-1}). The long-term changes in the environmental variables could be well reflected in global GPP. Overall, the revised EC-LUE model is able to provide a reliable long-term estimate of global GPP. The GPP dataset is available at https://doi.org/10.6084/m9.figshare.8942336 (Zheng et al., 2019)." (Line 18-40 in the revised manuscript)

3. Line 31-32 "The global GPP derived from different datasets exist substantial uncertainty in magnitude and interannual variations." Which datasets and which models were used here? Do the

authors mean different datasets used to drive the revised EC-LUE model? Or other models?

Response: We mean different GPP datasets simulated by other models in different studies. We modified the sentence as follow:

"At the global scale, GPP derived from light use efficiency models, machine learning models, and process-based biophysical models exist substantial differences in magnitude and interannual variations." (Line 33-34 in the revised manuscript)

4. Line 48 Do the authors mean process based ecosystem models by biophysical models? And empirical or data-driven models by satellite-based models?

Line 48: Similarly, a model comparison showed that none of the examined 16 biophysical models nor the 3 satellite-based models could consistently reproduce the observed interannual variations in carbon exchange at 11 forest sites in North America (Keenan et al., 2012).

Response: This sentence cited the results of Keenan et al., 2012, which includes 16 process-based biophysical models (i.e., BEPS, BIOME-BGC, Can-IBIS, CNCLASS, DLEM, ECOSYS, ED2, EDCM, ISAM, LoTEC-DA, LPJml, ORCHIDEE, SiB, SiB-CASA, SSiB2, and TECO) and 3 satellite-based model dataset (i.e., BESS, MODIS C5, and MODIS C5.1). BESS (Breathing Earth System Simulator) is a process-based model, and uses satellite-based leaf area index as driver. MODIS C5 and MODIS C5.1 indicate two MODIS-GPP products, and are based on MODIS-GPP algorithm which is satellite-based light use efficiency model. We changed the original sentences to make it clear:

"Similarly, a model comparison showed that none of the examined 16 process-based biophysical models or the 3 remote sensing products (BESS, MODIS C5, and MODIS C5.1) could consistently reproduce the observed interannual variations in GPP at 11 forest sites in North America (Keenan et al., 2012)." (Line 51-53 in the revised manuscript)

5. Line 50 The starting and ending years could be given while reporting a trend.

Line 50: Seven LUE models simulated the long-term trends of global GPP varied −0.15 to 1.09 Pg C yr^{-1} (Cai et al., 2014).

Response: Thanks for your advice. We added starting and ending years as follow:

"Seven LUE models simulated the long-term trends of global GPP varied from −0.15 to 1.09 Pg C yr^{-1} over the period 2000–2010 (Cai et al., 2014)." (Line 53-54 in the revised manuscript)

6. Line 70-90 (Major concern) The ratio of diffuse PAR is of course an important regulator of LUE for dense canopy. However, the amount of total PAR should not be ignored. LUE could rapidly decrease with the amount of total PAR because in clear sky the incident PAR could easily exceed light saturation point.

Response: Thanks for your deep thoughts. It is indeed that light saturation is an important response of GPP to varying PAR. The instantaneous LUE decreases rapidly when PAR exceed light saturation point. This is an instantaneous phenomenon which is obvious and nonnegligible at the hourly scale. The revised EC-LUE model was developed at the 8-day scale, and the light saturation can hardly be observed for the accumulation of GPP from hourly to 8-day temporal scale.

As an example, we examined the relation between GPP and PAR at hourly and 8-day scale at US-Ha1 site, respectively (Fig. R1). At hourly scale, there are obvious light saturation phenomenon when PAR exceeds 200 W m^{-2} (Fig. R1a). However, at 8-day scale, the "ratio between GPP and LAI" (named GPP/LAI hereafter) keep increasing when PAR around its maximum value at 120 W m^{-2} (Fig. R1b).

Some low GPP/LAI values may introduced by unfavorable climate conditions (e.g., low temperature or high VPD) or the uncertainty/error of the EC measurements. So we did not integrate the light saturation phenomenon in our current model.

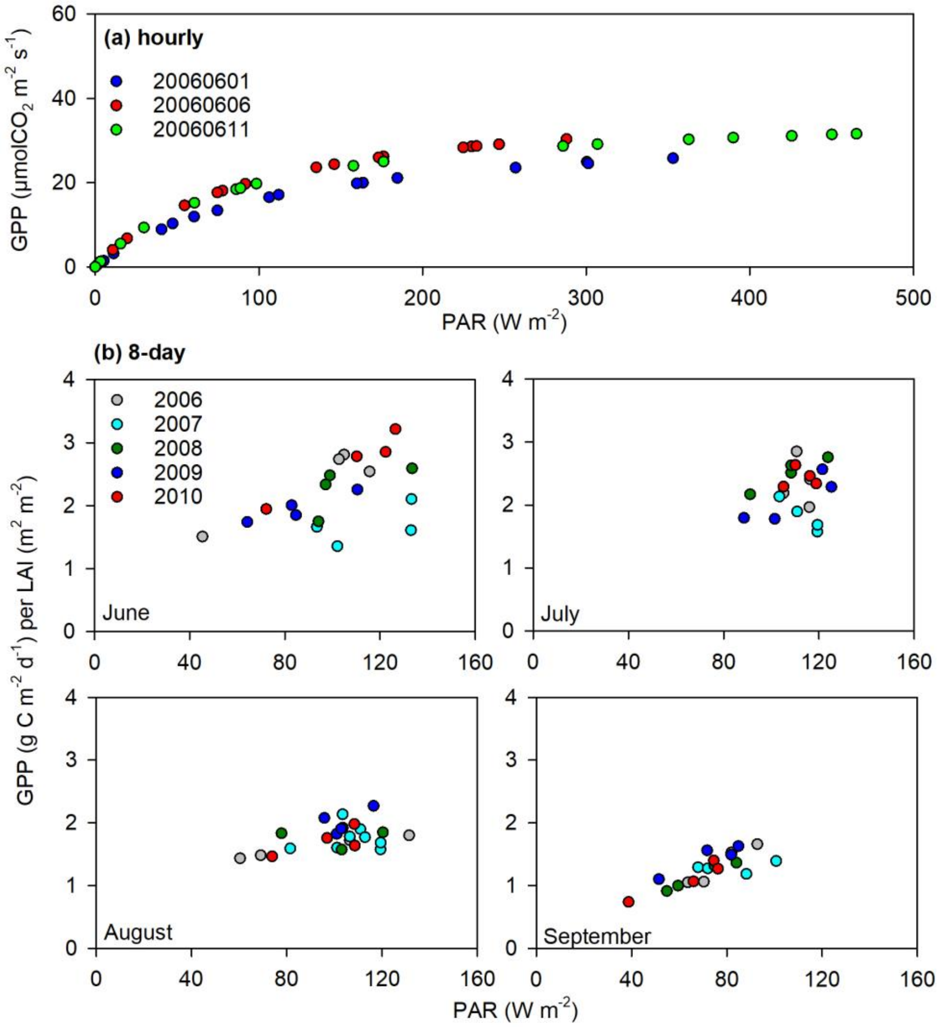

Figure R1: Correlations of GPP and PAR at hourly and 8-day scale, taking US-Ha1 site as an example. At 8-day scale, we used the ratio between GPP and LAI to eliminate the influence of season patterns of LAI on GPP.

7. Section 2.1 At which temporal and spatial resolutions were the model run? And some the variables in the equations were not explained, e.g. epsilon in eq 4. Line 113 intercellular [CO2]? Line 114 add concentration after the second CO_2. How was 356.51 in eq 5 determined?

Line 113-123: where φ is the CO_2 compensation point in the absence of dark respiration (ppm); C_i is the leaf internal CO_2 concentration; C_a is the atmospheric CO_2 concentration; χ is the ratio of leaf internal to atmospheric CO_2 which can be estimated as follows (Prentice et al., 2014; Keenan et al., 2016):

$$\chi = \frac{\varepsilon}{\varepsilon + \sqrt{VPD}} \quad (4)$$

$$\varepsilon = \sqrt{\frac{356.51K}{1.6\eta^*}} \quad (5)$$

$$K = K_c\left(1 + \frac{P_0}{K_0}\right) \quad (6)$$

$$\mathbf{K_c = 39.97 \times e^{\frac{79.43\times(T-298.15)}{298.15RT}}} \quad \textbf{(7)}$$

$$\mathbf{K_o = 27480 \times e^{\frac{36.38\times(T-298.15)}{298.15RT}}} \quad \textbf{(8)}$$

where K_c and K_o are the Michaelis–Menten constants for CO_2 and O_2; P_o is the partial pressure of O_2; Ta is air temperature (K); η^* is the viscosity of water relative to its value at 25 ℃ depending on the air temperature (Korson et al., 1969); R is the molar gas constant (8.314 J mol^{-1} K^{-1}).

Response: The model was run at 8-day temporal resolution and 0.05 °×0.05 °spatial resolution. We added the information in the method section 2.4 (in the revised manuscript):

"Using the averaged value of the optimized parameters (Table 3), a global GPP dataset at 0.05 °×0.05 °spatial resolution and 8-day temporal resolution over 1982-2017 was produced." (Line 207-208 in the revised manuscript)

About the Eqs. (4)-(8) (in the original manuscript), we referred from Prentice et al. (2014) and Keenan et al. (2016). ε in Eq (4) is a parameter related to the 'carbon cost of water', which means the sensitivity of VPD to χ. We added the explanation of ε in the revised manuscript.

The 356.51 in Eq. (5) can be estimated using Eq (4)-(8) assuming the value of ε at 25°C as 0.8 (T=298.15 K; VPD=1 kPa) described in Keenan et al. (2016), and we cited this paper.

In line 113 (in the original manuscript), we think the "leaf internal CO_2" and "intercellular CO_2" have a same meaning, so both are OK.

According to the response above, we modified this part as following:

"The effect of atmospheric CO_2 concentration on GPP is determined by the following equations (Farquhar et al., 1980; Collatz et al., 1991):

$$C_s = \frac{C_i - \varphi}{C_i + 2\varphi} \quad (5)$$

$$C_i = C_a \times \chi \quad (6)$$

where φ is the CO_2 compensation point in the absence of dark respiration (ppm); C_i is the leaf internal CO_2 concentration; C_a is the atmospheric CO_2 concentration; χ is the ratio of leaf internal to atmospheric CO_2 concentration which can be estimated as follows (Prentice et al., 2014; Keenan et al., 2016):

$$\chi = \frac{\varepsilon}{\varepsilon + \sqrt{VPD}} \quad (7)$$

$$\varepsilon = \sqrt{\frac{356.51K}{1.6\eta^*}} \quad (8)$$

where ε is a parameter related to the 'carbon cost of water', which means the sensitivity of VPD to χ; K is the Michaelis–Menten coefficient of Rubisco; η^* is the viscosity of water relative to its value at 25 ℃ (Korson et al., 1969).

$$K = K_c\left(1 + \frac{P_o}{K_o}\right) \quad (9)$$

where P_o is the partial pressure of O_2; K_c and K_o are the Michaelis–Menten constants for CO_2 and O_2 (Keenan et al., 2016):

$$K_c = 39.97 \times e^{\frac{79.43\times(T_a-298.15)}{298.15\times R\times T_a}} \quad (10)$$

$$K_o = 27480 \times e^{\frac{36.38\times(T_a-298.15)}{298.15\times R\times T_a}} \quad (11)$$

where T_a is air temperature (unit: K); R is the molar gas constant (8.314 J mol^{-1} K^{-1}).” (Line 155-170 in the revised manuscript)

8. Line 145-155 The fluxnet GPP contains many datasets of GPP according to the reference CO_2 profile between sensor and canopy. Which dataset was used? And what is the temporal resolution of GPP, 30-min, daily, or 8-day?

Response: In the FLUXNET2015 dataset, GPP was calculated considering flux portioning methods and friction velocity (USTAR) threshold. In our manuscript, we used the GPP variable GPP_NT_VUT_REF at daily temporal resolution in the FLUXNET2015 dataset. And, to match the temporal resolution of the remotely sensed LAI, we aggregated the daily GPP to 8-day temporal resolution. We modified the corresponding part to:

“The FLUXNET2015 dataset (http://www.fluxdata.org) includes over 200 variables of carbon fluxes, energy fluxes, and meteorological variables collected and processed at sites by the FLUXNET community. In our study, ninety-five EC sites in FLUXNET2015 dataset were utilized to optimize the parameters and evaluate the performance of the revised EC-LUE model, including nine major terrestrial ecosystem vegetation types (Table 1): evergreen broadleaf forests (EBF), evergreen needleleaf forests (ENF), deciduous broadleaf forests (DBF), mixed forests (MF), grasslands (GRA), savannas (SAV), shrubland (SHR), wetlands (WET), and croplands (CRO). More information about the characteristics of these sites can be referred to the FLUXNET website. For each site, the daily GPP, PAR, air temperature (Ta), and VPD were used in our study. The GPP variable (GPP_NT_VUT_REF) used in this study was estimated from night-time partitioning method. The corresponding net ecosystem exchange (NEE) was generated using friction velocity (USTAR) threshold for each year (VUT), in which 40 versions of NEE were created by using different percentiles of USTAR thresholds. The model efficiency between each version and the others 39 versions were calculated to test their similarities and the reference (REF) NEE was selected as the one with higher model efficiency sum (the most similar to the others 39). The daily meteorological variables were gap-filled or downscaled from the ERA-interim reanalysis dataset in both space and time (Vuichard and Papale, 2015). The gap-filled technique of the carbon flux measurements and meteorological variables is the marginal distribution sampling (MDS) method described in Reichstein et al. (2005). For each variable, we aggregated the daily values to 8-day time step. Only the 8-day measurements with more than 5-day valid values were used” (Line 108-123 in the revised manuscript)

9. Line 164 Daily mean air temperature?

Line164-165: In our study, we obtained the daily air temperature (Ta, ℃), dew point temperature (Td, ℃), direct PAR, and diffuse PAR at 0.625° in longitude by 0.5° in latitude from 1982 to 2017.

Response: Yes, modified.

“In our study, we obtained the daily mean air temperature (Ta, °C), mean dew point temperature (Td, °C), total PAR (PAR_{dr}, MJ m^{-2} d^{-1}), and total diffuse PAR (PAR_{df}, MJ m^{-2} d^{-1}) at 0.625 ° in longitude by 0.5 °in latitude from 1982 to 2017.” (Line130-132 in the revised manuscript)

10. Line 203-207 Those lines should go to method section.

Line 203-207: This study used EC measurements at 42 sites to calibrate the parameter values and 43 sites to validate the model accuracy of the revised EC-LUE model. The parameters (ε_{msu}, ε_{msh},

φ, and VPD_0) of each vegetation type are shown in Table 3. We evaluated the model performance by using the tower-derived meteorology data and global reanalysis meteorology, respectively. In general, the revised EC-LUE model could effectively reproduce the spatial, seasonal, and annual variations in the tower-estimated GPP at most of the calibration and validation sites (Figs. 1–4).

Response: Yes, we agree that the contents about "calibration and validation" and "parameters" in these lines should be moved to method section. According to the suggestion of the second reviewer, we have used cross-validation method to estimate model parameters, and we rewrite this part and put them into method section "section 2.4 Model calibration and validation":

"Cross-validation method was used to calibrate and validate the revised EC-LUE model. Fifty percent of the sites were randomly selected to calibrate model parameters for each vegetation type, and the remaining 50% of the sites were used to validate the model. This parameterization process was repeated until all possible combinations of 50% sites were achieved for each vegetation type. The nonlinear regression procedure (Proc NLIN) in the Statistical Analysis System (SAS, SAS Institute Inc., Cary, NC, USA) was applied to optimize the model parameters (ε_{msu}, ε_{msh}, φ, and VPD_0) using 8-day estimated GPP based on EC measurements. The mean GPP simulations of 8-day from all validation runs only were used to model validation. Mean calibrated parameter values from all model runs were used to simulate GPP over the global scale (Table 3)." (Line 189-195 in the revised manuscript)

After consideration, we keep the result contents in these lines "In general, the revised EC-LUE model could effectively reproduce the spatial, seasonal, and annual variations in the tower-estimated GPP at most of the calibration and validation sites (Figs. 1–3)." in "section 3.1 Model performance".

11. Figure 4 (Major concern) Fig 4 could be expanded to better compare the performance of the revised EC-LUE model with other models in capturing the inter-annual and intraannual GPP variations, to show the improvement of the revised EC-LUE model. This is important because there are a number of the existing models (process-based and the empirical LUE models as well the machine learning method). While the results about spatial and temporal variations of the GPP (from the new model and other models) should be compressed or even dropped.

Response: Thank you. The main objective of our manuscript is focused on the improvement of the LUE models and produced a long-term GPP dataset. So, we compare the interannual variations of the revised EC-LUE model with other LUE models (CASA, CFix, CFlux, MODIS, VPM, VPRM, and the original EC-LUE model) as shown in Fig. 4. It is a good idea to compare with other kind models (process-based models and machine learning methods). However, we really appreciate the understanding that this comparison is quite beyond the field of this study. Moreover, due to large data gaps of measurements derived from eddy covariance towers, we need run process-based models at eddy covariance towers and obtain the corresponding simulations with observations of GPP in order to evaluate the model performance. This work needs contributions of model PIs, and which probably need take long time and great efforts. In addition, previous studies have provided the insights on this issue. Keenan et al. (2012) compared the performance of 16 process-based biophysical models and 3 satellite-based models (including the MODIS product) in reproducing the interannual variations in GPP. The result indicated the MODIS model performance was comparable to the process-based biophysical models. In our manuscript, the revised EC-LUE model (averaged R^2 = 0.44) was significantly better than the MODIS model (averaged R^2 = 0.17) at interannual scale. Therefore, we can conclude the similar result that our model was better than the process-based biophysical models compared in Keenan et al. (2012).

We rearranged the figures, Fig. 3 in the revised manuscript is the original Fig. 4.

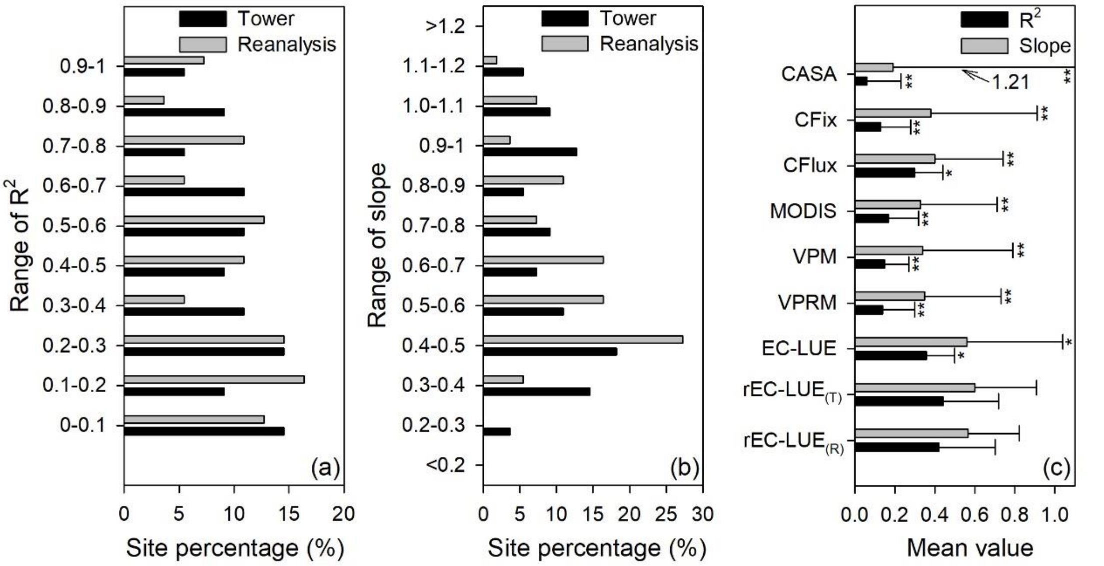

Figure 3: Site percentage of (a) correlation coefficients (R^2), and (b) regression slopes between the model simulated and tower-based interannual variabilities in GPP. (c) Averaged values (error bars represent the standard deviations) of R^2 and slope for various LUE models. rEC-LUE$_{(T)}$ and rEC-LUE$_{(R)}$ indicate the revised EC-LUE models derived from tower-derived meteorology data and meteorological reanalysis dataset. The R^2 and slopes of the other seven LUE models (i.e., EC-LUE, VPRM, VPM, MODIS, CFlux, CFix, and CASA) in the figure were obtained from the study by Yuan et al. (2014). ** and * indicate a significant difference in statistic variables (R^2 and slope) between the rEC-LUE$_{(T)}$ and other LUE models (i.e., rEC-LUE$_{(T)}$ and other seven LUE models) at p-value < 0.01 and p-value < 0.05, respectively.

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