Journal: ESSD

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

MS No.: essd-2019-126

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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Sun Yat-sen University, Zhuhai 519082, Guangdong, China

Email: yuanwpcn@126.com

Response to Reviewer #2:

1. This paper reported some improvements of global gross primary production using the revised EC-LUE model. Overall, it lacks in detailed explanation and thorough validation to show the novelty of the proposed model if any. English must be significantly improved. Thus, I recommend rejecting the paper. Please see several major comments below.

Response: Thanks for your deep thoughts and comments. The poor model performance in reproducing the interannual variability of GPP has been one of the most important uncertainties of satellite-based models, which will restrict our ability for quantifying the long-term trend of GPP over regional and global scales. This study aims to improve the model performance of a LUE model in reproducing interannual variability and produce a new long-term global GPP dataset. Meanwhile, we revised the manuscript according to your comments, and added detailed information on model parameterization and validation (please refer the following responses).

2. Details are missing in many parts. Justification should follow when a decision or selection is done. For example, what is the rationale of dividing data into calibration and validation, and how was it done? How was the parameter optimization conducted? How was the collocation of different input data done? These are just a few of them. Readers don't know what and how the authors exactly did, which limit the understanding of the proposed model and its evaluation.

Response: Sorry for confusion. We checked carefully the manuscript and made sure to represent the method, data and result clear. Here, the reviewer mentioned the model parameterization method, and we responded details in the next comment.

3. Calibration vs. validation. As empirical models are dependent on data, a more robust approach should be adopted. Calibration sites were randomly selected? What if different calibration sites are used? A bootstrapping method might be adopted to see if consistent results can be achieved using different calibration data. Or n-fold cross validation would work. If consistent results were not obtained, the proposed model would be inherently unstable.

Response: Thanks for your constructive comments. In the revised manuscript, we used cross validation method to calibrate model parameters. Cross validation method need more sites for each vegetation types, so we added the study sites from 84 to 95. We updated all the related method and result sections thoroughly (including all the tables and figures, and the related methods and results). And we produced and analyzed the global GPP datasets using the new parameters. Here we show the cross-validation method and the optimized parameter table. Other related modifications are too long to show here, please see them in the revised manuscript.

The detailed description on the cross-validation method is:

"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)

The table of the optimized parameters are shown in Table 3:

Table 3: Optimized parameters (ε_{msu}, ε_{msh}, φ, and VPD_0) of the revised EC-LUE model for different vegetation types.

Vegetation Types	DBF	ENF	EBF	MF	GRA	CRO-C3	CRO-C4	SAV	SHR	WET
ε_{msu} (g C MJ^{-1})	1.28 ±0.36	1.72 ±0.42	1.67 ±0.85	1.38 ±0.21	1.16 ±0.15	1.25 ±0.42	2.46 ±0.78	2.24 ±0.68	1.21 ±0.25	1.34 ±0.26
ε_{msh} (g C MJ^{-1})	3.59 ±0.66	3.87 ±0.58	4.35 ±0.72	3.29 ±0.63	1.91 ±0.46	2.46 ±0.52	5.64 ±1.02	4.26 ±0.95	2.71 ±0.52	2.62 ±0.49
φ (ppm)	32 ±8.25	25 ±7.59	20 ±6.36	49 ±11.25	57 ±11.85	43 ±9.56	54 ±15.36	54 ±12.23	34 ±7.59	36 ±10.32
VPD_0 (kPa)	1.15 ±0.25	1.34 ±0.26	0.57 ±0.15	0.62 ±0.14	1.69 ±0.35	1.02 ±0.19	1.53 ±0.31	1.65 ±0.26	1.34 ±0.21	0.62 ±0.12

Additionally, we examined the variability of model performance by using different combinations of calibration and validation sites (Fig. R1). We calculated the mean R^2 and RMSE across all validation sites for each combination, and used the coefficient of variation (CV) of R^2 and RMSE of all combinations to indicate the impacts of combinations on model performance. The averaged R^2 over all combinations ranged from 0.62 (EBF) to 0.88 (DBF) among various vegetation types, and the CV values of R^2 were mostly less than 0.11 (except EBF, CV = 0.32) (Fig. R1a-b). The averaged RMSE ranged from 1.33 g C m^{-2} d^{-1} (CRO-C3) to 5.84 g C m^{-2} d^{-1} (SRH) with CV varying from 0.06 to 0.30 (Fig. R1c-d). From statistics (mean, SD, and CV) of R^2 and RMSE, we can conclude our proposed model is robust with high accuracy.

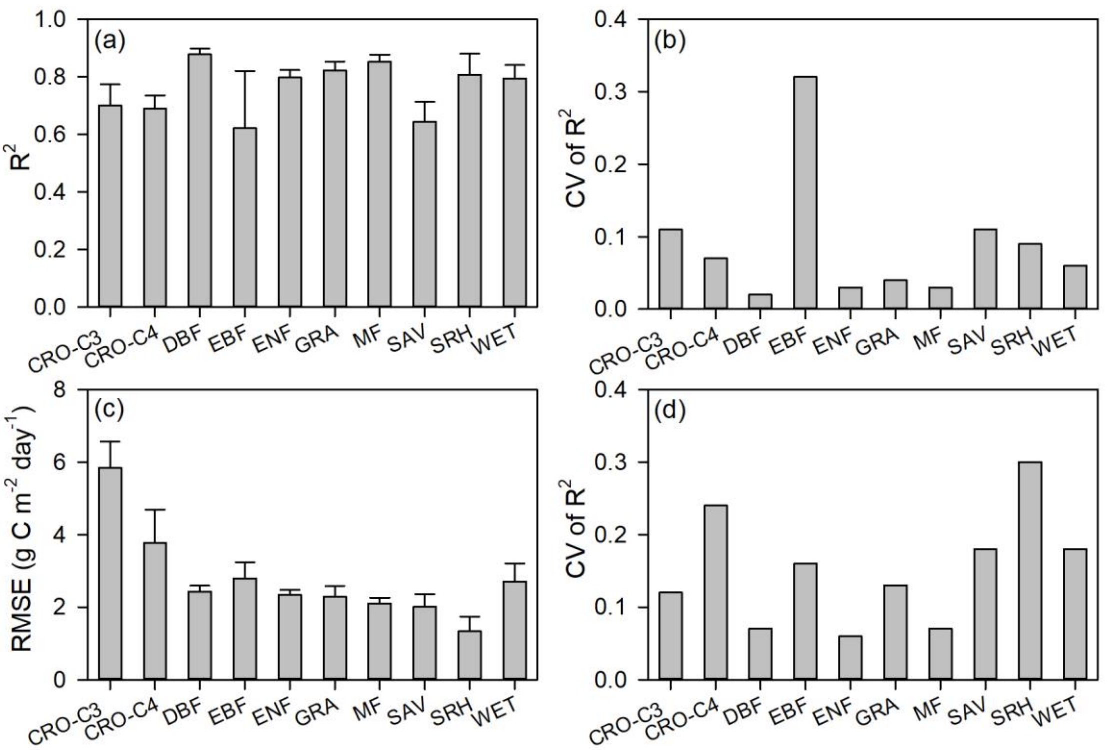


Figure R1: Model performance for all the combinations of calibration and validation sites in cross-validation. (a) Averaged values of R^2 (error bars represent the standard deviation, namely SD), (b) coefficient of variation (CV) of R^2 (CV = SD/mean); (c) Averaged values of RMSE (error bars represent the SD), (b) CV of RMSE.

4. Seasonal analysis using time-series data should be conducted. Figs 2 and 3 are not sufficient to say that the proposed model showed a good performance in reproducing the seasonal variations in GPP as they don't contain any seasonal information. You may conduct statistical analysis by season, not simply based on stations.

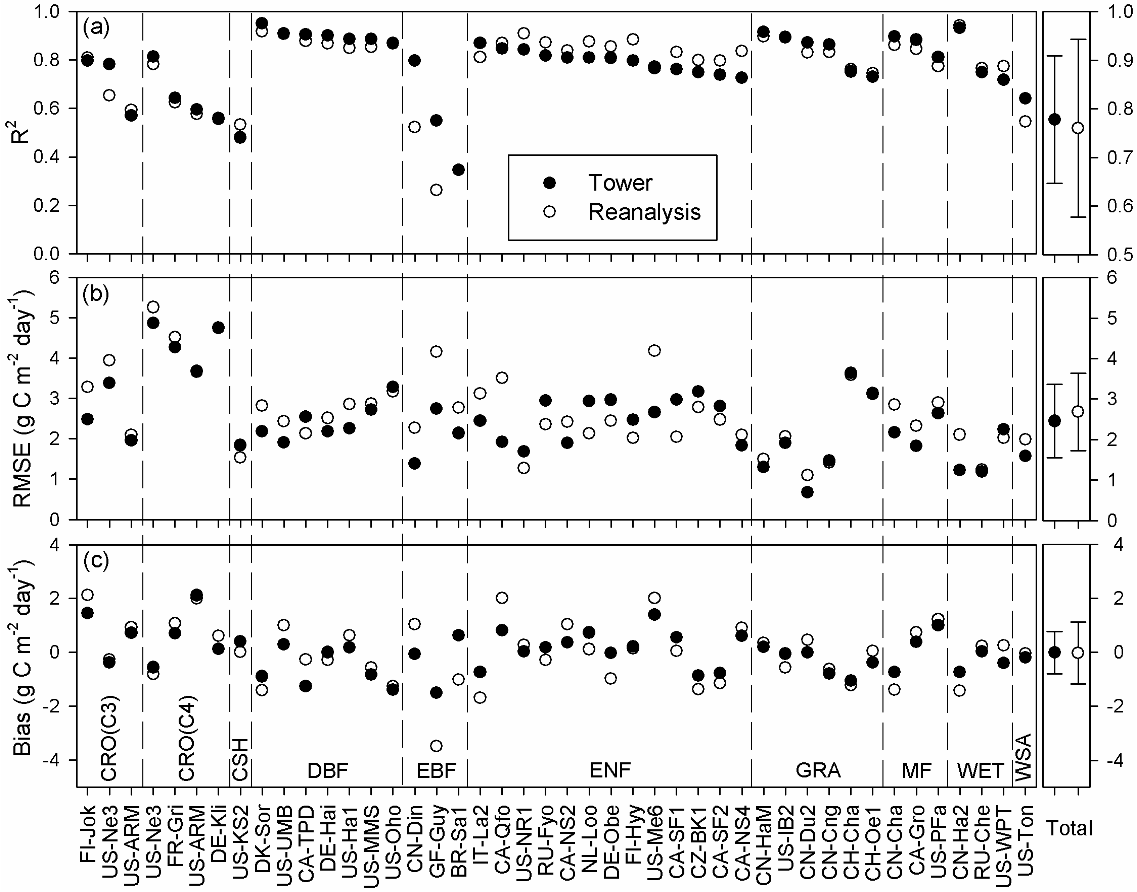


Figure 2: Comparisons of 8-day mean GPP between the observations at 42 calibration sites and the model simulations. Solid and open dots indicate the GPP simulations derived from tower-derived meteorology data and meteorological reanalysis dataset, respectively.

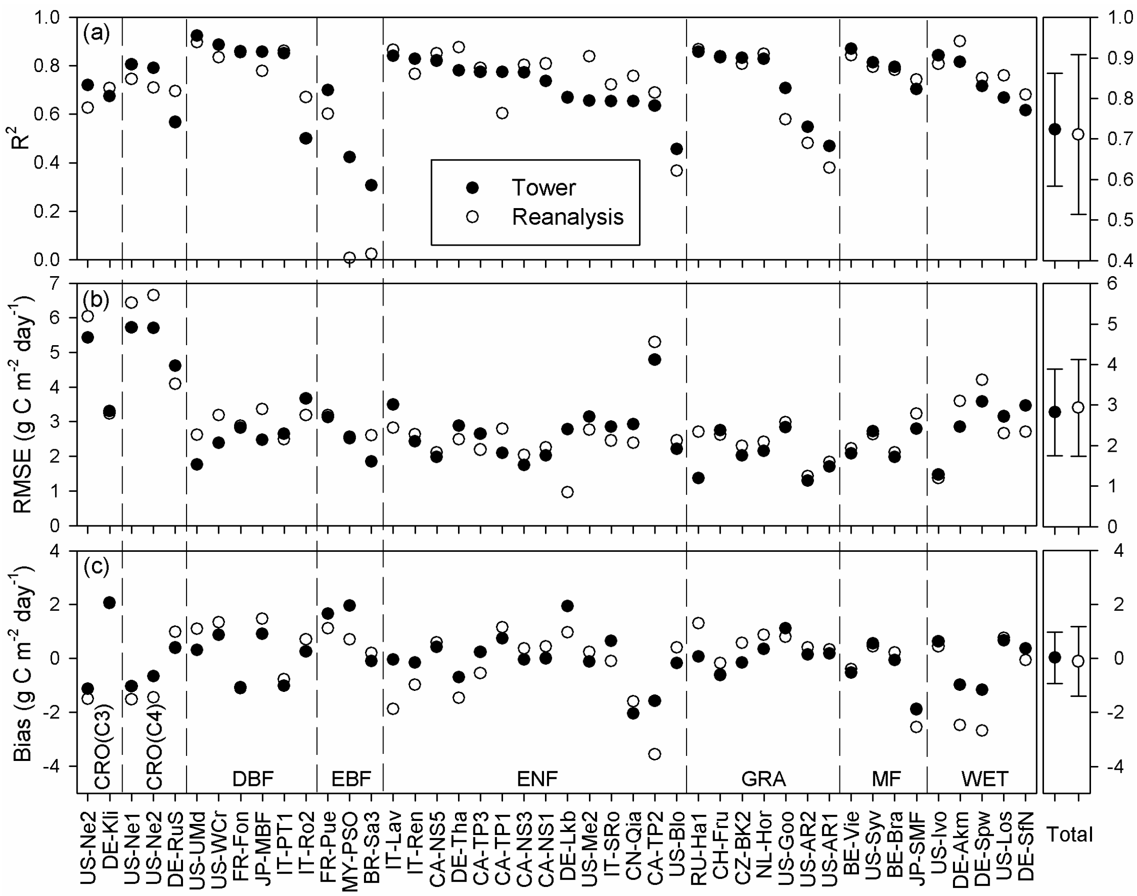


Figure 3: Comparisons of 8-day mean GPP between the observations at 43 validation sites and the model simulations. Solid and open dots indicate the GPP simulations derived from tower-derived meteorology data and meteorological reanalysis dataset, respectively.

Response: In the revised manuscript we used cross-validation method, so we combined Figs. 2-3 to Fig. 2. In Figs. 2-3 (in the original manuscript), we calculated the correlation (R^2) between simulated and observed GPP at 8-day step for each site, and the correlation (R^2) indicates the consistence of temporal changes between GPP simulations and observations. We added these explanations as following:

"In Fig. 2, we compared the modelled GPP and tower GPP at 8-day step for each site to examine the capacity of our model in reproducing the seasonal variations." (Line 237-238 in the revised manuscript)

In addition, in the revised manuscript, we also added another index (Kendall's coefficient of rank correlation τ) to further quantify the agreement between the simulated and tower estimated GPP at seasonal patterns (Fig. 2d). We updated the Methods (Section 2.4 Model calibration and validation), Results (Section 3.1 Model performance), and Fig. 2d in the revise manuscript as following.

Methods (Section 2.4 Model calibration and validation):

"Additionally, Kendall's coefficient of rank correlation τ (Kanji, 1999) was used to quantify the agreement of seasonal changes between the simulated and tower estimated GPP. The Kendall coefficient measured the tendency coherence between predicted and observed GPP by comparing the ranks assigned to successive pairs. If $GPP_{sim,j} - GPP_{sim,i}$ and $GPP_{obs,j} - GPP_{obs,i}$ have the same sign (positive or negative), the pair would be concordant, or discordant. A time-series data with n observations, the Kendall's coefficient of rank correlation τ can be expressed:

$$\tau = \frac{C - D}{n(n-1)/2} \qquad (20)$$

where $n(n-1)/2$ is the total combination of pairs, C is the number of concordant pairs, and D is the number of discordant pairs. The Kendall's coefficient ranged from -1 ($C = 0$) to 1 ($D = 0$). The Kendall's coefficient is much closer to 1, which means a stronger positive relationship between the seasonal patterns of the simulated and tower estimated GPP." (Line 197-206 in the revised manuscript)

Results (Section 3.1 Model performance):

"The averaged Kendall's correlation coefficient (τ) was 0.63, indicating that the model simulated GPP had a strong seasonal coherence with tower estimated GPP. Similar to R^2, the lower Kendall's correlation coefficient (τ) value sites were also located in the tropical forest areas." (Line 244-246 in the revised manuscript)

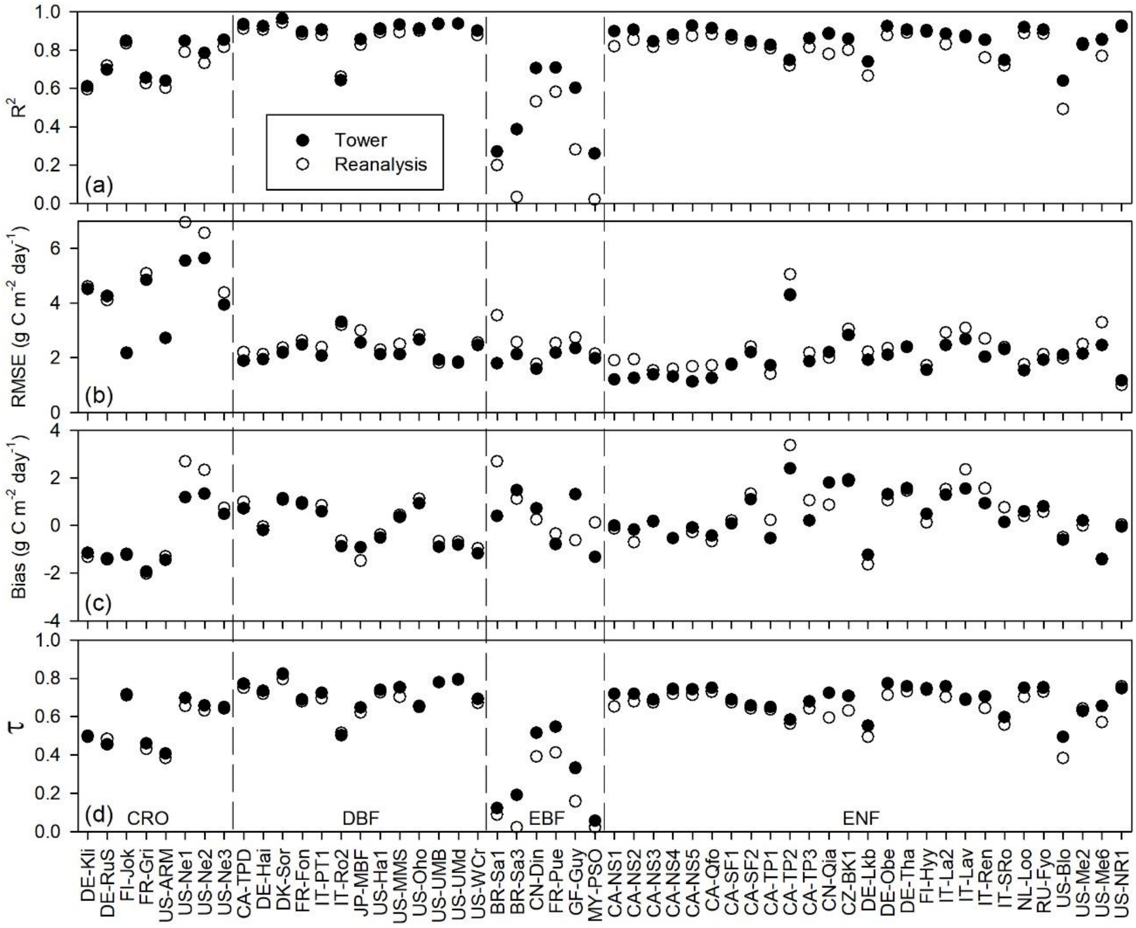
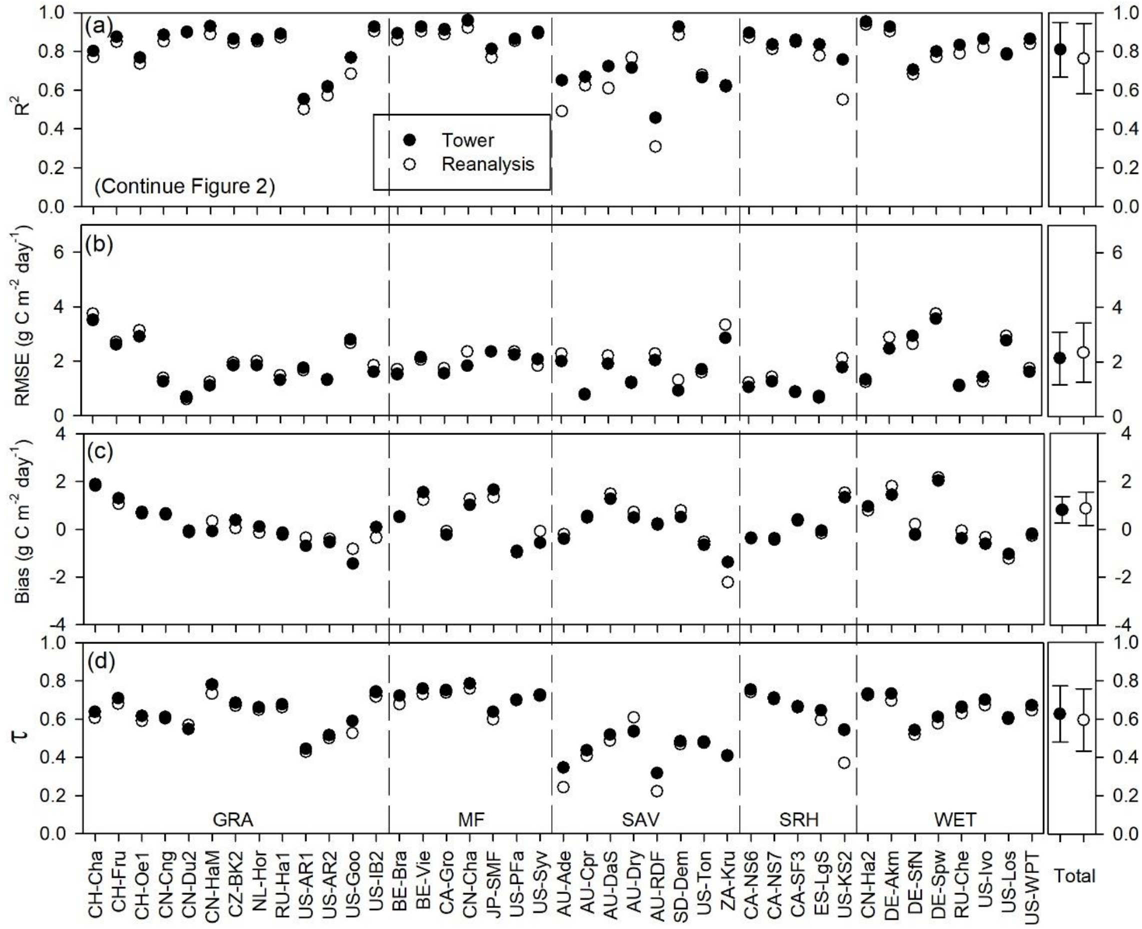


Figure 2: Comparisons of 8-day mean GPP between the model simulated GPP and tower estimated GPP. Solid and open dots indicate the GPP simulations derived from tower-derived meteorology data and meteorological reanalysis dataset, respectively.

Figure 2 (continue)



5. More supporting references should follow in lines 250-251 if you want to say the decreased GPP was due to excessive precipitation and hot temp. In other words, both precipitation and temperature in Amazon significantly increased from 1982 to 2017? Seasonal factors might affect? Line 250-251: The decreased GPP areas were mainly distributed in the tropic regions with abundant precipitation and high temperature, particularly in the Amazon forest.

Response: Sorry for confusion. It is not our purpose to say the abundant precipitation and high temperature is the cause of decreased GPP in tropic regions. We revised the sentence to:

"The decreased GPP was found in the tropic regions, especially in the Amazon forest." (Line 274 in the revised manuscript).

The decreased GPP in the tropic regions were mainly due to the suppression of the increased atmospheric water demand indicated by atmosphere vapor pressure deficit (VPD). We have reported the detailed cause of GPP decreases responded to the increased VPD in our recent paper (Yuan et al., 2019), therefore, we appreciate your understanding that we did not discuss the details. In addition, the main objective of this manuscript is to introduce the revised EC-LUE model and long-term global GPP dataset produced by EC-LUE model.

6. Scale issues should be carefully examined. Input data have different scales and the ground GPP measurements don't have the same scale with input data. What kinds of approaches were conducted when matching input data on the same spatial domain? How did the authors mitigate or consider the different scale issues between site GPP data and input variables?

Response: At global scale, the spatial resolution of satellite-based GLASS LAI dataset is 0.05 °latitude by 0.05 °longitude. We downscaled the meteorological reanalysis data (temperature, direct PAR, diffuse PAR, and VPD) to 0.05 °latitude by 0.05 °longitude using the bilinear interpolation method to match the spatial resolution of LAI. We have reported the detailed method in the manuscript:

"We aggregated the daily variables (air temperature, VPD, direct PAR, and diffuse PAR) to 8-day interval temporal resolution. And these variables were resampled to the spatial resolution of 0.05 ° latitude by 0.05 ° longitude using the bilinear interpolation method." (Line 136-138 in the revised manuscript)

At site level, we calibrated and validated the model using the tower observed meteorology data and global reanalysis meteorology data, respectively. The tower observed meteorology data were directly obtained from the measurement of FLUXNET and the global reanalysis meteorology data were extracted from the processed global 0.05 °×0.05 ° reanalysis data. The model performance slightly decreases when using the meteorological reanalysis compared to that driven by tower-derived meteorology data (please refer to the section 3.1 in the revised manuscript). To further mitigate the uncertainty, we used the parameters optimized by global reanalysis meteorology data to simulate the GPP at global scale.

And we discussed the uncertainty introduced by the mismatches between eddy covariance flux footprint and image pixels of the input dataset in section 4.3 Model uncertainty:

"Additionally, the uncertainty of the revised EC-LUE model may arise by scale mismatches between eddy covariance flux footprint and input dataset. The eddy covariance flux footprint is generally less than 3 km^2 and varies depending on the wind speed, wind direction and the atmospheric stability (Tan et al., 2006). In our studies, the revised EC-LUE model was run at 0.05 degree (~5 km^2) spatial resolution. The uncertainty of simulated GPP introduced by the scale effect is inevitable but smaller than that introduced by the model structures, parameters or input datasets (Sjostrom et al., 2013; Zheng et al., 2018)." (Line 392-396 in the revised manuscript)

7. Lines 282-285. Needs more uncertainty analysis by factor (e.g., radiation) to support this.

Line 282-285: **In contrast, 74% of the sites showed higher R^2 values (>0.5) for the revised EC-LUE model. The improvements of the revised EC-LUE model in reproducing interannual variations are owing to the integration of several important environmental drivers for vegetation production (i.e., atmospheric CO_2 concentration, radiation components, and VPD), which exhibited large variations and contributed significantly to vegetation production at interannual scale.**

Response: This statement is based on the results presented by Fig. 3 in the revised manuscript (namely Fig. 4 in the original manuscript). The comparison showed the revised EC-LUE model has the better performance for reproducing the interannual variability in GPP compared to the original EC-LUE and other LUE models. It is a very good idea to identify the contributions of various factors to improve the model ability. However, to our knowledge, there is no recognized methods to conduct the uncertainty analysis by factors, and it will be very interesting to develop this method. However, we appreciate your understanding that it will beyond the scope of this study, and this manuscript is data description paper and the main purpose is to introduce the model methods and describe the global dataset of GPP with long-term series.

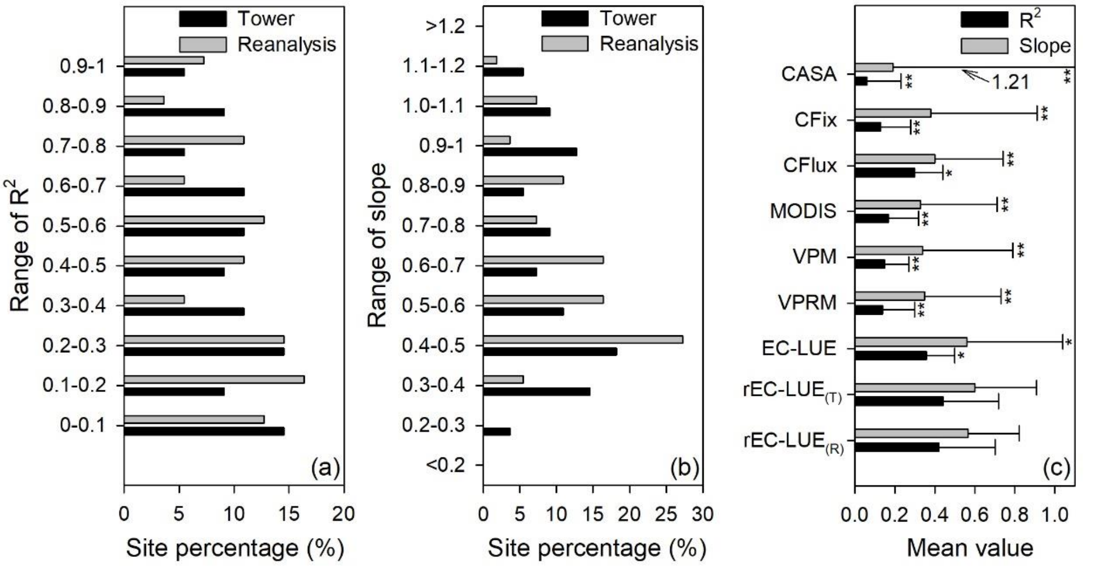


Figure 3: Site percentage of (a) correlation coefficients (R^2), and (b) regression slopes between the model simulated and tower-based interannual variabilities in GPP. (c) Averaged values (error bars represent the standard deviations) of R^2 and slope for various LUE models. rEC-LUE$_{(T)}$ and rEC-LUE$_{(R)}$ 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.

8. Line 325. throughout the seasons? or different results by season? Again, seasonal analysis should be conducted.

Line 325: The revised EC-LUE model showed the lowest accuracy for the evergreen broadleaf forests in the tropic areas (Figs. 2–3).

Response: "throughout the seasons". As the response of comment #4, we test the seasonal performance of the revised EC-LUE model for each site. We also added another index (Kendall's coefficient of rank correlation τ) to further quantify the agreement between the simulated and tower estimated GPP at seasonal patterns in the revised manuscript (Fig. 2d in the revised manuscript).

9. Figure 8. Comparison by region (or continent) would make the paper robust. Are there any merits of using the proposed model in terms of the spatial domain?

Response: As your suggestion, we added the comparison between our model and other models across bioclimatic zones in the Köppen-Geiger climate classification map (Beck et al., 2018) before the Fig. 8 (in the original manuscript). Because we have rearranged the figures in our manuscript, the comparison across bioclimatic zones is Fig. 7 in the revised manuscript. We added the following comparison:

"At regional scale, we compared the annual mean GPP between the revised EC-LUE model and other models across the bioclimatic zones in the Köppen-Geiger climate classification map (Beck et al., 2018) (Fig. 7). The GPP of the revised EC-LUE model was comparable to the mean value of other models for each bioclimatic zone (Fig. 7a). The GPP of different models exhibited large discrepancies in tropical regions (Af/Am/Aw) (Fig. 7a). The correlations (R^2) of GPP across all the bioclimatic zones between the revised EC-LUE model and other models ranged from 0.73 (LPX-Bern) to 0.95 (FLUXCOM

MARS, FLUXCOM RF) (Fig. 7b).” (Line 325-331 in the revised manuscript)

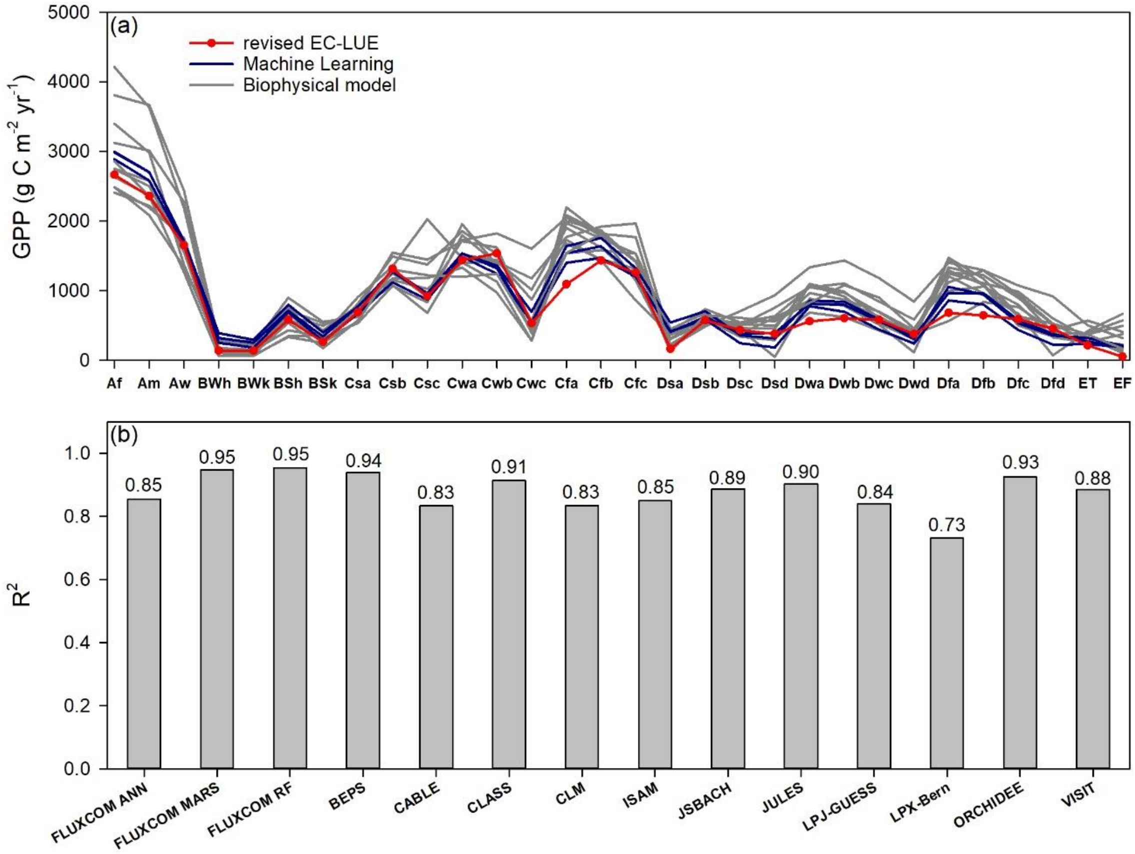


Figure 7: Comparisons of long-term (1982 to 2010s) averaged GPP between the revised EC-LUE model and other models across bioclimatic zones in the Köppen-Geiger climate classification map (Beck et al., 2018). (a) the regional averaged value (b) correlation coefficients (R^2) of GPP at all the bioclimatic zones between the revised EC-LUE model and other models. These models including machine learning models (FLUXCOM ANN, FLUXCOM MARS, FLUXCOM RF; Jung et al., 2017), biophysical models BEPS (Ju et al., 2006; Liu et al., 2018), and ten biophysical models in TRENDY (CABLE, CLASS, CLM, ISAM, JSBACH, JULES, LPJ-GUESS, LPX-Bern, ORCHIDEE, and VISIT). The abbreviations for the bioclimatic zones are as follows: Af, tropical, rainforest; Am, tropical, monsoon; Aw, tropical, savannah; BWh, arid, desert, hot; BWk, arid, desert, cold; BSh, arid, steppe, hot; BSk, arid, steppe, cold; Csa, temperate, dry summer, hot summer; Csb, temperate, dry summer, warm summer; Csc, temperate, dry summer, cold summer; Cwa, temperate, dry winter, hot summer; Cwb, temperate, dry winter, warm summer; Cwc, temperate, dry winter, cold summer; Cfa, temperate, no dry season, hot summer; Cfb temperate, no dry season, warm summer; Cfc, temperate, no dry season, cold summer; Dsa, cold, dry summer, hot summer; Dsb, cold, dry summer, warm summer; Dsc, cold, dry summer, cold summer; Dsd, cold, dry summer, very cold winter; Dwa, cold, dry winter, hot summer; Dwb, cold, dry winter, warm summer; Dwc, cold, dry winter, cold summer; Dwd, cold, dry winter, very cold winter; Dfa, cold, no dry season, hot summer; Dfb, cold, no dry season, warm summer; Dfc, cold, no dry season, cold summer; Dfd, cold, no dry season, very cold winter; ET, polar, tundra; EF, polar, frost.

10. Lines 371-372. Don’t see any conclusive results to say that the model has a unique superiority in reproducing the inter annual variations in GPP at both site level and global scales. Superiority to what? Any comparison with other models (e.g., machine learning or physical models) to show

the inter annual variations?

Line 371-372: The revised EC-LUE performed well in simulating the spatial, seasonal, and interannual variations in global GPP. Particularly, it has a unique superiority in reproducing the interannual variations in GPP at both site level and global scales.

Response: In our manuscript, we compared the model performance at interannual variations of the revised EC-LUE model with other LUE models, such as the original EC-LUE model, CASA, CFix, CFlux, MODIS, VPM, and VPRM. The result showed the revised EC-LUE indeed has a unique superiority in reproducing interannual variations than other LUE models. Over the sites with longer 5-year observations, the averaged R^2 between annual mean tower-estimated and model simulated GPP are 0.44 for the revised EC-LUE model, 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), and these results have been represented at Fig. 3 (in the revised manuscript).

We appreciate your understanding that we don't compare it with other kind models because the main objective of our manuscript is focused on the improvement of the LUE models and produced a long-term GPP dataset. 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).

In order to emphasize that we conducted the comparison with other LUE models, we revised these sentences you mentioned (Line 371-372 in the original manuscript) as following:

"The revised EC-LUE performed well in simulating the spatial, seasonal, and interannual variations in GPP across the globe. Particularly, it has a unique superiority in reproducing the interannual variations in GPP (R^2 = 0.44) compared with the 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)." (Line 405-407 in the revised manuscript)

The comparisons with other LUE models are shown in the abstract, result, and discussion section.

In the abstract section:

"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)." (Line 29-33 in the revised manuscript)

In the result section:

"The result showed that the revised EC-LUE model could effectively determine the interannual variations in GPP (Fig. 3). Approximately 42% and 40% of the sites showed higher R^2 values (>0.5) by using the tower-derived meteorology data and the meteorological reanalysis dataset (Fig. 3a).

The averaged R^2 for the revised EC-LUE model was 0.44 by using the tower-derived meteorology data, which was significantly higher than the 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) (Fig. 3c). The averaged R^2 for the revised EC-LUE model was 0.42 by using the meteorological reanalysis dataset. The averaged slopes of the revised EC-LUE model were 0.60 and 0.57 by using the tower-derived meteorology data and the meteorological reanalysis dataset (Fig. 3c)" (Line 252-259 in the revised manuscript)

In the discussion section:

"Numerous studies have shown that most GPP models can reproduce the spatial changes in GPP but failed to reproduce the temporal variations (Keenan et al., 2012; Yuan et al., 2014). Therefore, the capacity to reproduce realistic interannual variations for a GPP model is significantly important. In our study, the revised EC-LUE model performed a higher accuracy in reproducing the interannual variations in GPP than did the original EC-LUE model and other LUE models. Yuan et al. (2014) reported that the averaged slope of the regression relation between the mean annual GPP simulated by seven LUE models and the mean annual GPP estimated from EC tower ranged from 0.19 to 0.56 (Fig. 3c). While the revised EC-LUE model showed a higher slope of regression relation (0.60), which is much closer to 1 than that obtained from other LUE models (Fig. 3c). The VPM GPP showed less interannual variations across most biomes (R^2 <0.5), probably because of the insensitivity of the environmental stress factors at the interannual scale (Zhang et al., 2017). In contrast, 42% of the sites showed higher R^2 values (>0.5) for the revised EC-LUE model." (Line 296-305 in the revised manuscript)

11. English needs to be carefully revised.

Response: We thoroughly checked and improved English usages of the revised manuscript. And we also polished the English in a professional agency.

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