Reply to anonymous referee #1

We wish to thank the reviewer for her/his constructive comments. We reply to each comment below (original comments in bold and our response in regular font).

General Comments

This study tested the robustness of globally constant vegetation specific parameters to simulate GPP based on light use efficiency (LUE) GPP models; how globally constant parameter works for GPP simulation for different vegetation types. The authors conducted two simulations, one is to use globally constant model parameter, and the other is plant functional type specific parameters using 7 LUE GPP models. By optimizing model parameters using eddy-covariance based GPP, the authors analyzed the differences in model performances of the parameter setting based on globally constant or PFT-specific parameters.

The scientific question of this study, "Are vegetation specific model parameters required for estimating GPP?" is an interesting and important question. I agree that satellite based land cover map might be one of the causes of model uncertainties. Therefore, as the authors stated, it will be nice if we don't need to rely on the vegetation-specific parameter, which requires accurate land cover data.

I read this paper interestingly. However, I found that some potentially important information is missing at this stage. To try to answer such an important scientific question, this paper requires more clarification and proof. For example, the method section does not express the procedure of the experiment well (see below). In addition, the results section were not also described properly (see below). Thus, my suggestion is major revision is required before acceptance. This paper can be significantly improved after the authors rewrite it more precisely.

Thanks for the positive comments. Yes, we studied carefully the comments and improved the manuscript accordingly.

1. I could not get clear idea how model parameters were optimized. I guess the model

parameters were optimized using the eddy-flux based GPP, but I have no idea how the model were optimized with what (for example, to minimize RMSE of monthly GPP ? yearly GPP ? or something else? Or to maximize R2? Or something else?).

The nonlinear regression procedure (Proc NLIN) in the Statistical Analysis System (SAS, SAS Institute Inc., Cary, NC, USA) was used to optimize the model parameters by minimizing the residual sum of squares. We added this explanation into the revised manuscript.

2. There are many parameters in each models. Please describe how many parameters out of model parameters were used for model optimization and why the authors chose them.

We introduced all seven LUE models in the supplemental online material, and Table 1 listed all selected model parameters which were optimized. We selected the parameters which are the default parameters within the original models. We added the explanation in the revised manuscript.

3. I am sure that description of each model in supplement materials are very important to understand the contents. Therefore, please move model descriptions in supplement materials into main text or appendix. Adding one table which describes model overview will be helpful.

Yes, we introduced model algorithms at the main text and added a table to summarize the model.

4. Some major vegetation types were not covered in this study (e.g. cropland, shrubland, deciduous needleleaf). Please add if any data exist.

Thanks, we added shrubland and wetland ecosystems into the analyses. There is no deciduous needleleaf site included in the FLUXNET dataset, and please refer the FLUXNET data summary (http://www.fluxdata.org/DataInfo/Dataset%20Doc%20Lib/SynthDataSummary.aspx). Moreover, we did not consider cropland and savanna, because C4 plants are dominant at these ecosystems, and theoretically, potential light use efficiency at C4 plants is larger compared with that of C3 plants. Future study should investigate the potential light use efficiency of C4 plants for global simulating. We added one paragraph to discuss this issue.

5. As far as I know, at least two earlier studies (e.g. Still et al. 2004; Yang et al. 2007) inversely estimated ε_0, and found that ε_0 varies in different vegetation types. Please mention the differences and their potential causes with previous studies.

Still et al (2004) combined atmospheric CO_2 measurements, satellite observations, and an atmospheric transport model and estimated the actual light use efficiency (i.e. $\varepsilon_0 \times f$ (t, w, ---)), not potential light use efficiency (ε_0). Our study compared the potential light use efficiency of seven models among two model experiments.

Yang et al (2007) first trained the Support Vector Machine (SVM) to predict flux-based GPP from 33 AmeriFlux sites between 2000 and 2003, and then estimated ε_0 of MODIS GPP algorithm using 2004 SVM GPP for the conterminous U.S.

First, there are large uncertainties on the SVM GPP estimations, and the results showed that annual SVM GPP prediction error was 32.1% for non-forest ecosystems and 22.2% for forest ecosystems. Therefore, using SVM GPP will result into the large uncertainties of optimized ε_0.

Second, Yang et al (2007) used MODIS land cover product (MOD-12) to identify vegetation types, however, the accuracy of the MODIS land cover product is only about 75% (Friedl et al., 2010). The bias of vegetation type classification will result into the uncertainty on the conclusion.

Third, Yang et al (2007) reported the differences of parameters among ecosystem types and different sites of the same ecosystem types, however, they did not conduct the statistical tests on significant differences of inversed parameters. Therefore, we cannot assume their conclusion is different with ours.

We added one paragraph to discuss this issue.

6. Figure 1 is not clear. (1) very hard to identify each vegetation type in GPP mean figures.

We improve the Fig.1 in order to clearly present validation results at various vegetation types.

(2) No information on the temporal resolution of RMSE calculation (e.g. RMSE of annual? monthly? daily? GPP?) were given.

In this study, we estimated GPP at the 8-day time scale. Therefore, all statistical analyses were conducted at the 8-day scale. We added this information into the revised manuscript.

(3) how the authors calculated R2. using annual mean, monthly mean, or daily mean etc.

Same with the above, we compared the correlation between tower-based GPP and simulated GPP at the 8-day scale. We added this information into the revised manuscript.

7. Differences in model performance were given, however, no direct evaluation of the model was given. It will be helpful to add one Table which shows RMSE and R2 in each vegetation type for the two experiments.

We added the Table to indicate the RMSE and R^2 values in all vegetation types.

8. In some models (e.g. CASA, CFlux, MODIS), I see clear systematic differences in model performance between vegetation-invariant parameter simulation and vegetation dependent parameter simulation. Any comments?

Yes, the GPP estimates of two experiments showed the systematic differences at some ecosystem types of CASA (DBF), CFlux (DBF and EBF) and MODIS (GRS). However, these systematic differences only showed at few ecosystem types, and model performance probably is major cause. We have added the discussion on this issue.

9. It looks like models work poorly in some sites (e.g. sites with low R2 and high RMSE values). Any comments?

It is true that model performance is poor at some eddy covariance towers. However, it will not change the conclusion. According to the Fig.1, there were no significant differences of GPP estimates between the two different parameterization schemes at sites with high or low model performance. We added one paragraph to integrate this issue into the discussion section.

References

Still et al. (2004) Large-scale plant light use efficiency inferred from seasonal cycle of atmospheric CO_2. Global Change Biology, 10, 1240-1252.

Yang et al. (2007) Developing a continental scale measure of gross primary production by combining MODIS and AmeriFlux data through Support Vector Machine approach. Remote Sensing of Environment, 110, 109-122.