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Interactive comment on "Bayesian integration of flux tower data into process-based simulator for quantifying uncertainty in simulated output" *by* Rahul Raj et al.

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We thank for the constructive and helpful comments for our manuscript. We will carefully consider all comments and these will be incorporated in our revised manuscript accordingly. We have inserted our response to each comment. We use "R2C" for referee #2's comment and "A2C" for author's response to referee #2.

R2C 1: The main problem of this manuscript is the use of time-varying parameters. The authors themselves recognise this as a problem (see page 13, lines 11/12). If I understand their use of time-varying parameters correctly ('engineering' a times series of GPP based on independent monthly sub-time series) it actually violates Bayes theorem, mass conservation and model dynamics. Of course one can do such an experi-

ment to better understand the model dynamics and identify missing or misrepresented processes, but the authors are not taking this step and analysing the consequences of their results with the time-varying parameters in terms of model structure and formulation.

A2C 1: We understand the concern of referee about the use time varying parameters. We found that the response of simulated GPP to weather conditions is rather similar among months: The simulated GPP was mainly driven by the meteorology, and much less by seasonal phenology. We then hypothesized that some important state variables (such as LAI and carboxylation capacity) may not have a pronounced seasonal cycle in the model. In the second experiment, we calibrated Biome-BGC to the GPP of each month separately, as if the data for the other months did not exist. In that way neither mass conservation nor the Bayes theorem is violated. If some of the parameters have different optimum values when calibrated to different months of data, then this is an indication that the relation between these parameters and important state variables that (should) change during the season, may require improvement. The problem only arises when we combine the results in a time series. We then merge different simulations outputs into one. The objective was indeed to better understand the dynamics (or lack of dynamics) of the model. We decided to avoid the term 'time varying parameters' in the revision. We will mention above points in the revised manuscript.

R2C 2: Another concern is the use of GPP derived from eddy-covariance flux measurements as the observations in the calibration process. Eddy-covariance towers measure the net exchange ïňĆux, essentially NEE, and GPP is the derived from this net flux by employing a model. So essentially, the authors calibrate the BIOME-BGC parameters against another model, in this case the NRH model which makes its own assumptions about the dependency of GPP on environmental conditions.

A2C 2: We would like to mention following points on using partitioned GPP instead of NEE data in this study:

A. Indeed in our approach, the output of the process-based simulator was validated against the output of another model, notably the flux partitioning model. Although this approach has been used in other studies to validate the output of process-based simulator as well (Collalti et al., 2016, Liu et al., 2014, Yuan et al., 2014, Zhou et al., 2016), it could lead to error propagation. We clarify that the flux partitioning model (NRH model, Raj et al., (2016)) was tuned to the Eddy Covariance data in blocks of 10 days. Because the NHR and the relationship of respiration with temperature and moisture were tuned for these short blocks separately, we expect that the GPP still reflects realistic responses to environmental drivers, and does not depend much on model assumptions.

B. Calibration of BIOME-BGC using NEE data is more challenging as NEE is the difference between fluxes caused by two processes (assimilation and respiration) We argue that calibration of such a complex model to NEE instead of GPP may not be a good idea, but calibration to NEE or respiration in addition to GPP is possible. However, we limited this study to the primary productivity, because this was our primary interest. A future study should be done to include both GPP data and ecosystem respiration data (can also be achieved by partitioning of NEE data) in a Bayesian calibration of BIOME-BGC. This may ensure the accuracy of all related carbon budget terms (GPP, NEE, and respirations).

We will discuss all above points in our revised manuscript.

R2C 3: The whole Section 4.4 is not needed and does not provide any new insights, it is obvious that a dynamical model with state variables such as BIOME-BGC then also depends on its state variables.

A2C 3: We will remove section 4.4 in the revised manuscript.

R2C 4: So essentially the remaining part of the manuscript concerns experiment 1 and becomes rather light-weighted as a thorough analysis of the results from experiment 1 is missing. For example, how does the posterior error covariance matrix look like and

what consequences does this have on the parameters (identifiability) and model? How does the posterior uncertainty compare to prior uncertainty? What is the impact of the observations on other simulated quantities (NEE, NPP), both in terms of their mean and uncertainty? How does the variability and the temporal autocorrelation compare to the prior?

A2C 4:

A. In the revised manuscript, we will add a brief explanation and a plot showing the correlations in the posterior parameter distributions obtained in Experiment 1. We found a strong positive correlation between the posterior distributions of C:Nleaf (carbon and nitrogen ratio) and FLNR (Fraction of leaf N in Rubisco) with r=0.95 (r is correlation coefficient). This strong positive correlation is in-line with the formulation of FLNR that shows direct proportionality with C:Nleaf (see Appendix A in Raj et al., 2014, for details). The parameters C:Nleaf and FLNR showed similar negative, but weak (> -0.5), correlation with Wint (Canopy water interception coefficient) (r $\approx$ -0.4). This can be explained by the fact that the simulated GPP is expected to vary inversely with Wint via soil water potential and stomatal regulation and directly with FLNR and C:Nleaf (see Section 5.1 in the manuscript, for details of BIOME-BGC internal routines). The parameter SD (effective soil depth) had similar positive, but weak (< 0.5), correlation with FLNR and C:Nleaf (r $\approx$ 0.4). This can be explained by the fact that the simulated GPP is expected to vary directly with SD (via soil water potential and stomatal regulation), and FLNR and C:Nleaf .Two parameters of any other pair combinations did not show any notable correlation.

B. We have already compared posterior and prior uncertainty in the section 4.2 of the manuscript (Fig 2 and P9 L22-25).

C. As far as the impact of the observations on other simulated quantities (NEE, NPP) is concerned, this is out of the scope of the present study. We mainly focused on the simulated GPP and already presented a lot of results.

D. This study modelled the temporal correlation in the residuals during the calibration by adding the nuisance parameter ÑĎ in the likelihood function (see Section 3.3.2 in the manuscript). We had assumed uniform prior distribution of phi between -1 and +1. In the posterior, we obtained the range of phi from 0.56 to 0.93 with a mean at 0.75 (Fig 1g and P9 L15-18 in the manuscript). This showed the reduction in posterior uncertainty in phi compared to prior. We will mention the choice of prior uncertainty in phi in the revised manuscript.

R2C 5: Also the terminology used in the manuscript is somewhat confusing. Sometimes the authors refer to simulated, sometimes to predicted GPP and sometimes to predicted flux tower GPP. In that context they also use the phrase 'posterior flux tower GPP', it is not clear to what the posterior refers?

A2C 5: We apologize for this confusion. We would like to clarify that the term "posterior" refers to the GPP obtained with posterior distribution of parameters. We agree that we had not used the terminology consistently. In the revised manuscript, we will make the terminology consistent as mentioned below:

A. "Flux tower GPP" - We will use this single term throughout the revised manuscript to indicate GPP partitioned from flux tower observation of net ecosystem exchange.

B. "Posterior GPP" - We will use this single term throughout the revised manuscript to indicate GPP simulated by BIOME-BGC at the posterior distribution of parameters.

C. "Prior GPP" - We will use this single term throughout the revised manuscript to indicate GPP simulated by BIOME-BGC at the prior distribution of parameters.

D. "Simulated GPP" – Sometimes, We will use this term in the revised manuscript to give the general description of GPP simulated by BIOME-BGC irrespective of GPP simulated at prior or posterior distributions.

We will clarify this in the revised manuscript.

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