Dear Editor Müller,

Thank you very much for your time spent handling our manuscript entitled “Identification of key parameters controlling demographically structured vegetation dynamics in a Land Surface Model [CLM4.5(ED)]”. The reviewer comments were really useful and we have carefully revised the manuscript to address all of them. Please see below our response to the review comments line by line. We feel the manuscript is substantially improved and hope that it is now acceptable for publication at GMD.

Yours
Chonggang

On behalf of all coauthors

Interactive comment on "Identification of key parameters controlling demographically structured vegetation dynamics in a Land Surface Model [CLM4.5(ED)]" by Elias C. Massoud et al.

Nancy Kiang (Referee)
nancy.y.kiang@nasa.gov

Received and published: 22 February 2019

Comment: This paper uses the Fourier Amplitude Sensitivity Test (FAST) method to perform a parameter sensitivity study for the CLM4.5(ED) model. The study simulates the variance range and first and second order sensitivities for particular diagnostics relative to parameter perturbations drawn from uniform sampling within ±15% of the model default values for 87 parameters, including biophysical (including temperate response), allometric, allocation, reproduction and establishment, mortality, leaf optical, leaf longevity parameters, and a "competitive exclusion" parameter. The study is performed for one PFT at an Amazon forest site with 25 years of recycled meteorological forcing at 1◦x1◦, with 5000 simulations (a little less than the ~100 x number of parameters called for by Xu and Gertner, 2011, so it seems ~37 of the 87 parameters were not "important") 130
years in length.

Response: It is quite rare of have >50 important parameters and thus we feel that 5000 simulations should be adequate for our simulations.

Comment: This study serves more as a template and foundation for further work to perform later parameter optimization and more rigorous analysis relative to data, so as such it provides good documentation of methods of setup and analysis. The authors largely acknowledge typical concerns about the shortcomings of sensitivity studies like this, including that the parameter sampling is not based on observed distributions, only one PFT is simulated, and the mortality sensitivity to hydraulic failure is not a model sensitivity but rather a site meteorological forcing result. The choice of this particular site was obviously just expedient based on available drivers, so this reviewer views the study more as preliminary setup and test of concept, rather than new findings about DGVMs or about nature.
While the results are largely confirming what is already known about the model, such as the overshading of understory trees with the PPA, and the non-linearity of responses by tree size (and some of the results could have been obtained analytically from the equations in the DGVM), the technique illustrates a method quantitatively to stratify or rank the sensitivity of a diagnostic by parameters in a way not available through just Monte Carlo sampling.

Response: We agree with your assessment of our paper. We do want to highlight that this paper represent the first comprehensive sensitivity analysis for FATES and thus should not only provide a framework of sensitivity analysis but also a baseline to understand the model behaviors through time during continued model development.

Comment: For the sake of a sensitivity analysis method, the authors should add more to the discussion about the following:

1) Whether the 25-year periodicity of the meteorological forcings (very apparent in Figures 3c and 3d) affects the purported parameter sensitivity.

Response: Yes, CLM4.5 is sensitive to climate forcing. Following your suggestions, we have added a new figure to show the cycles of climate driver (Fig. 1 in the revised manuscript) and have calculated a rank correlation coefficient between parameter sensitivity indices and the climate driver of temperature, precipitation and relative humidity (Fig. 7 in the revised manuscript). We do found some strong correlations and added one paragraph as following into section 3.2 (Page 14 Line 11-19) as follows,

"*…To understand how climate will impact sensitivity results, we also calculated the Spearman's rank correlation coefficients between the first-order sensitivity index and the corresponding climate drivers (Fig. 10). Our results show that target carbon storage and maintenance respiration rate are negatively correlated with annual mean precipitation and relative humidity, but are positively correlated with annual mean air temperature. This suggests that they are more important for the stressed conditions with low precipitation, low humidity and high temperature. For the leaf allometry coefficient b, it is positively correlated with annual mean precipitation and relative humidity. This suggests the leaf carbon allocation is more important under the favorable environmental conditions for growth with less mortality. In general, our results suggest the climate has a larger impact on the parametric sensitivities for short-term carbon fluxes (GPP and NPP) and vegetation status (LAI) but has a smaller impact on parametric sensitivities for long-term vegetation carbon stocks…*"

Comment: 2) A little more explanation about the 30-year intervals chosen to average the sensitivity values. The authors say, "This is done in view that the transient and abrupt changes across different size categories in the annual model outputs could make the FAST analysis only account for a minor amount of the variance contribution from each parameter." If the FAST sensitivities are a function of temporal averaging period, this is rather important to address! In that case, it seems running means and a spectral averaging approach would make sense to identify time scales of sensitivity. This perhaps is a missed opportunity to show something interesting in terms of the model sensitivity; e.g. there are model-dependent fast and slow processes updated at short time scales, some processes updated at longer time scales, as well as event–driven processes
dependent on meteorological forcing.

Response: Thank you for this comment and it is a great point. We do agree that fast and slow process could play a potential role, which is captured in the manuscript (e.g., GPP and NPP for flow process and accumulation of biomass for a slow process). However, in this case, we think it is mainly because the abrupt transition across different sizes based on the size classification of small, medium and large trees. Thus, we feel there is no need to do the time-averaging as it will yield very similar results to our current analysis (see new Fig. D1).

Comment: 3) For the sake of readers not familiar with FAST, how does the underlying distribution of parameters propagate to the calculation of the variance, the latter by definition assuming Gaussian distributions. Some sentences on this would be good to add, citing statistical theory papers, and not just application papers.

Response: Thank you for this point. FAST can applicable for any kind of parameter distributions. We have updated the FATES description to capture this (Page 5 line 27-28).We have updated the FAST description section to add theoretical citations for FAST including the theoretical derivation of FAST for parameter interactions (Xu and Gertner 2011a) and the theoretical estimation of sensitivity standard errors (Xu and Gertner 2011b).

Comment: 4) That the sensitivity values change with time and community structure, but the parameters do not change their relative rank to each other: is this a result of the model structure (one PFT, fixed sensitivities in the physics) or a result of the site meteorology?

Response: Thanks for this question. We would like to point out that the rank of parameter sensitivities can change over time, and this can be seen in the sensitivity figures. What we report are the rank of the average parameter sensitivity over the 130-year simulations. So in other words, if a parameter is ranked first in sensitivity, that is because it has the highest mean sensitivity over the simulation period. If a parameter is ranked second in sensitivity, that is because it has the second highest mean sensitivity over the simulation period, etc. The parameter ranking can change through time (e.g., Fig 3 e) and we do add a new figure (Fig 7) to show how the parameter sensitivity is impacted by the climate drivers.

Comment: 5) A suggestion/question: Is it possible to do surface analysis of two-variable sensitivities, and would that reveal any useful relations?

Response: The surface analysis of two-variable sensitivity should be close to the two parameter interactions, which were investigated and shown in the appendices of our manuscript (Figures D6-8, D12).

Comment: Other small things to fix: Section 1 of the paper needs to be proofread for grammar and subject verb agreement. There are a lot of sentences that are a bit sloppy. After the Section 1, this problem disappears!
Response: We have proofread section 1 and it is much improved for grammar.

Comment: Overall, the paper is clearly written, well documented, figures illustrate results well. As the Holm et al. (2018, In Review) paper cited picks up where this paper leaves off with data on the parameter distributions to provide for some quantitative understanding of the system being profiled, this paper by Massoud et al as primarily a methodological exercise is fine for a journal like GMD.
Response: Thank you so much for the positive feedback and helpful comments.

Interactive comment on "Identification of key parameters controlling demographically structured vegetation dynamics in a Land Surface Model [CLM4.5(ED)]" by Elias C. Massoud et al.

Xiangtao Xu (Referee)
xu.withoutwax@gmail.com

Received and published: 23 February 2019

Comment: This paper applies the Fourier Amplitude Sensitivity Test (FAST) to a land surface model that accounts for vegetation demography. In particular, the authors try to conduct a comprehensive assessment of the sensitivity in the simulated vegetation dynamics to over 80 input parameters that describe plant biochemical, allometric, and demographic traits. The analysis is performed for a tropical rainforest region in the Amazon, where model bears large uncertainty. Limited by data and computational cost, the paper only included one plant functional type and found that model results are very sensitive to allometric parameters across all time-scales.

Generally, I feel the study is somewhat interesting for GMD in the sense that it introduces FAST to vegetation demography and ecosystem modeling, and that it includes allometric parameters. However, I think the paper can be improved in several aspects to be more useful to the community.

Response: Thank you very much for the positive assessment of our manuscript.

Comment: 1. [P6L32-33] I understand the challenge to include trait-covariation in such analysis. However, the current assumption of absolute orthogonality between parameters makes it hard to interpret the results. For instance, Diaz et al. 2015 shows that the actual ecophysiologically-viable trait space might only be 2% of the total N-dimensional parameter space. It would be helpful to include some more discussions to help interpret the results

Díaz, S., Kattge, J., Cornelissen, J.H.C., Wright, I.J., Lavorel, S., Dray, S., Reu, B., Kleyer, M., Wirth, C., Colin Prentice, I., Garnier, E., Bönisch, G., Westoby, M., Poorter, H., Reich, P.B., Moles, A.T., Dickie, J., Gillison, A.N., Zanne, A.E., Chave, J., Joseph Wright, S., Sheremet'ev, S.N., Jactel, H., Baraloto, C., Cerabolini, B., Pierce, S., Shipley, B., Kirkup, D., Casanoves, F., Joswig, J.S., Günther, A., Falczuk, V., Rüger, N., Mahecha, M.D. & Gorné, L.D. (2015) The global spectrum of plant form and function. Nature

Response: Thank you very much for the great comments. We added a new section in the introduction to distinguish two types of studies: sensitivity analysis study and uncertainty quantification study (page *1, line 30 to page 2, line 8)* . Our study is the sensitivity analysis study and thus we did not explore the trait coordination and trade-offs. We have incorporated your suggested paper and points in the discussion section 4.3 for future uncertainty analysis studies.

Comment: 2. Since the analysis uses a vegetation demography model, one interesting question is how parameters influence ecosystem demography/structure. I like the results showing the sensitivity for different size groups. An additional interesting diagnostic is how the fraction of small/large trees change with parameters. This information can help future modeling practices to diagnose biases in ecosystem structures. In addition, a theoretical analysis by Falster et al. 2018 suggests that the trait influence on growth can change non-linearly with size. It would be interesting to see whether the results of this study are consistent.

Falster, D.S., Duursma, R.A. & FitzJohn, R.G. (2018) How functional traits influence plant growth and shade tolerance across the life cycle. Proceedings of the National Academy of Sciences, 115, E6789–E6798.

Response: Thanks for this suggestion and we have now added the suggested sensitivity analysis for fraction of small/medium/large size trees (see Fig D6). Our analysis does support that the trait influence on growth changes with size (e.g., Fig. 5) and we have incorporated your suggested paper and points in our citation in the discussion section 4.1 (see Page 16 Line 1-2).

Comment: 3. Of course, allometry can influence the results by a lot. But is a 15% change in the stem allometric coef c (the exponent in the allometric equation) justifiable? This is actually linked to the limitation that no parameter distribution is included. But I would suggest including some discussion for the most sensitive parameters.

Response: We added to the introduction the distinction between two types of studies: sensitivity analysis study and uncertainty quantification study (Page 2 Line 30-Page 3 Line 8). This paper is a sensitivity analysis study focusing on the understanding of model behaviors. We point out in discussion section 4.3 that ongoing and future studies of uncertainty analysis that specify the parameter distributions will help us understand the uncertainty contributions from each parameter. In the revised manuscript, we do point out why allometrics are important due to their non-linearity and there is a large amount of variability for allometry coefficients in the reported literature (e.g., Feldpausch et al. 2011) (see Page 14 line 25-line 35).

Comment: 4. The most sensitive parameters (e.g. target storage carbon) seems to be a rather model-specific one. What does this imply for other models or ecophysiology?

Response: We did point out a lot of similarity to other model sensitivity analysis in section 4.1. In the revised manuscript, we added our comparison to a new sensitivity analysis based on the size-structured model, 3D-CMCC-CNR, by changing the parameters one-at-a-time for 10% deviation from their default values [*Collalti et al.*, 2019]. Their study also showed the importance of allometric parameters. The importance of target carbon storage could be model specific; however, it is in agreement with the main control of plant mortality on vegetation stocks from other models (Sargsyan et al., 2014). Following your suggestion, we also discussed the potential bias of target carbon storage as an important parameter, as carbon starvation is the main mortality mechanism that kills trees in our simulations (see page 15 line 1-6).

Comment: 5. I feel the manuscript can benefit from some re-organization of figures to condense the scientific finding. Most importantly, it seems the sensitivity does not change much with time after a few years, which is expected to me given that only one PFT is included. In this case, I would suggest not to show the changes in sensitivity with time. Instead, just pick two time frame (early succession ~ 5-10 years, and late succession ~ 80-100 years, just like Figure 9) and use bar plots to show how variance is partitioned into different parameters grouped by category shown in Table D1 (Allometry, Photosynthetic, Regrowth, Mortality, etc.).

Response: Thanks for this comments. We feel that pick only two time points will lose some important message on the cycle of parametric sensitivity, especially with the newly added Figure 1 and 7 to check the impact of climate on parametric sensitivity, based on the comment from reviewer #2. Following reviewer Sebastian Lienert, we did reorganize the figures by merging the model output ranges and the parametric sensitivity figures, which saved space for the manuscript.

Comment: Stylistic comments: I noticed quite a few typos and inaccurate descriptions over the text. Here I name a few. I would suggest an overall editorial check of the manuscript.
Response: Thank you for pointing this out and we have carefully proofread the revised manuscript by our coauthors.

Comment: Title missing space between demographically and structured

Response: Done. Thank you.

Comment: P1L2 'aimed' to 'that aims'

Response: Done. Thank you.

Comment: P3L23 allometry

Response: Done. Thank you.

Comment: P7L8 'bare ground', usually it is called near-bare ground since the model assumes a certain seed bank/seedlings to start with.

Response: Done. Thank you.

Comment: Figure 9, please make the last panel the same size.

Response: We have updated this Figure 9, which is now Figure 8 in the revised manuscript.

Interactive comment on "Identification of key parameters controlling demographically structured vegetation dynamics in a Land Surface Model [CLM4.5(ED)]" by Elias C. Massoud et al.

Sebastian Lienert (Referee)
lienert@climate.unibe.ch

Comment: The presented study performs a sensitivity analysis of parameters in the land model CLM4.5(ED), featuring demographic vegetation. The Fourier Amplitude Sensitivity Test (FAST) is applied to a set of 87 parameters governing vegetation processes. The parameters are sampled using a uniform distribution limited by a +/-15% variation of the default parameter values. The model is run at a single tropical site with one PFT enabled and starting from bare ground conditions. The sensitivities of demographic and carbon cycle quantities are reported and the simulations are qualitatively compared to observations.

The study is successful in identifying key parameters controlling vegetation dynamics in the model in a quantitative manner. This is a useful starting point for further studies optimizing model parameters and investigating parameter related uncertainty. Furthermore, the FAST method is introduced in the context of LSMs. Potential shortcomings of the presented sensitivity analysis are acknowledged in the study, including the choice of the parameter sampling range, potential additional correlation of parameters and the use of a single model configuration at a specific site. Some of the raised caveats might be explored further. For instance, the effect of the used climate forcing could be qualitatively investigated by performing a simulation using climate data of a different gridded reanalysis product (e.g. CRU-NCEP) and comparing it to the observed spread of the simulation ensemble. Nevertheless, I think the study fits the scope of the journal GMD.

Response: Thank you very much for your positive assessment of our manuscript.

Comment: In the following some more specific remarks/suggestions:

-Section 2.1: Average period of 30 years: Maybe expand a bit on this choice, would a shorter/longer period substantially alter the results?

Response: We have explored 20- and 40- year intervals and we get similar results. See the new Figure D1 in the revised manuscript and we have incorporate this point in the manuscript (Page 5 Line 15-16).

Comment: Section 2.4 Data and Model Setup: I think this section is a bit brief and could be improved. The 1x1 degree grid in the first sentence might be confusing since it suggests multiple grid cells. I was also missing information about the atmospheric forcing of CO2 or nitrogen deposition (if enabled).

Response: We have added the climate drivers (Fig. 1) and updated CO_2, nitrogen deposition and fire component in the Data and Model Setup section.

Comment: Figures 1-6: I wonder if it might not be better to combine the change in the parameters and their respective sensitivities in a single 4x2 figure. This would also reduce the overall number of figures, allowing to include the plot of the number of trees per size class (Figure D2) in the main text, which is quite an important figure in understanding how the sensitivities of the size classes translate to all trees.

Response: Thank you for this suggestion. We have reorganized all figures of sensitivity results with their corresponding model outputs. Following your suggestion, we have also moved Fig. D2 into the main text as the new Fig. 2.

Comment: 'Most important parameter' in Results 3.1 and Figure 2,4,6 captions: Mention somewhere that this refers to the sensitivity at the end of the simulated period/equilibrium.

Response: Thanks for this good point. What we report are the rank of the average parameter sensitivity over the 130-year simulations. We have pointed out this in Fig 2 caption with other figures refer to that.

Comment: P10L11: Briefly mention again what H2 is (allometric parameters important for vegetation growth)

Response: Done. Thank you.

Comment: Figure 9: Comparison would be easier if rows had identical y-axes. Also, axes are not aligned properly.

Response: We have updated this figure to follow your suggestions on both x-axes and y-axes.

Comment: Some typos I noticed:

P3L15: Extra space in Farquahr , 1989

Response: Done. Thank you.

Comment: P3L18-25: Three times "Therefore, we hypothesize"

Response: We have revised the manuscript to avoid the repetition.

Comment: P3L23: allmoetry → allometry

Response: Done. Thank you.

Comment: P4L10: Missing whitespace: structure.CLM4.5

Response: Done. Thank you.

Comment: P9L10: purpose → purposes

Response: Done. Thank you.

Comment: P10L1: Extra whitespace after medium

Response: Done. Thank you.

Response to short comment by Vick Prasad
vik7prasad@gmail.com

Received and published: 13 February 2019

Comment: In this study, the authors used a type of sensitivity analyses method to understand the behavior of a developed land-surface model (CLM4.5(ED)) to changes in parameter values. They arrive at results which other land surface models such as those that focus more on bio-geochemistry (e.g. CLM4.5) or those that focus more on vegetation dynamics (e.g. ED) could have also come up with if these models were ran separately. While their sensitivity analyses method is okay, their results are trivial. I have concerns regarding the actual simulation method they have used in this study.

Response: This is the first comprehensive sensitivity analysis for FATES. In this study, we considered > 80 parameters and assessed their sensitivities for carbon fluxes, stocks, growth and mortality for different sizes of trees and their linkage to climate conditions. In view that FATES is the next generation dynamic vegetation model with a large user community that supported by both DOE and NCAR, our analysis on FATES should guide the understanding of model behaviors and thus help future model parameterization, improvement and applications. It is a very important step for FATES and will also be potentially helpful for other models with a similar model structure.

Comment: My concerns are on the bias and uncertainties the authors may have in their results. I list the points below, which are likely to be interconnected.

1) The entire parameter space of the model was not explored so how can this be even called a global sensitivity analyses? You looked at 87 parameters in this study. How much uncertainty you have in your existing results for the parameters that you have ignored?

Response: There are two types of uncertainty and sensitivity studies for models. One type of study aims to understand the model behaviors by exploring the baseline sensitivity of model outputs to parameter changes, which is normally an equal amount of deviation from the mean values of default parameters. They are commonly referred to as model sensitivity or elasticity analysis studies [e.g., *Benton and Grant*, 1999; *Collalti et al.*, 2019; *Menberg et al.*, 2016] . Another type of study aims to quantify how much uncertainty is in the model outputs and what contributes to the uncertainty. They are commonly referred to as uncertainty quantification studies. It is possible that a parameter is very sensitive for a model output in the sensitivity analysis study, but could contribute to a small amount of uncertainty in the model output in the uncertainty quantification study there is only a small amount of uncertainty in the parameter estimate. Both types of studies are useful for model development with the sensitivity analysis studies focusing on understanding the baseline of model behaviors and the uncertainty quantification studies focusing on guiding field and laboratory measurements [e.g., *Xu et al.*, 2010]. Our study belongs to the sensitivity analysis studies. The main difference between these two types of studies lies in the difference in research goals with similar uncertainty and sensitivity analysis approaches. We have laid out these two types of studies in the introduction (page *1, line 30 to page 2, line 8)* to clarify the purpose of this paper.

The "global" in this paper refer to the fact that we change all the parameters simultaneously for understanding the impact of parameter of model outputs given the parameter range we defined. There is confusion on how we define "global" sensitivity analysis. A sensitivity analysis is considered to be global when all the input factors are varied simultaneously and the sensitivity is evaluated over their entire range of interest [*McRae et al.*, 1982; *Xu and Gertner*, 2008; *Zhou et al.*, 2008]. From methodological perspective, the global sensitivity analysis changes the parameters simultaneously. From the scientific perspective, the global sensitivity analysis samples the entire range of interest. For sensitivity analysis studies, the entire range of interest could be a certain percentage of default values of parameters. For uncertainty quantification studies, the entire range of interest could be the distributions of parameter estimated from laboratory measurements, field observations and expert knowledge. Campolongo [2000] suggested to classify local and global sensitivity analysis based largely on the extent of the input variable range that the technique assesses; however, this arrangement is ambiguous because the classification depends on whether the range is sufficiently large to be perceived as global [*Song et al.*, 2015]. We have clearly laid out these details in our introduction to avoid confusion (page 3, Line 17-24).

Comment: 2) How does these results of CLM4.5(ED) compare with the other versions of CLM e.g.
with CLM-DGVM or CLM-FATES?

Response: This version of model [CLM4.5(ED)] is the initial version of CLM-FATES. We changed the name from ED to FATES about 2 years ago. We have made the name change from ED to FATES to avoid confusions. As far as we know, we are not aware of studies for CLM-CNDV, which is an original version of the dynamic vegetation for CLM. We did compare our results with CLM and ED in the manuscript (Section 4.1). We also added our comparison to a new sensitivity analysis based on the size-structured model, 3D-CMCC-CNR, by changing the parameters one-at-a-time for 10% deviation from their default values [*Collalti et al.*, 2019]. Their study also showed the importance of allometric parameters. We have incorporated this comparison in the discussion section 4.1.

Comment: 3) The model simulations are performed for 1 deg x 1 deg (approximately at 100 km). This resolution is quite coarse. If you are trying to understand the large-scale vegetation responses to changes in parameter values, then I think that needs to be made clear (at-least in the abstract as well as in the introduction). If not, then you need to address how much your results will change if you did the sensitivity analyses at the local scale using local weather conditions.

Response: We have included a statement on the resolution for both abstract and the introduction. We also discussed the model sensitivity to climate drivers in section 4.3 (Page 21 Line 16-26).

Comment: 4) This simulation is only carried out at one site. Why was this specific site chosen?

Isn’t this already a bias? Will you get similar results at other biomes?

Response: This a good question. We chose this site because CLM (FATES) is already set up for this site and it is common test site for the tropical biome. We will expect to see different results for other biomes, or possibly other tropical sites with different climates, but we will expect the main results will stay valid. That is, what parameters fell out as driving the model uncertainty would still show up for a different tropical site. This is the first sensitivity test of CLM (FATES) and we know other research groups are working on different sites to improve our understanding of the model at different locations. We have included a statement in the section of 4.3 as below:

“ … it is possible that the parameter sensitivity could be different if we use different model inputs, different sites, and different structures of subcomponents within the model. For example, using site level climate drivers, instead of the reanalysis meteorological drivers used in this study could lead to different sensitivity values since our preliminary analysis showed that simulated vegetation demography is quite sensitive to different climate drivers. Furthermore, there are ongoing development activities to improve different components of the models. For example, there are current efforts to incorporate different representations of tree allometry within CLM4.5(FATES), which have different formulations between size and biomass, the allocation of nitrogen and thus the photosynthetic process. Therefore, model improvements such as these can affect corresponding sensitivity analysis results. To understand the impact of site level variations on model dynamics, similar sensitivity analysis across different sites can be conducted to understand how climate variability will affect the sensitivity analysis results. “

Comment: 5) The climate data was recycled, which might be okay, but you used climate data from 1942 to 1972? I don‘t think you can compare your modeled results with observations unless you believe that the climate at your studied site didn’t change much or if your measurements were carried out around 1972? Further, isn’t CLM4.5(ED) sensitive to climate forcing?

Response: Yes, CLM4.5 is sensitive to climate forcing and we incorporate a new paragraph to assess the climate condition on parametric sensitivity (Page 13 Line 32-Page 14 Line 6). We understand your concern about the climate driver and I agree with you of the potential bias in model-data comparison. We want to point out that it is common for CLM simulations to use recycled climate and in the paper that comparison with data is meant as a range/sanity check but not a validation, in view that main focus of the paper is on the relative impact of different parameters on model output. We do point out this potential bias in our comparison in section 4.1 (page 16, line 28-30).

Comment: 6) The simulation was carried out for about 130 years, where the changes in parameter values (+/- 15%) was relatively small compared to the default value. This % change was fixed for all parameters. Isn’t there any parameter out of 87 that has a wider range in reality. If so, how can one be really sure about these results then?

Response: As we pointed out at beginning of response, this study is a sensitivity analysis study focusing on understanding of the model behaviors in our response to your comment #1. Ongoing studies of uncertainty quantification will help us understand the uncertainty contributions from realistic parametric distributions. We have also laid out this caveat in our section of limitation of methods in the discussion (section 4.3).

Comment: 7) The authors should quantify the relative impacts on the carbon fluxes or vegetation stocks due to parameter changes, and state whether these impacts are statistically significant or not. At present, it is unclear how much the identified parameters control the carbon fluxes or stocks.

Response: We would like to point the reviewer to Fig. 1-6 where we did plot the sensitivity indices of parameters (i.e., the proportion of variance in the model output contributed by each parameter, which measures the relative impacts of parameters on carbon flux and vegetation stocks) through time for carbon fluxes and stocks. We also plotted the impact of key parameter on GPP, NPP, LAI and Biomass through cubic splines (see Fig. 8 in the revised manuscript). Thus, we are a bit confused regarding the suggested change by the reviewer. Do you want us to plot the contributions of identified important parameters to fluxes or vegetation stocks on a single plot for an easier comparison of the relative contributions? We do have the standard errors of estimated sensitivities based on the delta method. See details from Chonggang Xu & George Gertner (2011) Reliability of global sensitivity indices, Journal of Statistical Computation and Simulation, 81:12, 1939-1969. Following our understanding of your suggestion, we have introduced the standard error estimation in FAST description (Page 6 Line 26-28) and plotted the sensitivity and associated standard errors in the updated Fig. D9.

References

Benton, T. G., and A. Grant (1999), Elasticity analysis as an important tool in evolutionary and population ecology, *Trends Ecol Evol*, *14*(12), 467-471, doi:Doi 10.1016/S0169-5347(99)01724-3.

Campolongo, F., A. Saltelli, T. M. Sørensen, and S. Tarantola (2000), Hitchhiker's guide to sensitivity analysis, in *Sensitivity analysis*, edited, pp. 15-47, IEEE Computer Society Press.

Collalti, A., P. E. Thornton, A. Cescatti, A. Rita, M. Borghetti, A. Nole, C. Trotta, P. Ciais, and G. Matteucci (2019), The sensitivity of the forest carbon budget shifts across processes along with stand development and climate change, *Ecol Appl*, *29*(2), e01837, doi:UNSP e01837 10.1002/eap.1837.

McRae, G. J., J. W. Tilden, and J. H. Seinfeld (1982), Global sensitivity analysis - a computational implementation of the Fourier Amplitude Sensitivity Test (FAST), *Comput Chem Eng*, *6*(1), 15-25.

Menberg, K., Y. Heo, and R. Choudhary (2016), Sensitivity analysis methods for building energy models: Comparing computational costs and extractable information, *Energ Buildings*, *133*, 433-445, doi:10.1016/j.enbuild.2016.10.005.

Song, X. M., J. Y. Zhang, C. S. Zhan, Y. Q. Xuan, M. Ye, and C. G. Xu (2015), Global sensitivity analysis in hydrological modeling: Review of concepts, methods, theoretical framework, and applications, *J Hydrol*, *523*, 739-757, doi:10.1016/j.jhydrol.2015.02.013.

Xu, C., and G. Z. Gertner (2008), Uncertainty and sensitivity analysis for models with correlated parameters, *Reliab Eng Syst Safe*, *93*, 1563-1573.

Xu, C., M. Legros, F. Gould, and A. L. Lloyd (2010), Understanding Uncertainties in Model-Based Predictions of <italic>Aedes aegypti</italic> Population Dynamics, *PLoS Negl Trop Dis*, *4*(9), e830, doi:10.1371/journal.pntd.0000830.

Zhou, X., H. Lin, and H. Lin (2008), Global Sensitivity Analysis, in *Encyclopedia of GIS*, edited, pp. 408-409, Springer US, Boston, MA, doi:10.1007/978-0-387-35973-1_538.

Identification of key parameters controlling demographically structured vegetation dynamics in a Land Surface Model [CLM4.5(FATES)]

Abstract

Vegetation plays an important role in regulating global carbon cycles and is a key component of the Earth System Models (ESMs) that aim to project Earth’s future climates. In the last decade, the vegetation component within ESMs has witnessed great progress from simple ’big-leaf’ approaches to demographically-structured approaches, which have a better representation of plant size, canopy structure, and disturbances. These demographically-structured vegetation models typically have a large number of input parameters, and sensitivity analysis is needed to quantify the impact of each parameter on the model outputs for a better understanding of model behaviors. In this study, we conducted a comprehensive sensitivity analysis to diagnose the Community Land Model coupled to the Functionally Assembled Terrestrial Simulator, or CLM4.5(FATES). Specifically, We quantified the first and second order sensitivities of the model parameters to outputs that represent simulated growth and mortality as well as carbon fluxes and stocks for a tropical site with an extent of 1x1 degrees. While the photosynthetic capacity parameter ($V_{c,max25}$) is found to be important for simulated carbon stocks and fluxes, we also show the importance of carbon storage and allometry parameters, which determine survival and growth strategies within the model. The importance of parameter changes with different sizes of trees and climate conditions. The results of this study highlight the importance of understanding the dynamics of the next generation of demographically-enabled vegetation models within ESMs to improve model parameterization and structure for better model fidelity.

Deleted: ED

Deleted: a key

Deleted: aimed

Deleted: progresses

Deleted: has

Deleted: The

Deleted: are

Deleted: controlled by

Deleted: generally

Deleted: use the Fourier Amplitude Sensitivity Test (FAST)

Deleted: Ecosystem Demography Model

Deleted: ED).

Deleted: investigate

Deleted: .

Deleted: are shown here to

Deleted: vegetation demography and carbon stocks through their impacts on

Deleted: .

Deleted: highlights

Deleted: toward improved

Deleted: model

1 Introduction

Earth System Models are abstract representations of nature used to simulate physical, chemical, and biological processes across the interacting domains of the Earth system to estimate past, present, and future climate claussen2002earth,dunne2012gfdl,arora2013carbon,hurrell2013community. The land component of Earth System Models, land surface models (LSMs), are capable of representing vegetation dynamics through the use of dynamic global vegetation models foley1996integrated,cox2000acceleration,krinner2005dynamic,friedlingstein2006climate,sato2007seib,arora2013carbon. The first generation dynamic vegetation models represent plant communities and their competition using a single area-averaged representation of plant functional types (PFTs) within each land grid cell cox2000acceleration,pan2002biogeochemistry,hickler2004using. Recently, a number of vegetation models that can represent plant demographic processes have emerged to better capture coexistence and competition driven by light-competition between different sizes of trees in a vertical canopy structure at different successional stages through the representation of disturbance history moorcroft2001method,thonicke2001role,sitch2003evaluation,hickler2004using,fisher2010assessing,scheiter2013next,fisher2018vegetation. These demographic models allow comparison with many more observed vegetation processes than first generation models, but also contain more degrees of freedom leading to great complexity.

Deleted: While

Deleted: each

Deleted: type (PFT) for

Deleted: climatic

Deleted: , second-generation

Deleted: models

Deleted: as well as

Deleted: dynamics

Deleted: next generation

Deleted: causing them to be more complex and subject to high variability.

LSMs typically contain a suite of different parameters to resolve the carbon, water, and energy fluxes and pools at the land-atmosphere interface noilhan1989simple,bastidas1999sensitivity,gupta1999parameter,masson2003global,sargsyan2014dimensionality. Many of these parameters can be estimated directly in the field, but others are difficult or impossible to measure due to various complications such as the lack of a physical meaning, technological limitations, or spatial/temporal aggregation entekhabi1989land,kumar2006land. Parameters that are observable in the field are also often subject to large natural variability, including changes through space and time wood1992land,masson2003global,fisher2015taking. For example vegetation parameters can be used to describe different root profiles vrugt2001one,zeng2001global or photosynthetic capacities leuning2002temperature,rogers2014vcmax, however, model parameter values are often taken from literature publications or databases, and may not represent local variation or capture seasonal or ontogenetic changes. For parameters of critical importance, even a small difference in parameter values can lead to significant divergence for multi-model ensemble projections or uncertainty in model predictions from different models sitch2008evaluation,dietze2014quantitative,mcdowell2015multi,rogers2017roadmap. Since parameters are often defined in simulations with limited prior knowledge of their mean values and variation o1976bayes,kitanidis1986parameter,geromel1999optimal, model uncertainty or sensitivity analyses are typically required to adequately quantify the uncertainty in model outputs and importance of parameters to guide model calibration and improvement.

Deleted: a

Deleted: analysis is

Deleted: impact of the parameters on the

Deleted: for a better understanding of model dynamics

Deleted: identification of targeted

There are two types of uncertainty and sensitivity analysis studies. One type of study aims to understand the model behaviors by exploring the baseline sensitivity of model outputs to parameter changes, which is normally an equal amount of deviation from the mean values of default parameters. This is commonly referred to as model sensitivity or elasticity analysis studies (e.g., [Benton1999Elasticity, pappas2013sensitivity, Menberg2016Sensitivity, Collalti2019Sensitivity]). Another type of study aims to quantify the amount of uncertainty in model outputs and the corresponding contributions to this uncertainty by different sources, which is commonly referred to as uncertainty quantification studies (e.g., [Xu2010Mosquito, dietze2014quantitative]). It is possible that a parameter is very sensitive for a model output in the sensitivity analysis study, but could contribute to a small amount of uncertainty in the model output if the parameter contains a low level of variations dietze2014quantitative. Both types of studies are useful for model development and applications with sensitivity analysis studies focusing on understanding the baseline of model behaviors and uncertainty quantification studies focusing on guiding field and laboratory measurements. Despite the need for such studies, systematic investigation of the parameter sensitivity and output uncertainty of LSMs is not standard practice, potentially on account of the high dimensionality involved (although c.f. [zaehle2005effects, fisher2010assessing, pappas2013sensitivity]).

Today, many sensitivity analysis techniques are available sobol1990sensitivity,helton1993uncertainty, saltelli2000sensitivity,razavi2016new. Some of these methods examine the response of the outputs by varying input parameters one at a time and holding other parameters at their default values saltelli2000sensitivity. However, the sensitivity index derived by this type of assessment depends on the default values of the other parameters, and the assumption these values are satisfactory is questionable (e.g. [da1996vegetation, sen2001impact, groenendijk2011assessing, schwalm2010model]) since the discrepancies in LSM predictions are strongly tied (through feedbacks of momentum, energy, mass and biogeochemistry) to the differences in their representation of the land surface crossley2000uncertainties,rosolem2013towards. Therefore, it is desirable to use more extensive sensitivity analysis techniques that examine the response of model outputs averaged over the variation of all the parameters. These 'global' methods are generally preferred when computing power is not a limiting factor as they require a relative large number of ensemble runs. A sensitivity analysis is considered to be global when all the input factors are varied simultaneously and the sensitivity is evaluated over their entire range of interest McRae1982fast, Xu2008Sensitivity, Zhou2008Sensitivity. For sensitivity analysis studies, the entire range of interest could be a certain percentage deviation of default values of parameters. For uncertainty quantification studies, the entire range of interest could be the distributions of parameter estimated from laboratory measurements, field observations and expert knowledge. [Campolongo2000Hitchhiker] suggested to classify local and global sensitivity analysis based largely on the extent of the input variable range that the technique assesses; however, this classification is ambiguous as it depends on whether the range is sufficiently large to be perceived as global Song2015sensitivity.

Our goal of this study is to conduct a comprehensive sensitivity analysis for the CLM4.5(FATES) at a tropical site with an extent of 1x1 degrees to 1) understand the baseline model behaviors of vegetation carbon stocks and fluxes and vegetation demography in relation to different model parameters and 2) provide directions for improved model parameterization toward a better model fitting to observations. Specifically, we aim to answer the following question: what are the main parameter controls on vegetation processes such as growth and mortality and on the resulting dynamics of carbon fluxes and stocks? Based on our understanding of simulated processes in CLM4.5(FATES), we propose to test three hypotheses. Our first hypothesis is related to photosynthetic capacity. The carbon input for vegetation growth is through photosynthesis and in most LSMs, it is simulated based on the Farquhar model Farquhar1989photosynthesis with the photosynthetic capacity represented by the maximum

Deleted: calibration.

Deleted:

Deleted: . In this study, we apply a 'global' sensitivity analysis to determine the influential parameters over a specified region of the parameter space. So far, there are several uncertainty and sensitivity analyses being conducted for size-structured land surface models pappas2013sensitivity,lebauer2013facilitating,wang2013parameter,dietze2014quantitative. To the best of our knowledge, this paper presents one of few formal global sensitivity analyses for an LSM with cohort-based vegetation demography (see [pappas2013sensitivity]) and thus could provide important knowledge for model calibration and understanding of the model structure.

Deleted: for

Deleted: apply

Deleted: global

Deleted: , the Fourier Amplitude Sensitivity Test (FAST), to

Deleted: ED),

Deleted: ED

carboxylation rate at 25 ^{o} C ($V_{c,max25}$) and maximum electron transport rate at 25 ^{o} C (J_{max25}). J_{max25} is commonly simulated in proportion to $V_{c,max25}$ in many models and previous sensitivity analysis studies pappas2013sensitivity,sargsyan2014dimensionality,dietze2014quantitative have shown that $V_{c,max25}$ is generally an important parameter that affects simulated carbon fluxes. Therefore, we hypothesize that the photosynthetic capacity parameter, $V_{c,max25}$, is a key control on simulated carbon fluxes in CLM4.5(FATES) (H1). Second, for demographic models, the allometry of trees determines the amount of carbon input to different tissues (e.g, leaf, root and stem). If the carbon is allocated more to leaf compared to stem, the tree will have a higher productivity but can also lead to lower stem growth and thus less height growth for light competition. Thus, we hypothesize that allometry parameters are important for vegetation growth and long-term carton stocks (H2), as they will determine plant's growth strategies. Finally, the carbon stock for vegetation is affected not only by the input of carbon through photosynthesis, but also by the loss of carbon through mortality. We hypothesize that the parameters determining the mortality are important drivers of the long-term vegetation carbon stocks (H3), as they will control the length of carbon turnover time.

2 Materials and methods

2.1 CLM4.5(FATES)

CLM4.5(FATES) is an open-source land surface model coupled with a demographically structured dynamic vegetation model to predict climate-vegetation interactions. The CLM is used within various Earth system modeling frameworks, including the Community Earth System Model (CESM) and the Norwegian Earth System Model (NorESM) lawrence2011parameterization,bonan2011improving. The FATES is developed from the Ecosystem Demography Model (ED), which scales up the behavior of forest ecosystems by aggregating individual trees into representative 'cohorts' based on their size and PFT, and by aggregating groups of cohorts into representative 'patches' (conceptually similar to a forest plot) that explicitly tracks the time between disturbances moorcroft2001method. The main property of the ED concept that differs from most commonly used 'big-leaf' models is the capacity to predict distribution, structure, and composition of vegetation directly from their given physiological traits described by the model parameterization fisher2015taking. This is achieved via the means of trait-filtering, whereby plant traits affect plant growth and survival, growth in turn affects the acquisition of light resources, and feeds back onto growth, survival and reproduction. Differences in growth, survival and reproduction rates thus directly control the relative distributions of vegetation types and their traits as well as the overall carbon stocks. CLM4.5(FATES) can be simulated with different modes including point mode for individual sites, regional mode for watershed or regional scales, and global mode for the global scale. See supplementary model description in [fisher2015taking] for details on specific components of the model structure. CLM4.5(FATES) represents vegetation using size-structured groups of plants (cohorts) which co-exist on various successional trajectory-based land units. CLM4.5(FATES) simulates growth by integrating photosynthesis across different leaf layers for each cohort. The model allocates photosynthetic carbon to different tissues such as leaf, root and stem based on the allometry of different tree species. Mortality rates are an important drivers for the simulated forest dynamics in CLM4.5(FATES). It includes five modes of mortality: 1) fixed background mortality, 2) hydraulic failure based on a threshold of very low soil moisture; 3) carbon

Deleted: affect

Deleted: ED

Deleted: Therefore

Deleted: allmoetry

Deleted: Therefore, we

Deleted: ED

Deleted: ED

Deleted:) is a dynamic vegetation model that

Deleted: ED

Deleted: ED

Deleted: ED

Deleted: , and stress-based mortality by plant carbon starvation and hydraulic failure fisher2015taking, in addition to a background mortality rate, tree-fall impact mortality, and fire starvation resulting from the depletion of carbon storage in plants (see Appendix C for details); and 4) impact mortality resulting from the falling of big trees fisher2015taking; and 5) fire.

In this original version of CLM4.5(FATES), there are two challenges for the model to simulate tropical forests. First, it is difficult for the model to represent the coexistence of PFTs due to the dominance of growth and reproductive feedbacks and potentially the absence of additional stabilizing mechanisms fisher2010assessing, fisher2018vegetation, therefore, in this initial analysis we focus only on a single broadleaf evergreen tree PFT, which is a typical vegetation type for the study region (the Amazon). We want to point out that, because of the high species diversity of tropics, it is always a challenge for models to capture diverse traits with a limited number of PFTs in typical ESMs. By limiting our sensitivity analysis to one PFT in this study, our sensitivity analysis will help us understand the main control on demographic rates of growth and mortality that will essentially affect the outcome of competition for multiple PFTs. Thus, we expect that our sensitivity analysis can be used to guide the selection of traits for the presentation of trait trade-off for diverse tropical forests and improve the simulation of PFT coexistence for model calibration and improvement. Second, the model generally underestimates leaf area index (LAI). We expect that our sensitivity analysis will be used as a guidance to adjust identified key model parameters in order to better fit model predictions to the observations.

Deleted: ED

Deleted: lack of representation of plant trait trade-off between different PFTs. Therefore,

Deleted: . Even though we have only

The CLM4.5(FATES) tracks different size class of plants (generally >10) through time. To facilitate our analysis, we aggregate cohorts into 3 size categories: small (<10 cm), medium (10-50 cm) and large trees (> 50 cm). For sensitivity analysis of each size category (small, medium and large trees), we choose to average the outputs over 30 year intervals. This is done in view that a large amount of variability in model outputs could be caused by the transient and abrupt changes across size and thus only a small amount of variability is affected by parametric variations. Our analysis shows that the identified key parameters and the corresponding magnitude of sensitivity are similar with averaging over different number of years from 20 to 40 years (Fig. ?).

Deleted: ED

Deleted: different

Deleted: categories in the annual model outputs could make the FAST

Deleted: only account for a minor amount of the variance contribution

Deleted: each parameter.

2.2 Sensitivity Analysis: The FAST method

Global sensitivity analysis aims at quantifying the contributions of input variables to the variability of the outputs of a physical model by simultaneously sampling values of parameters from their corresponding statistical distributions. There are many methods for global sensitivity analysis. Two popular variance-based approaches are the Sobol's method sobol1990sensitivity and the Fourier Amplitude Sensitivity Test (FAST) cukier1973study. The Sobol's method has received much attention since it provides clear description of the importance index of model parameters based on variance decomposition. However, the full description requires the evaluation of 2^n Monte Carlo integrals sudret2008global, which is not practically feasible unless n is low (n here represents the dimensionality of the model, or the number of active parameters). Compared to Sobol's method, FAST is more computationally efficient. It can be used effectively for nonlinear and nonmonotonic models sudret2008global,xu2011understanding. FAST uses a periodic sampling approach to draw samples from parameter space defined by probability distributions with a characteristic periodic signal for each parameter. These samples will then be fed into model for ensemble simulations. Finally, a Fourier transformation is applied to decompose the variance of a model output into partial variances contributed by different model parameters based on the characteristic periodic signal assigned for each parameter. Only the first order sensitivity indices referring to the "main effect" of parameters were calculated in the original method. In the 1990's, an extended FAST method able to calculate sensitivity indices

Deleted: variance

Deleted:

Deleted: sample the

Deleted: and

Deleted: .

referring to "total effect" was developed sobol1990sensitivity,archer1997sensitivity,saltelli1999quantitative. This "total effect" of a parameter's sensitivity refers to the sum of a parameter's individual contribution (1^{st} order sensitivity) and the contribution from its interaction with other parameters (higher order sensitivity) on the overall variance of the model output; that is, the total effect includes all the higher order interactions. [xu2011understanding] further derived equations within the FAST framework to calculate specific higher order interactions for different sampling approaches. The FAST method has found widespread use in many different fields of study including sensitivity analysis of the parameters of models that represent the land surface collins1994evaluation, chemical reaction haaker2004local, nuclear waste disposal lu2001sensitivity, erosion wang2001uncertainty, hydrologic systems francos2003sensitivity, atmospheric systems kioutsioukis2004uncertainty, crop growth wang2013parameter, or matrix population and forest landscape models xu2009uncertainty,xu2009uncertainties.

In this study, we quantify both the 1^{st} and 2^{nd} order sensitivities of the model parameters using FAST. It is possible to identify higher order interactions with FAST; however, because of the sample size limitations for a larger tri-variate parameter space, the FAST-based estimation of third-order sensitivity indices would be less reliable xu2011understanding. Specifically, the 1^{st} order sensitivity is used to measure the importance of the variations in one parameter to the model outputs. If one parameter x_i is important to a model output y at time t [i.e., $y(t)$], we expect that the mean value of $y(t)$ will change substantially with different values of x_i. Statistically, we expect to see a large variance of the expected value of $y(t)$ given x_i [i.e., large $V(E(y(t)|x_i))$, where $E(\cdot)$ is the expected value of the output, $V(\cdot)$ is the variance calculated in the parameter space]. Similarly, if the combined impact of x_i and x_j is important, we expect to see a large variance of the expected value of $y(t)$ given x_i and x_j [i.e., large $V(E(y(t)|x_i,x_j))$]. Therefore, we calculate the 1^{st} and 2^{nd} order sensitivities, α_{x_i} and $\alpha_{x_ix_j}$, respectively, of the model parameters for each output of interest and at each time step as follows,

$$\alpha_{x_i}(t)=\frac{V(E(y(t)|x_i))}{V(y(t))} \qquad (1)$$

$$\alpha_{x_i,x_j}(t)=\frac{V(E(y(t)|x_i,x_j))-V(E(y(t)|x_i))-V(E(y(t)|x_j))}{V(y(t))},i\neq j. \qquad (2)$$

where $V(y(t))$ is the total variance of model output $y(t)$. In FAST, the variances are estimated through periodic samples in the θ space between 0 and 2π, which are linked to the samples in the parameter space through a search function. Further details on the FAST toolbox used for this study can be found in [xu2007extending, xu2009uncertainty, xu2011understanding] or [xu2009uncertainties]. We are aware that FAST can provide robust estimates of the sensitivity coefficients in high-dimensions wang2013parameter, especially since the CPU-demands of CLM4.5(FATES) mandates application of a method like FAST due to its ability to derive sensitivity values with sparse sampling. Due to the random parametric sampling, there will be errors in the estimates of sensitivity indices. In this study, we estimate the standard error of

Deleted: ED

Deleted: This allows FAST

Deleted: compute with less forward runs from

Deleted: original model. What is more, the parameter space used in this study is confined to a relatively small area around the default CLM4.5(ED) values (see next section). This further assures that the

Deleted: is sufficient to capture accurate

Deleted: values.

FAST-based sensitivity index derived by [xu2011reliability], with lower errors for a larger sample size.

To better understand how parameters affect specific CLM4.5(FATES) output variables (i.e., the relationship between model parameters and outputs), we also fitted cubic splines to the scatterplots between samples of parameters identified as important by FAST and the corresponding output variable of interest using the R SemiPar package ruppert2003semiparametric.

Deleted: ED

Deleted: ,

Figure 1: Recycled climate drivers for the study area including annual mean precipitation, relative humidity, and air temperature for year 1948-1972. The annual radiation and air pressure are not plotted as they are quite stable across years.

2.3 Parameter Selection

In total, there are more than 200 parameters for all land surface processes including surface energy exchange, hydrology, biogeochemistry, plant physiology, and demographic processes within CLM4.5(FATES). In this study, we focus solely on vegetation components and select 87 parameters that are relevant to vegetation processes, including parameters for photosynthetic processes, temperature response, allometry description, radiative transfer, recruitment, turnover and mortality. See Table D1-D4 in the appendix for a complete list of the parameters used in this study, with corresponding description, units, default values, and applied ranges. Refer to Appendix A for the allometry equations, Appendix B for the temperature response curve (photosynthesis) equations, and Appendix C for the carbon storage equations used in CLM4.5(FATES).

Deleted: There

Deleted: in

Deleted: ED

Deleted: with

Deleted: ED

To conduct the sensitivity analysis, we have extracted many parameters in the model that were 'hard-wired' in previous CLM versions. The FAST algorithm requires valid ranges to be chosen for each parameter, which creates the possible parameter space to sample from. In theory, each parameter has a corresponding observational distribution that produces the ideal space for sampling lebauer2013facilitating. However, in this study there are both a large parameter set and a scarcity of appropriate data sources for Amazonian forests for many of the relevant quantities, therefore obtaining a robust data-supported distribution for each parameter was difficult. Because we only aim to understand the baseline model structure, the parameter ranges in this study were generated by applying a uniform distribution over a range that spans +/- 15 % of the default parameter values of CLM4.5(FATES) (i.e. default parameter values for tropical evergreen trees). We choose a rather conservative range of +/- 15% of the default CLM4.5(FATES) values so that global sensitivity indices can be estimated in the reasonable vicinity of the default parameters. We suggest that a more robust uncertainty analysis based on realistic parameter ranges is needed for guidance on additional field measurements.

Deleted: We use a broad definition of parameter and extract numerous features of

Deleted: , such as the parameters defined in the equations of Appendices A and B

Deleted: ED

Deleted: ED

Figure 2: Simulated change in tree density (NPLANT; N ha^{-1}) and the corresponding 1st order parametric sensitivity indices. The left panels show the simulated ranges of tree density for all trees (a) and the corresponding fraction of b) small (*diameter*<10 cm), c) medium (10 cm <*diameter*<50 cm), and d) large trees (*diameter*>50 cm). Shown are the mean simulation (black line) with 95% spread of the simulation ensemble. Right panels show the sensitivity for top 6 most important parameters for e) density of all trees, f) small tree density, g) medium tree

Deleted: 1

Deleted: diameter at breast height (dDBH; cm yr^{-1}

Deleted:)

Deleted: a)

Deleted: ,

density, and h) large tree density, in order of importance based on the mean parametric sensitivity across years (red is the most important and blue is the least important). The jumps seen in years 10, 40, 70, and 100 for small, medium and large trees are due to the temporal averaging mentioned in the materials and methods section. The figures also show sensitivities of the remaining parameters in light grey (1st order sensitivity index for all other parameters) as well as the sensitivity of parameter interactions in dark grey (higher order sensitivity index for all parameters).

Using FAST, 5000 parameter combinations are sampled from the parameter space. The sample size was determined using the heuristic method of [xu2011understanding] where it is appropriate to use 100 times the number of effective (important) parameters. The 5000 model runs cost about 32 CPU hours for each simulation, and thus we ran our simulations for a total of 160,000 CPU hours on the Los Alamos National Laboratory (LANL) Conejo super computer.

In this analysis, we assume the majority of CLM4.5(FATES) parameters to be non-correlated with uniform probability because our study is focused on the model parametric sensitivity for model behaviors and there is a limitation of data for estimating covariance among the 80+ parameters. However, we do need to take care of the correlation among parameters in the temperature response functions (Appendix B) in order to generate realistic temperature response curves. These parameters are tested for correlation using a published dataset leuning2002temperature, which showed that the photosynthetic parameters for activation energy (e.g. $V_{c,max,ha}$) are not necessarily correlated with the other photosynthetic parameters. However the parameters for deactivation energy (e.g. $V_{c,max,hd}$) and those related to entropy terms (e.g. $V_{c,max,se}$) are highly correlated as expected (correlation = 0.99+). Thus, each of these parameters' samples are generated from the same location in their relative parameter spaces, which maintains their correlation.

Figure 3: Simulated change in diameter at breast height (dDBH; cm yr^{-1} tree^{-1}) and the corresponding 1st order parametric sensitivity indices. The left panels show the simulated ranges of dDBH for a) all trees, b) small (*diameter*<10 cm), c) medium (10 cm <*diameter*<50 cm), and d) large trees (*diameter*>50 cm). Right panels show the sensitivity for top 6 most important parameters for e) all trees, f) small, g) medium, and h) large trees, in order of importance. See Fig. ? for the details of legends.

In this study, the CLM4.5(FATES) model simulations are setup for a 1° by 1° grid in a moist-tropical forest in the State of Pará, The Amazon, Brazil (7° S, 55° W), which is a default tropical setup for CLM. The climate conditions for this site are from [qian2006simulation] representative of data from 1948-1972 and recycled for the 130 year simulations (Fig. ?). The CO2 concentration is set as 284.7 ppm. No nitrogen deposition is simulated as the FATES currently does not have the nutrient limitation yet. We initialized the runs with a near-bare ground, or a state with no vegetation but available seeds, and simulated the forest dynamics for 130 years, which we determined was enough time for the ecosystem to reach equilibrium because simulated outputs and corresponding sensitivity values for biomass, basal area and various carbon fluxes had stabilized by this time. By choosing to start from near-bare ground and running the model until it reaches a quasi-steady-state size distribution, rather than by examining short runs initialized from observed initial forest size distributions (e.g. [dietze2014quantitative]), we are

Moved (insertion) [1]

Deleted: .

Formatted: Indent: First line: 0.21"

Deleted: ED

Deleted: due to

Deleted: covariate traits for

Deleted: in this study

Deleted: 2: Sensitivity index of the model parameters (1st order) for

Deleted:) outputs from CLM4.5(ED) (outputs of dDBH are in units [

Deleted:]

Deleted: index is unitless) for a)

Deleted: trees

Deleted: trees

Deleted: Shown are

Deleted: (red is the most important and blue is the least important).

Moved up [1]: The jumps seen in years 10, 40, 70, and 100 for small, medium and large trees are due to the temporal averaging mentioned in the materials and methods section. The figures also show sensitivities of the remaining parameters in light grey (1st order sensitivity index

Deleted: all other parameters) as well as the sensitivity of parameter interactions in dark grey (higher order sensitivity index for all parameters).

Deleted: ED

Deleted: is

Deleted: dynamics since the

Deleted: Therefore, the specific behavior of our demographic model emerges in a shorter time scale, i.e. 130 years, compared to what would naturally occur for a forest to reach stable states from bare ground in reality. By choosing to start from deliberately allowing the ecosystem demographic structure itself to be an outcome of the parametric variance rather than a separate, possibly non-self-consistent, initial condition variance. The fire component is turned off in view that the study site has limited fire disturbances.

3 Results

In this section, we highlight the outputs of CLM4.5(FATES) from the 5000 simulations obtained for the FAST analysis, and then show the important parameters that control variance in the outputs. We first investigate the forest demographic dynamics, diagnosing the growth and mortality processes simulated in CLM4.5(FATES), i.e. outputs representing the change in diameter at breast height (dDBH), the mortality rate, and the resulting basal area (BA). Then we analyze the carbon fluxes and stocks in the model simulations, including Gross Primary Production (GPP), Net Primary Production (NPP), LAI, and total forest biomass.

3.1 Forest demographic dynamics: growth and mortality

One of the key properties of CLM4.5(FATES) is that vegetation is represented as cohorts of varying sizes for more realistic simulation of light competition in the canopy. To illustrate how different parametes impact different size classes of trees, we group various cohorts of trees into 3 size categories for analysis purposes: small, medium, and large trees. Since the model runs are initialized from a near-bare ground state, all simulated plants are considered 'small' with an initial density of half-centimeter diameter saplings.

For the stem growth (dDBH averaged per tree, Fig. ? a-d), small trees have lower rates of growth compared to medium or large trees as they are mostly in the understory and thus lack of light for photosynthesis. However, the fraction of overall stem diameter growth is dominated by the small trees (Fig. ? a) due to their high densities (Fig. ? b). The trees grow faster at the beginning of the simulation when the canopy has not reached full closure. Correspondingly, the parametric sensitivities tends to vary at the beginning of the simulation and then state through time. The most sensitive parameters for tree growth are the target storage carbon and stem allometry parameters, however, the importance magnitude varies with time and sizes of trees (Fig. ? e-h). The stem allometry is the most sensitive parameter at the beginning of simulation (<20 years), which is transitioned toward the dominance of target carbon storage parameter after simulation year 70 (Fig. ? a). We observe that the stem allometry coefficient c is the dominant parameter that controls dDBH for medium and large trees, and the target carbon storage is the most important parameter for small trees. A higher value of stem allometry coefficient c, or a higher allocation of carbon to stem, will lead to faster DBH growth in the initial life stage of small trees (Fig. ? a). However, for medium and large trees, a higher allocation of carbon to stem can lead to lower proportion of carbon allocated to leaves for productivity and thus a slower DBH growth (Fig. ? b, c). This outcome supports hypothesis H2, which states the importance of allometric parameters. The target carbon storage determines the target amount of carbon for the plant to store relative to the leaf biomass (see Appendix C for details). Smaller trees have less stem biomass and are less impacted by the stem allometry coefficient c parameter. Furthermore, small trees are vulnerable to changes in the amount of target carbon storage which affects carbon allocation to growth (see Eq. A9 in Appendix C). Our sensitivity analysis also shows specifically important parameters for different sizes of trees. For example, leaf allometry is important for small trees, $V_{c,max25}$ for medium trees, and seed allocation for large trees.

Deleted: The climate conditions for this site are from [qian2006simulation] representative of data from 1948-1972 and recycled for the 130 year simulations.

Deleted: ED

Deleted: ED

Deleted: forest carbon cycles, specifically the

Deleted: , i.e. outputs representing

Deleted: ¶
Figure 3: Simulated mortality rates (fraction dead per year) for a) all trees, b) small trees (*diameter*<10 cm), c) medium trees (10 cm <*diameter*<50 cm), and d) large trees (*diameter*>50 cm). Shown are the mean simulation (black line) with 95% spread of the simulation ensemble.¶

Deleted: ED

Deleted: We

Deleted: purpose

Deleted:

Deleted: in terms of

Deleted: (

Deleted: 1

Deleted: with a

Deleted: growth.

Deleted: D1

Deleted: D2). Our first-order sensitivity analysis based on FAST shows that

Deleted: for different sizes of trees (Fig. 2).

Deleted: a larger allocation of carbon to stem and thus a

Deleted: D3

Deleted: D3).

Deleted: support

Figure 4: Simulated change in tree mortality rates ([*fraction* yr^{-1}]) and the corresponding 1st order parametric sensitivity indices. The left panels show the mortality rate for a) all trees, b) small (*diameter*<10 cm), c) medium (10 cm <*diameter*<50 cm), and d) large trees (*diameter*>50 cm). Right panels show the sensitivity for top 6 most important parameters for e) all trees, f) small, g) medium, and h) large trees, in order of importance. See Fig. 2 for the details of legends.

In this analysis, carbon starvation emerged as the main driver for the tree mortality (Fig. ?). The Carbon-starvation-based mortality uses a threshold of carbon storage to trigger mortality (see Appendix C). Under shaded conditions, lower carbon stores caused by the balance of NPP, respiration and tissue growth/maintenance should lead to a higher mortality rate. As expected, the smaller tree size classes represent a much larger fraction of the total mortality (Fig. ? b-d). The first-order sensitivity analysis of predicted mortality rate (percentage of mortality per year) shows that the dominant parameter for predicting mortality of large trees is the target carbon storage (Fig. ? h); however, for small and medium trees, other parameters such as allometric and photosynthetic parameters that could potentially determine their height growth and competitive advantages in the canopy are also important (Fig. ? f, g). Specifically, for medium size trees, the mortality rate is affected by both the stem allometry coef c and targeted carbon storage (Fig. ? g). For the small trees, important parameters include the photosynthetic capacity parameter ($V_{c,max25}$), stem allometry coefficient c, mortality rate under stress, and maintenance respiration, with the target carbon storage having high sensitivity for small trees in the early years (Fig. ? f).

The simulated basal area (BA) of the forest, which is the total stem cross-sectional area per ground surface area, results from the combination of both DBH growth and mortality. The BA reaches equilibrium for different sizes of trees around year 70 (Fig. ? a). Our FAST analysis shows that a key parameter that controls BA in different tree size classes is the stem allometry coefficient c (Fig. ? e-h), which is a major parameter that determines the DBH growth (Fig. ?). We also found that the target carbon storage parameter that dominantly controls mortality is an important parameter for the simulated BA (Fig. ? e-h). Different from parameters important for DBH growth at the individual tree level and mortality rate, a new parameter that becomes important for BA of small and medium trees is the minimum crown spread, which determines the ratio of crown radius to DBH. A larger crown spread can lead to a smaller number of trees in the canopy and thus a lower BA (Fig. ?). The identified important parameters for the simulated tree density and fraction of trees are very similar to those identified for the simulated BA, except that the leaf allometry coefficient b become very important for simulated small tree densities (Fig. ? e-h) and minimum height for fraction of trees(Fig. ?).

For the second order sensitivity analysis, parametric interactions between stem allometry coefficient c and the proportion of carbon for seed allocation and target carbon storage, are found to be important for the prediction of total BA (Fig. ?). For trees of different sizes, parametric interactions between stem allometry coefficient c and minimum crown spread, target carbon storage, and maximum DBH, are important for small, medium and large trees, respectively. For the prediction of dDBH and mortality, the contribution of most parametric interactions are relatively small except for large trees (Fig. ?). The interactions between stem allometry coefficient c and the proportion of carbon for seed allocation, maximum DBH, and stem allometry coefficient b are important for the prediction of dDBH for large trees. With respect to large tree mortality, the interaction between stem allometry coefficient c and target carbon storage is found to be important (Fig. ?).

Deleted: Sensitivity index of the model parameters (1st order) for the mortality outputs of CLM4.5(ED) (outputs for mortality are

Deleted: units [

Deleted:]

Deleted: index is unitless)

Deleted: trees,

Deleted: trees,

Deleted: . Shown are the

Deleted: (red is the most important and blue is the least important). The jumps seen in years 10, 40, 70, and 100

Deleted: small, medium and large trees are due to the temporal averaging mentioned in the materials and methods section. The figures also show sensitivities of the remaining parameters in light grey (1st order sensitivity index for all other parameters) as well as the sensitivity of parameter interactions in dark grey (higher order sensitivity index for all parameters).

Deleted: Mortality is an important driver for the simulated forest dynamics in CLM4.5(ED). It includes four modes of mortality: 1) fixed background mortality, 2) hydraulic failure based ...

Deleted: less

Deleted: storage as determined

Deleted: target carbon storage

Deleted: ,

Deleted: NPP could

Deleted: 3).

Deleted: 4

Deleted: 4

Deleted: 4).

Deleted: .

Deleted: 5).

Deleted: sizes of trees

Deleted: 6

Deleted: 2). Meanwhile,

Deleted: also

Deleted: 6). A

Deleted: D5).

Deleted: D6).

Deleted: three other parameters, which are the

Deleted: parameters

Deleted: D7).

Deleted: parameters,

Deleted: For the prediction of

Deleted: for large trees (Fig. D8).

3.2 Forest carbon cycles: carbon fluxes and stocks

To investigate the key parametric control on carbon fluxes and stocks, we specifically investigate parameter sensitivities for GPP, NPP, LAI, and total forest biomass. Our results show that GPP and NPP increased consistently for the first 10 years of the simulations, which is expected for a forest growing from bare ground (Fig. ?). However within a fairly short period of 5-10 years, GPP, NPP and LAI and their variance reached a quasi-stable rate. This amount of time to reach equilibrium is much shorter compared to the basal area (Fig. ? a) and the total biomass accumulations (Fig. ? d).

The first-order sensitivity analysis based on FAST shows that, for carbon fluxes of GPP and NPP, the photosynthetic capacity parameter ($V_{c,max25}$) is the most sensitive parameter (Fig. ? e, f), which supports our hypothesis H1. Furthermore, specifically for NPP, the respiration parameters such as the growth and leaf maintenance respiration rate show high sensitivity (Fig. ? f). For LAI, the leaf allometry parameter is the most important as it determines carbon allocation for leaves (Fig. ? g). The stem allometry parameter is the most important for total biomass (Fig. ? h) as it determines carbon allocation to the stem, which supports our hypothesis H2. See Fig. ? for an easier comparison of parametric sensitivities for different model outputs. A common sensitive parameter is the target carbon storage which is important for GPP, NPP, LAI and total biomass. This results from the fact that the target carbon storage is a key driver for mortality especially for medium and large trees in the simulations (Fig. ? e-h), which account for a large proportion of total biomass (Fig. ?) and GPP (Fig. ?). This result supports hypothesis H3. For the second order sensitivity, the contribution of most parametric interactions are relatively small (Fig. ?) as the first-order sensitivity accounts for a majority of the total variance in model outputs (Fig. ? e-h).

To understand how climate will impact sensitivity results, we also calculated the Spearman's rank correlation coefficients between the first-order sensitivity index and the corresponding climate drivers. Our results show that the sensitivity of target carbon storage and maintenance respiration rate is negatively correlated with annual mean precipitation and relative humidity, but is positively correlated with annual mean air temperature. This suggests that they are more important during the period of stressed conditions comprised of low precipitation, low humidity and high temperature (Fig. ?). For the leaf allometry coefficient b, it is positively correlated with annual mean precipitation and relative humidity. This suggests the leaf carbon allocation is more important under favorable environmental conditions for growth. In general, our results suggests the climate has a larger impact on the parametric sensitivities for short-term carbon fluxes (GPP and NPP) and vegetation status (LAI) but has a smaller impact on parametric sensitivities for long-term vegetation carbon stocks.

Our bi-variate spline analysis wahba1990spline shows that, for $V_{c,max25}$ and target storage carbon, an increase in either of these parameters will cause an increase in the output of GPP, NPP, LAI and biomass (Fig. ?). For the parameters related to leaf and stem allometry, however, the relations may differ depending on the output and the year of interest. At year 130, the higher leaf allocation normally leads to higher fluxes (NPP and GPP) but less biomass. Meanwhile, higher stem allocation lead to higher biomass but smaller fluxes (NPP and GPP). This suggests that the trade-offs between carbon allocation to stem vs leaf tissues leads to a corresponding trade-off between carbon stocks and productivity in the model predictions.

Moved down [2]: ¶
Figure

Deleted: 5: Simulated basal area (BA, units are in m^2 ha^{-1}) from CLM4.5(ED) for a) all trees,and its fractional distribution for various tree sizes classes, including b) small (*diameter*<10 cm), c) medium (10 cm <*diameter*<50 cm), and d) large trees (*diameter*>50 cm). Shown are the mean simulation (black line) with 95% spread of the simulation ensemble. The fractional outputs shown in Panels B-D are the percentage of total BA that is associated with each tree size.¶

Deleted: 7).

Deleted: 5a

Deleted: 7d

Deleted: 8), which supports our hypothesis H1. This result is not surprising as this parameter controls leaf-level carbon uptake. Interested readers should refer to [fisher2015taking] for details on how $V_{c,max25}$ is involved in calculation of production and respiration of simulated forests in CLM4.5(ED).

Deleted: 8

Deleted: .

Deleted: 4

Deleted: D9 in the appendix)

Deleted: D10).

Deleted: D11)

Deleted: 8).

Deleted: 9).

Deleted: tradeoff

Figure 5: Simulated change in basal area (BA, m^2 ha^{-1}) and the corresponding 1^{st} order parametric sensitivity indices. The left panels show the simulated ranges of BA for a) all trees, b) small (*diameter*<10 cm), c) medium (10 cm <*diameter*<50 cm), and d) large trees (*diameter*>50 cm). Right panels show the sensitivity for top 6 most important parameters for e) all trees, f) small, g) medium, and h) large trees, in order of importance. See Fig. ? for the details of legends.

4 Discussion

4.1 Comparing parameter sensitivities to other models

While second generation vegetation demographic models such as CLM4.5(FATES) provide new opportunities to predict the global carbon cycle, the larger number of parameters also creates challenges for identifying key processes for further investigation. In this study, we apply a global sensitivity analysis to determine the influential parameters over a specified region of the parameter space. So far, several uncertainty and sensitivity analyses have been conducted for size-structured land surface models pappas2013sensitivity,lebauer2013facilitating,wang2013parameter,dietze2014quantitative,Collati2019Sensitivity. In comparison with previous sensitivity analyses of size-structured models, our study considers a much larger number of parameters, i.e. > 80 compared with ~20-35 parameters pappas2013sensitivity,lebauer2013facilitating,wang2013parameter,dietze2014quantitative, the difference in parametric sensitivity for different tree sizes, and the interactions among the key parameters. In general, our analysis shows similar results to sensitivity analysis on first generation 'big-leaf' vegetation models (e.g., [sargsyan2014dimensionality]), which show the importance of photosynthetic capacity, $V_{c,max25}$, for predicting GPP and NPP. However, we do show important parameters that are unique to LSMs with second generation vegetation demography. Specifically, results shown here indicate the importance of leaf and stem allometry parameters, which control dynamic carbon allocation strategies based on size, and thus control the general vegetative state and size structure of the forest ([waring1998net, waring2010forest]). Importantly, a significant amount of variability in allometry is reported for different species and regions of the world for the tropic forest feldpausch2011allometry. The importance of allometric parameters could result from the fact that the relationship between allometric coefficients and carbon allocation is highly non-linear based on a power function (see Appendix A for details). This result is in agreement with the results from a recent sensitivity analysis study using a size-structured vegetation model Collalti2019Sensitivity. Our sensitivity analysis also shows the importance of carbon storage to the prediction of mortality rate and thus the total biomass. This is in agreement with other sensitivity analyses of CLM which show the plant mortality rate as a key parameter for the prediction of total biomass sargsyan2014dimensionality. However, we do want to point out that there could be a potential bias as carbon starvation is the main mechanism that kills trees in the simulations in our study; however, in reality, there could be many other causes of mortality such as wind, insects and fire (see [mcdowell2018mortality] for a review). The current implementation of hydraulic failure is only based on very low soil moisture thresholds and more mechanistic representation of plant hydrodynamics (e.g., [christoffersen2016hydraulics]) could result in the importance of hydraulic traits for mortality and vegetation dynamics. By exploring parametric sensitivity for small, medium and large trees, we show that the ranking of parameter importance changes with size of plants (e.g., Fig. ?). This

Deleted: 6: Sensitivity index of the model parameters (1^{st} order) for

Deleted:) outputs from CLM4.5(ED) (outputs of BA are in units [

Deleted:]

Deleted: index is unitless)

Deleted: trees

Deleted: trees

Deleted: Shown are

Deleted: 8

Deleted: (red is the most important and blue is the least important). The jumps seen in years 10, 40, 70, and 100 for small, medium and large trees are due to the temporal averaging mentioned in the materials and methods section. The figures also show sensitivities of the remaining parameters in light grey (1st order sensitivity index

Deleted: all other parameters) as well as the sensitivity of parameter interactions in dark grey (higher order sensitivity index for all parameters).¶
¶

Figure 7: Simulated GPP and NPP (in kg C m^{-2} $year^{-1}$), LAI (in m^2 m^{-2}), and biomass (in kg C m^{-2}) from CLM4.5(ED) model. Shown are the mean simulation (black line) with 95% spread of the simulation ensemble. The system is initialized with a bare ground, and this is shown with initial values of 0 for the different outputs.

Deleted: ED

Deleted: us great

Deleted: cycles with LSMs

Deleted: .

Deleted:]) in view that

Deleted: is a key parameter

Deleted: fluxes

Deleted: also

Deleted: coefficient c

Deleted: ([sargsyan2014dimensionality]).

result is in agreement with a recent study that showed the influence of certain functional traits varied with size Falster2018traitsize.

In our analysis, we observed a number of key similarities in model response to parameter variations in photosynthetic capacity, mortality and respiration parameters pappas2013sensitivity,lebauer2013facilitating,wang2013parameter,dietze2014quantitative; however, there are differences in the order of parameter importance. For example, [dietze2014quantitative] showed that growth respiration fraction was the most important parameter for the simulation of NPP, and $V_{c,max25}$ only ranked as the 7th most important parameter. For our analysis, $V_{c,max25}$ and growth respiration fraction are the first and second most important parameters. This difference in parameter sensitivity rank may result from the fact that [dietze2014quantitative] used variable parameter ranges based on data (i.e., an uncertainty quantification study) while our sensitivity analysis uses equal percentage variations (see details in the discussion subsection: *Limitation of methods*). We also found that some parameters that are identified as important in other studies are not found to be important in our analysis. For example, [dietze2014quantitative] showed that water conductance that determines the upper boundary of transpiration is the second most important parameter for simulated NPP, but a similar parameter (smpso; Table D2) that defines soil water potential for opening stomata is not important in our analysis. This could be related to the fact that our site is much wetter than the temperate forests simulated by [dietze2014quantitative]. [pappas2013sensitivity] showed that the root distribution parameter that determines the fraction of fine roots in the upper soil layer is one of the top five parameters for the simulations of vegetation carbon fluxes and stocks; however, in our sensitivity analysis, the two root distribution parameters ($root_a$ and $root_b$: Table D2) are not important for both vegetation carbon fluxes and stocks. This difference could also result from a wider range of variations (~+/-30%) in the study of [pappas2013sensitivity] compared to our 15% variations of the default parameters. Finally, our analysis shows the importance of allometry parameters, which are not considered in previous studies pappas2013sensitivity,lebauer2013facilitating,wang2013parameter,dietze2014quantitative. Due to the large uncertainties that are associated with allometry dietze2008capturing, it would be important to consider better parameterization of allometry for second-generation vegetation demographic models within LSMs.

Deleted: Specifically, we found consistencies in which parameters are sensitive for simulated carbon fluxes and stocks, which are the

Deleted: is

Figure 6: Simulated change in carbon fluxes and stocks, and the corresponding 1st order parametric sensitivity indices. The left panels show the simulated ranges for a) GPP (kg C m^{-2} year^{-1}), b) NPP (kg C m^{-2} year^{-1}), c) LAI (m^{2} m^{-2}), and d) Total biomass (kg C m^{-2}). Right panels show the sensitivity for top 6 most important parameters for e) all trees, f) small, g) medium, and h) large trees, in order of importance. See Fig. ? for the details of legends.

Deleted: 8: Sensitivity index of

Deleted: model parameters (

Deleted:)

Deleted: ,

Deleted: ,

Deleted: ,

Deleted: units

Deleted: each output are shown in Fig. 7 and sensitivity index is unitless). Shown are the

Deleted: (red is the most important and blue is

Deleted: least important). The figures also show sensitivities of the remaining parameters in light grey (1st order sensitivity index for all other parameters) as well as the sensitivity of parameter interactions in dark grey (higher order sensitivity index for all parameters).

4.2 Comparing simulations with observations

The goal of our study is not to reproduce the observations but instead to identify important parameters that can be better estimated for the model to fit observations. Thus, we layout potential parameter estimation improvements to achieve this goal. We do want to highlight three caveats. First, improved estimation of the most sensitive parameters may not be most efficient if they have relatively small uncertainty or variability across different species and locations. Second, even if the estimates for most sensitive parameters are perfect, we may still not be able

Deleted: two

Deleted: the

to fit model predictions to observations if there is deficiency in the representation of key processes in the model. Third, the recycled climate drivers from 1948 to 1972 may not match the observational periods. Given observation data limitations for our site, we conduct a qualitative comparison of our model simulations to ranges reported in the literature for the tropics. Not surprisingly, our model results show a variation of model-data mismatch for key vegetation states. For LAI (Fig ? c), our simulated range is between ~1.9-6.0 m^2 m^{-2} which is lower than the observed range of ~3.0-6.9 m^2 m^{-2} based on LAI estimated from MODIS knyazikhin1999modis during 2000-2016 within a 0.5 degree window around our site. Our sensitivity analysis showed that leaf allometry coef b and target carbon storage are two key parameters affect simulated LAI (Fig ? g) and we expect that a better estimation of these parameters with data could potentially improve the model simulations. For GPP (Fig ? a), the simulated range is between ~1.0-3.0 kg C m^{-2} yr^{-1}, which is also lower than the observed range of ~2.4-3.7 kg C m^{-2} yr^{-1} based on extrapolation from eddy fluxes tower observations and climate during 1981-2010 jung2009towards. Our analysis suggests that photosynthetic capacity as represented by $V_{c,max25}$, target carbon storage and top of canopy specific leaf area are important parameters (Fig ? a) and an improved estimation of them could help improve model simulations of GPP. We are not able to access onsite data for other model outputs. Therefore, we compare our model outputs with ranges from multiple tropical sites to evaluate their validity. For biomass (Fig ? d), the simulated range of ~2.5-12.5 kg C m^{-2} is lower than the observed range of ~7.3-21.3 kg C m^{-2} from 21 transects within 3 tropical sites hunter2013tree. For BA (Fig ? a), the simulated range of ~5.0-30.0 m^2 ha^{-1} is also lower than the observed range of ~17.1-35.2 m^2 ha^{-1} from 5 tropical sites hunter2013tree. Our results show that stem allometry coef c is the most important control on BA and biomass, and an improved parameterization on stem allometry could help improve the model simulations. For the DBH growth, there are large variances in the observed values across different sites with the range of 0-3 cm/year lieberman1985growth,worbes1999annual,adams2014topography. The simulated average DBH growth is between 0-0.4 cm/year but could be as high as 4 cm/year for medium and large trees (Fig ?). Based on our sensitivity analysis (Fig ?), we expected an improved parameterization of both allometry coef c and target carbon storage could help fit the model predictions to data.

Figure 7: Spearman's correlation coefficients between climate drivers and six most important parameters identified for a) GPP, b) NPP, c) LAI, and d) Biomass.

We compare our mortality simulations with an extensive dataset of observed mortality of 1781 species from 14 pan-tropical large area ForestGEO forest dynamics plots Johnson2018NEE. For this study, the forest plots ranged from 2 to 52 ha each with 371 ha in total in which all recorded stems are ≥ 1 cm diameter at breast height. Our comparison shows that the CLM4.5(FATES) simulations of medium and large tree mortality (Fig ? c, d) are close to the 95% confidence interval of observed values, which is about ~0.5-5.7% per year. However for small and medium trees (Fig ? b, c), the simulated mortality rate of ~15-30% and ~1-10% is high when compared to the observed 95% confidence interval of mortality rate of ~0.6-11.3% and ~0.8-3.0% for small and medium trees, respectively. The high predicted mortality rate of small trees could result from the fact that the model predicts a very high mortality rate for very small trees (<1 cm) as they cannot survive after establishment due to low light conditions in the simulations. Since the small

Deleted: 7c

Deleted: imageries

Deleted: 8

Deleted: 7a

Deleted: 8

Deleted: 7d

Deleted: 1a

Deleted: 3).

Deleted: 4),

Moved (insertion) [2]

Formatted: Indent: First line: 0", Space Before: 12 pt

Deleted: ED

Deleted: 5CD

Deleted: 5BC

Deleted: establish themselves

trees have such a large fraction of the population in our simulations (Fig. ? b), the overall mortality rate (Fig. ? a) of ~15-30% is also high when compared to observations (~0.6-11.3%); however, if we separate the mortality rate of very small trees from the calculation of the overall mortality, then the simulated mortality rates of 1-10% (Fig. ? b) are in the range of observations. The very high mortality rate range of smaller trees (~10-30%; Fig. ? a) spans the reported seedling/sapling mortality rate, e.g., ~15-21% per year from 1-20 year old tropical forest stands in Costa Rica dupuy2006effects. However, there is potential for improvement for site-level simulations as the current recruitment algorithm within CLM(ED) depends only on the availability of seed bank but not on the density, light and water availability. The relatively high mortality rate of small and medium trees could also be linked to the fact that CLM(ED) uses the perfect plasticity approximation (PPA) to simulate the canopy light availability for understory trees fisher2018vegetation, which may create canopy closure too fast for the small and medium size trees to survive under low light conditions. We expect that future improvements on recruitment and representation of the light environment within the PPA could be helpful for a better prediction of tree mortality for small and medium size trees. Our sensitivity analysis indicates that key model parameters that can be better estimated for improved mortality predictions include stem allometrey parameters, $V_{c,max25}$, target carbon storage, and mortality rate under stress (Fig. ?).

Another reason for the data-model discrepancy could result from the limited representation of diverse tropical species or traits with the simulation of one single PFT. This is a limitation of many LSMs as they typically only have 2-3 PFTs for tropical forests (e.g., only evergreen and deciduous for tropical trees within CLM). CLM4.5(FATES) has the potential to better represent the trait diversity through trait filtering under different environmental conditions fisher2010assessing, fisher2015taking. One critical component to incorporate traits into the model is to represent the trait trade-off and coordination for different PFTs. Through our sensitivity analysis, we have identified key parameters for vegetation dynamics, which can be targeted for the representation of trait trade-off and coordination in the tropics. For example, our study shows that a higher stem carbon allocation could reduce the GPP and while a higher $V_{c,max25}$ could increase GPP (Fig. ?). The potential exploration of trade-off and coordination between these two parameters could be critical to resolve different PFTs to represent the trait variations. Even though the simulated ranges of the model outputs are different than the observations, our sensitivity analysis should still be valid in view that a primary end-goal of this research is to identify important parameters that can be better estimated for the model to better fit observations. For example, Holm et al (2018, In Review) utilize results from our study to implement their tropical forest parameterization, specifically by increasing their target carbon storage parameter to obtain higher survival and thus lower growth.

In addition to directly comparing the model outputs to observations, we want to highlight that the sensitivity analysis will also allow us to explore the functional relationships between model parameters and outputs. Future synthesis studies that show these functional relationships using data across different sites could be very useful to evaluate the fidelity of model structure to represent the key processes that control these relationships.

Figure 8: Relations between outputs of CLM4.5(FATES), including GPP, NPP, LAI, and biomass (units shown in Fig. ?), to the most sensitive parameters, i.e. $V_{c,max25}$ (unit

Deleted: see

Deleted: D2

Deleted: 3A

Deleted: D12

Deleted: D12

Deleted: 4).

Deleted: .

Deleted: CLM(ED

Deleted: 9).

Deleted: 9

Deleted: years 10 and 130 of the simulation

Deleted: CLM, i.e.

Deleted: Figure 7),

is $umol\ CO_2\ m^{-2}s^{-1}$), target storage carbon (unit is the ratio of leaf biomass), leaf and stem allocation [unitless parameters] for simulation year 10 (red) and 130 (blue). Shown are the mean relations, with the 95 % confidence intervals in grey envelopes. These figures show how an output will generally increase or decrease when a given parameter is changed.

Deleted: $umolCO_2m^{-2}s^{-1}$),

Deleted:].

Deleted: spread of the mean variance

Deleted: . For example, the relation between the photosynthetic parameter ($V_{c,max25}$) and all the outputs are positive, as is the case with storage carbon parameter

4.3 Limitation of methods

Our study is the first global sensitivity analysis for CLM4.5(FATES); however, it is subjected to several limitations that could be improved for future studies. First, our study uses an arbitrary choice of parameter ranges (+/- 15%), which determines the variance in the model outputs and the corresponding results of the sensitivity analysis. However, we expect that our analysis can reveal the importance of parameters given equal percentage of variations, which can help us gain a better understanding of the model structure. We do acknowledge that uncertainty analysis studies that specifically consider the potential variable ranges of values in the tropical forests based on observations could provide insights on what additional measurements are needed to explain variance in the model prediction.

Deleted: ED

Second, we only consider the correlation in pairs of parameters that determine temperature responses for deactivation energy and entropy in photosynthesis. We do want to point out that the potential correlation among other parameters Diaz2016trait, such as the trade-off between mortality and growth parameters and the correlation among coefficients for allometric equations, could affect the simulated model output ranges and the sensitivity results. However, our exploration of parameter sensitivity assuming their independence could still help us understand the baseline parameter control on model behaviors xu2009uncertainty. The exploration of trade-off and coordination among different parameters requires data analysis for multiple traits of the same species. The Predictive Ecosystem Analyzer (PEcAn) framework lebauer2013facilitating could be a useful tool to synthesize plant trait data to estimate model parameter distributions. The challenge is that, even though there are great efforts in the research community to compile plant trait data across the globe kattge2011try,kattge2011generic, there are still a limitation of data with observations of multiple traits for the same species. Future uncertainty analysis studies that explicitly consider the prior distributions and correlations for all the parameters can build on this analysis and gain further insights on where the uncertainty in the model predictions come from.

Finally, it is possible that the parameter sensitivity could be different if we use different model inputs, different sites, and different structures of subcomponents within the model. For example, using site level climate drivers, instead of the reanalysis meteorological drivers used in this study qian2006simulation, could lead to different sensitivity values since our preliminary analysis showed that simulated vegetation demography is quite sensitive to different climate drivers. Furthermore, there are ongoing development activities to improve different components of the models. For example, there are current efforts to incorporate different representations of tree allometry within CLM4.5(FATES), which have different formulations between size and biomass, e.g. [chave2014improved], or the current formulation of the photosynthetic process in the CLM4.5(FATES) can be replaced with a model that more accurately represents the allocation of nitrogen and thus the photosynthetic process (see [xu2013our, ali2016global]). Therefore, model improvements such as these can affect corresponding sensitivity analysis results. To understand the impact of site level variations on model dynamics, similar sensitivity analysis across different sites can be conducted to understand how climate variability will affect the sensitivity analysis results.

Deleted: ED

Deleted: ED

5 Conclusion

LSMs have many parameters that could potentially affect the outcome of their simulations. In this study, we use the FAST to conduct a high-dimensional global sensitivity analysis on CLM4.5(FATES). We use an intermediate complexity of simulation: runs are sufficiently long to permit short-term physiological variance to propagate into the long-term forest demographic structure. Even though we do not explore competitive dynamics between different PFTs, our sensitivity analysis will guide us on the selection of key plant traits for the consideration of trait trade-off and coordination in order to improve PFT coexistence within CLM(ED).

Deleted: ED

Our analyses show that the target carbon storage and stem allometry parameters are important for the simulation of DBH growth for individual trees and tree mortality. The photosynthetic parameter, $V_{c,max25}$, is the most important for the simulation of carbon fluxes including GPP and NPP. The combination of stem allometry, target carbon storage and $V_{c,max25}$ dominantly control the simulation of total BA and long-term carbon stocks. The importance of growth and survival parameters in this study highlighted the dominant component in understanding the dynamics of the next generation of demographically enabled LSMs toward improved model parameterization and model structure for better model fidelity.

Deleted: analysis

Deleted: emphasizes

Deleted: importance of

The results of the sensitivity analysis presented here can be utilized to construct the parameter-output response surface for the CLM4.5(FATES) model, which can assist future efforts for model calibration or diagnosis. These findings may help us better understand the overall model structure and guide the estimation of key model parameters with significant control over vegetative processes in these models for better model fitting to data. The FAST analysis provides a promising means of analyzing complex LSM components, and can be a powerful tool in understanding the necessarily high-dimensional representation of living systems within Earth System models.

Deleted: ED

To access the FATES source code, visit https://github.com/NGEET/fates. The FAST methodology described herein is available at sites.google.com/site/xuchongang/uasatoolbox. The version of the model codes used in this paper and the corresponding model simulations from all 5000 parameter combinations as well as simulation of the default parameter set are available at NGEE tropic data archive (http://dx.doi.org/10.15486/ngt/1497413) and also upon request from the corresponding authors.

Deleted: CLM4.5(ED)

Deleted: -release

Deleted: https://ngt-data.lbl.gov, data id: NGT0091

6 Allometry equations

The following equations are cohort-based calculations for allometry in CLM4.5(FATES). Interested readers are referred to [fisher2015taking] for more information. The parameters used for the allometry equations include $dbh2h_m$, $dbh2h_c$, $dbh2bd_a$, $dbh2bd_b$, $dbh2bd_c$, and $dbh2bd_d$ (all are unitless variables). Specifically, the dead wood biomass (BD; Kg C) is calculated as a function of diameter (DBH; cm), height (h; meter) and wood density (g cm^{-3}),

Deleted: ED

$$BD=(dbh2bd_a)(h^{dbh2bd_b})(DBH^{dbh2bd_c})(density_{wood}^{dbh2bd_d}) \quad (3)$$

The height (m) is calculated based on DBH (cm) as follows:

$$H=10^{dbh2h_c}(DBH^{dbh2bd_m}) \quad (4)$$

7 Temperature response curve

The parameters used for the temperature response curve equations include the equation to calculate the maximum carboxylation rate, $V_{c,max25}$, the maximum electron transport rate, J_{max}, and the Triose phosphate use (TPU) limited carboxylation rate, TPU (also all parameters here are unitless) fisher2015taking. The temperature response equations for $V_{c,max,z}$, $J_{max,z}$, and $TPUz$ are:

$$V_{c,max,z}=V_{c,max,25}(e^{\frac{vcmaxha}{(0.001rgas)(t_{frz}+25)}})(1-\frac{t_{frz}+25}{t_{veg}})(\frac{vcmaxc}{1+e^{-vcmaxhd+(vcmaxse)(t_{veg})}}) \quad (5)$$

$$J_{max,z}=J_{max,25}(e^{\frac{jmaxha}{(0.001rgas)(t_{frz}+25)}})(1-\frac{t_{frz}+25}{t_{veg}})(\frac{jmaxc}{1+e^{-jmaxhd+(jmaxse)(t_{veg})}}) \quad (6)$$

$$TPU_z=tpu25(e^{\frac{tpuha}{(0.001rgas)(t_{frz}+25)}})(1-\frac{t_{frz}+25}{t_{veg}})(\frac{tpuc}{1+e^{-tpuhd+(tpuse)(t_{veg})}}) \quad (7)$$

where t_{frz} is the freezing point of water in Kelvin (273.15 K).

8 Carbon storage in CLM4.5(FATES)

Deleted: ED

The target carbon storage is the *cushion* parameter shown in Table D3. Specifically, a higher value of this parameter will lead to a higher allocation of carbon to storage and thus lower allocation to growth at the specific time step. Also, carbon storage plays an important role for the simulated mortality through the parameter that controls the mortality rate under stress, *stress_mort* in Table D3. The tree will be under stress when it has low carbon storage (< leaf biomass). Therefore the target carbon storage parameter and the mortality rate under stress parameter play a large role in determining the level of mortality that occurs in the simulations.

Carbon storage, b_{store} (in kg C/cohort) plays a very important role in both growth and mortality fisher2015taking. Specifically, CLM4.5(FATES) assumes a target carbon storage determined by the multiplication of leaf biomass (b_{leaf}) and the target carbon storage parameter (i.e. the target amount of carbon plants store relative to leaf biomass; $S_{cushion}$, variable *cushion* in Table D3). At the specific time, the carbon balance for growth and storage is calculated as follows,

Deleted: ED

$$C=NPP-T_{md}f_{md,min} \qquad (8)$$

where T_{md} is the maintenance respiration and $f_{md,min}$ is the minimum fraction of the maintenance demand (storage priority parameter in Table D1) that the plant must meet each time step, which represents a life-history-strategy decision concerning whether leaves should remain on in the case of low carbon uptake (a risky strategy) or not be replaced (a conservative strategy).

The fraction of the carbon balance for each cohort allocated to the carbon storage pool (f_{store}) will be determined by the following equations:

$$f_{store}=e^{(-f_{tstore})^4} \qquad (9)$$

where

$$f_{tstore}=max(0,\frac{b_{store}}{S_{cushion}b_{leaf}}) \qquad (10)$$

Thus, the target carbon storage parameter, $S_{cushion}$, can affect carbon allocations. Specifically, a higher value of $S_{cushion}$ will lead to a higher allocation of carbon to storage and thus lower allocation to growth at the specific time step.

Carbon storage also plays an important role for the mortality. Specifically, carbon starvation mortality (M_{cs}) is calculated as follows:

$$M_{cs}=S_m max(0,1-\frac{b_{store}}{b_{leaf}}) \qquad (11)$$

where S_m is the stress mortality factor (i.e., *stress_mort* in Table D3).