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Interactive comment on "Bayesian Inference and Predictive Performance of Soil Respiration Models in the Presence of Model Discrepancy" *by* Ahmed S. Elshall et al.

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Anonymous Referee #2

Comment: The manuscript submitted by Elshall et al. is an interesting study dealing with the complexity of soil C model parameterization. In recent decades, the complexity of those model as well as the different tools to parameterize has increased substantially leading to potential misuses of powerful but complex mathematical approaches. The goal of Elshall et al is therefore to evaluate the impact on process-based model predictions of neglecting a couple of assumptions of the Bayesian framework as it is often done by soil modelers to avoid complexity.

Response: We thank the reviewer very much evaluating the manuscript and for providing constructive feedback and suggestions.

Comment: The present study might not be super novel for the entire modeling communities in geoscience as mentioned by the other referee. Nevertheless, it underlines a flaw of several carbon soil modeling studies and might be considered as novel in this context. It is a pity that the author may not freely communicate their models and scripts it would have definitely increased the impact of the paper.

Response: We feel sorry for this too, and we would love to share the code and the soil respiration models upon request.

Comment: Even though the objectives of the paper are important and deserve to be published, in my opinion, the manuscript in its present form is sometimes too hard to read and needs some simplifications. A first recommendation might be to have a table summarizing all the acronyms and try to reduce them when not necessary.

Response: We added a list of acronyms as follows:

Acronyms 4C Four carbon pool model 5C Five carbon pool model 6C Six carbon pool model CUE Microbial carbon use efficiency DOC Dissolved organic carbon ENZ Enzymes MCMC Markov chain Monte Carlo MIC Microbial biomass NSME Nash-Sutcliffe model efficiency PDF Probability density function RMS Relative model score SEP Skew exponential power distribution SEP-AC Skew exponential power distribution with autocorrelation SLS Standard least square SLS-AC Standard least square with autocorrelation SOC Soil organic carbon WLS Weighted least squared WLS-AC Weight least square with autocorrelation WSEP Weighted skew exponential power distribution WSEP-AC Weighted skew exponential power distribution with autocorrelation

Comment: Secondly, a workflow scheme might also be useful to understand the logic of the authors, which is not always super clear.

Response: We added a summary table of the data models and corresponding likelihood functions. The revised manuscripts states “A summary table of the eight data models with corresponding parameters is provided in the supplementary materials.” We added a workflow scheme as a supplementary figure. The revised manuscript reads " Our workflow scheme is presented in the supplementary materials.” The new table and figure are present in the attached supplementary pdf file.

Comment: Finally, I missed some definition to be sure I fully understood the text. In particular, it is not crystal clear to me what the author means by ’data model’. From my understanding, a data model is based on data but the observed data are presented quite fare from the data model.

Response: In the revised manuscript we clarified that “A data model that is also known as a residuals model or an error model is used to characterize residuals (i.e., the difference between data and corresponding model simulations).” In addition, please see our response to the previous comment.

Comment: Another point is that I still do not fully understood how the authors link their data model with their process-based model. I understood that the data models are used for posterior parameter estimation but sometimes the text makes me doubt.

Response: The parameters of the data model are jointly estimated with the parameters of the soil respiration model using MCMC. We clarified this in the revised manuscript “the posterior distributions of the data model parameters are jointly estimated with the soil respiration model parameters using the MT-DREAM(ZS) code (Laloy and Vrugt, 2012).” In addition, a summary of the data model parameters is presented in the supplementary materials as we clarified in a previous response.

Comment: I don’t understand why the author fixed the upper limit of the physical range of CUE to 0.6 (the mean over terrestrial systems) whereas in the paper they cited several observations are above 0.6

Response: The thermodynamic maximum limit of CUE is 0.6 and the empirical obser-

vations show that CUE over a wide range of field conditions converges to ~ 0.30 with a mean value of 0.55 for terrestrial ecosystems (Sinsabaugh et al., 2013). We used this upper limit for analysis only. We did not fix this limit for Bayesian inverse modeling to understand the impact of data model on parameter estimation.

Comment: Some typo: l121 ‘and’ not necessary L176 please correct the parenthesis L611: despite instead of desp8ite

Response: Thank you very much for pointing out these typos and we corrected them. Thank you very much.

Comment: I, therefore, think that this manuscript deserves publication after a deep rewriting to clarify the methods used

Response: Addressing the review comments helped us to rewrite and clarify several parts of the manuscript. Thank you very much.

Please also note the supplement to this comment:
https://www.geosci-model-dev-discuss.net/gmd-2018-272/gmd-2018-272-AC2-supplement.pdf

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