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Geoscientific Model Development Discussions

Interactive comment on "Simultaneous parameterization of the two-source evapotranspiration model by Bayesian approach: application to spring maize in an arid region of northwest China" *by* G. F. Zhu et al.

Anonymous Referee #3

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This is in general a well thought out and methodologically sound piece of work and the authors make a sufficient case that the work is novel for it to warrant publication.

While there are no fundamental issues with the work there are a number of ways in which it could be improved. These are mainly regarding key pieces of information that are currently missing from the manuscript.

The authors go to the trouble of conducting a Bayesian Calibration on six of the model parameters which is excellent since rather than employing an optimisation routine to merely 'tune' the model parameters they estimate the full conditional probability of the

parameters being probable given the ET and E data. However, once the calibration is made only a single parameter vector is selected and all the subsequent analysis versus the data is based on results of that single vector. This is an opportunity missed since they already have all the information they need to report the influence of posterior parameter uncertainty on model outputs. This could be done by calculating the 5th and 95th quantiles from their 3000 member parameter sample for example. This would make for a far superior analysis of model - measurement differences since the model output can now be represented by the full calibrated posterior distribution not just a single run.

The choice of an MCMC algorithm to sample the posterior is generally good one although assessing convergence requires special care as it is too easy to be fooled into believing that convergence has been obtained when in fact only a local maxima has been found. For this reason the manuscript is too light on details of the Gelman-Rubin numbers that were obtained that convinced the authors that the MCMC had converged. This should be reported especially since fig 4. k1, k2, k3 might suggest that convergence has not yet been reached.

The authors should give details of why they chose the 6 parameters that they did to be calibrated. Ideally a calibration should include all model parameters and if a subset is selected perhaps for reasons of computational practicality then an objective method such as Morris should be used to select the most important parameters.

In Bayesian Calibration the choice of the prior distribution is also important and should be discussed but this is currently missing.

The manuscript is also lacking details on the errors were used in the likelihood calculation to represent the random errors that were assigned to the measurements. This is again an important omission as these errors should be discussed and justified on the basis of analyses or from literature.

Detailed comments follow:

Throughout the manuscript the authors refer to "multiple measuring datasets". This doesn't work in English perhaps "multivariate datasets" might convey what the authors want?

Abstract: accounted -> account

p743 line4 has good performances -> performs well

p744 line8 in arid -> in the arid

p745 line18 synchronously -> synchronous

p746 line2 were-> was

line7 delete was

p747 line13 coefficient -> coefficients

line18 is -> are

p748 line16 is -> are

p750 line8 parameters needed -> parameters that needed

line13 dataset -> datasets

line17 The difference between the model and the observations should not be called model error as if the observations are 'truth'. A better description is model data mismatch recognising that both the model and the data contain errors. Also see above you need to discuss how the observational random error is obtained.

line22 "assuming the model error follows a Gaussian" no this is not a correct interpretation of likelihood. The likelihood is formally the "chance of getting the observations given the parameters". Therefore the Gaussian in the likelihood represents the errors in the observation rather than the model. The idea here is that random observational error (as quantified by the sigma and the Gaussian) is stopping us from always obtaining the observations from the parameters. The errors in the parameters are represented in the

prior and as it stands this calibration estimates the probability of the parameters being correct given the observations assuming that this is the correct model. That is to say an assumption of the calibration is that the model is correct. We know this is wrong but the Bayesian Calibration does not explicitly represent this. Of course the model data mismatch in the likelihood does implicitly quantify both model and data errors but this is not the formal understanding of the likelihood. Indeed later on you go on to suggest possible model improvements. As future work I would advocate creating a new version of the model with those improvements and formally quantifying whether the new model is more likely using Bayesian analysis. See Bayesian Model Comparison in Van Oijen, M.; Reyer, C.; Bohn, F.J.; Cameron, D.R.; Deckmyn, G.; Flechsig, M.; Härkönen, S.; Hartig, F.; Huth, A.; Kiviste, A.; Lasch, P.; Mäkelä, A.; Mette, T.; Minunno, F.; Rammer, W.. 2013 Bayesian calibration, comparison and averaging of six forest models, using data from Scots pine stands across Europe. Forest Ecology and Management, 289. 255-268. 10.1016/j.foreco.2012.09.043

p751 line10 formally I believe you are using the Metropolis algorithm rather than Metropolis-Hastings

line14 Which distribution are you using for the proposal density (multivariate normal?)

line22 I don't think you need to split the datasets in this way. Indeed the calibration would benefit from the inclusion of all of the data. The comparison against data that you make later on would be just as valid since this is more about identifying weaknesses in the structure of the model i.e. missing processes rather than parametrisation.

line23 dataset -> datasets

line24 optimised -> calibrated

p752 line11 posterior expectancy? Assume you mean the expectation of the posterior (i.e. the mean). See comments above about representing the full posterior in your analysis rather than just one parameter vector.

p753 line4 was -> are

p754 line8 contents -> content

line13 split plantshave

line22 were -> are

line23 predicate -> predict

line25 reword: something like "However, significant differences exist between measured and modeled half-hourly ET values for the spring maize in the arid desert oasis."

line27 regressive -> the regression

p755 line10 was -> is

line17 observed -> observe

line20 5 -> on the 5th of

line22 needed -> needs

p756 line4 was -> is

line10 on the 5th of July

line11 no gaps in time i.e. 12:00 20:00

line17 flows do not -> flows that do not

line18 representing -> represent

line19 attentions -> attention

Figure8: The text in this figure is currently too small

Interactive comment on Geosci. Model Dev. Discuss., 7, 741, 2014.