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## Reply on RC2

Yan Liu et al.

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Author comment on "Pitfalls and a feasible solution for using KGE as an informal likelihood function in MCMC methods: DREAM<sub>(ZS)</sub> as an example" by Yan Liu et al., Hydrol. Earth Syst. Sci. Discuss., <https://doi.org/10.5194/hess-2021-514-AC2>, 2022

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We thank the reviewer for the helpful comments to improve our manuscript. In the following text, **the reviewer comments are shown in regular font, and our point-by-point replies are shown in *italic***. Upon revision we will make the following major changes to the manuscript and Supplementary Material:

- ***We will provide the equation to show details on how the formal likelihood is computed. We will compare our adapted KGE with another formal likelihood functions as suggested, such as log transformation of model errors. In addition, we will also compare our approach with the GLUE framework.***
- ***We will compute the total uncertainty and provide it to the prediction of streamflow. We will discuss the potential influence of parameter uncertainty and total uncertainty on streamflow predictions.***

General comments:

This study suggests an approach to adapt the KGE through transformation with a Gamma distribution so that it can be better used as an informal likelihood function in calibration procedures. The study finds that the results and inference behavior when using this adapted KGE measure are very similar to the case when using the RMSE as a likelihood function. In a synthetic case study, it is also shown that the presented approach successfully re-infers the known true parameter values.

The manuscript presents an elegant and innovative approach to a solution for a very relevant problem and could therefore be of high value in many fields. The manuscript is very well written, carefully composed and logically structured, and all in all very convincing.

*We thank the review for the positive evaluation of our work.*

However, it is a bit too brief I feel in some respects and would need to be extended by some theoretical considerations among others (see comments below).

Major comments:

It is not clear to me what the "formal likelihood function" is in this case. The authors say

that it is the RMSE, but it would be useful to show an equation that explicitly states which assumptions w.r.t. distribution type (I assume the normal distribution) and standard deviation this corresponds to. For example, something along the lines of: using the RMSE is equivalent to assuming independently normally distributed errors at each time step in a formal Bayesian inference approach and assuming that the standard deviation is equal to a certain (which?) value at each time step, ideally including the full equation. As is mentioned by the authors, the RMSE is very sensitive to large flows and would not be a typical measure used in formal likelihood approaches in my opinion. There are assumptions that usually work better, such as a standard deviation that is proportional to the predicted streamflow, for example. For a comprehensive overview of the different assumptions on the standard deviation of the residual error (and associate transformations) in formal likelihood approaches, see for example McInerney et al. (2017). In my view, it would make more sense to use one of their suggested approaches as the “formal” approach in this study.

*Response: We will provide details of the equation on how the formal likelihood function used in DREAM<sub>(ZS)</sub>. Thank you for the very nice reference discussing different error models. As discussed by McInerney, et al. (2017), there is no perfect error model that fits for all catchments and simultaneously optimize all performance metrics (such as for both low flow and high flow). The standard error model assuming Gaussian distribution with zero mean and constant variance is widely used, we therefore compared our adapted KGE to it. But to show the robustness of the adapted KGE, we will add a comparison with one of our case studies using another formal likelihood function, such as the log transformation of model errors, which is also discussed and suggested for perennial catchments in McInerney, et al. (2017). We will also compare our approach with the GLUE framework suggested in the major comment 4 of Reviewer #1.*

On a related note, the standard deviation of the additive error in formal likelihood approaches is an important parameter that needs to be used in prediction as well. The authors infer the posterior parameter distributions of the model parameters and then use these posteriors for prediction. This is fine if only parametric uncertainty is relevant, but by this, they completely neglect all other sources of uncertainty. The residual uncertainty (i.e., additive error) is very important since it represents the lumped effect of the input uncertainties, model structural uncertainties and observational uncertainties (present here at least in case study 3 as mentioned by the authors). The neglect of all these uncertainties is also the reason for the very narrow distribution of the performance metrics in prediction (Fig. 7 and 9). If actual streamflow predictions including error bands were shown, we would probably see that the observations are not covered at all by the error bands, which is a serious shortcoming if we are interested in reliable predictions.

*Response: Thank you for the suggestion. In the current manuscript, we only show the uncertainty caused by parameter. In revision, we will add the other uncertainty to the prediction and discuss the influence of the parameter uncertainty and total uncertainty on streamflow predictions.*

Technical comments:

Line 44: It is not clear to me what you mean by “they can mimic the weight to small improvements in NSE”.

*Response: It means the small improvement in NSE can also be identified and leads to the chain evolution. We will make it clearer in revision.*

Line 55: did you mean “unsatisfactory”?

*Response: Yes, we will change it.*

Line 55-57: I find this sentence incomprehensible

*Response: Here we mean that the number of measurements cannot be considered. Therefore, with increasing number of measurements, the information added to the performance measure is little, thus preventing the improvement of chain evolution. In revision, we will update it to make it more comprehensible.*

Line 60: "rates" instead of "rate"

*Response: We will change it.*

Line 65: replace "theoretically statistical" with "statistically sound", also in other instances if needed

*Response: We will update it.*

## References

McInerney, D. et al. (2017) 'Improving probabilistic prediction of daily streamflow by identifying Pareto optimal approaches for modeling heteroscedastic residual errors', *Water Resources Research*. American Geophysical Union ({AGU}), 53(3), pp. 2199–2239. doi: 10.1002/2016wr019168.