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LETTER TO THE EDITOR

Response to comment by Keith Beven on “Equifinality of formal (DREAM) and informal (GLUE) Bayesian approaches in hydrologic modeling?”

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This is our reply to the comment by Beven (2008) on our paper “Equifinality of formal (DREAM) and informal (GLUE) Bayesian approaches in hydrologic modeling?” recently published in *Stochastic Environmental Research and Risk Assessment*.

There is strong disagreement in the hydrologic literature whether an appropriate framework for uncertainty estimation should have its roots within a proper statistical (Bayesian) context or such a framework should be based on a different philosophy and use non-statistical methodologies for assessing model predictive uncertainty. The stated goal of our paper (Vrugt et al. 2008) was to establish some common ground between these different viewpoints. In so doing, we highlighted that, under a variety of conditions, both Bayesian and informal Bayesian methods, such as the generalized likelihood uncertainty estimation (GLUE) method, can retrieve very similar estimates of total predictive uncertainty. Indeed, the GLUE results were based only on weighted simulations from the set of behavioral models, whereas the formal Bayesian results using Markov chain Monte Carlo (MCMC) simulations with DREAM used a first-order autocorrelated error model with explicit information from the streamflow observations.

Beven (2008) argues that this comparison is simply inappropriate and invalid. We disagree with his assessment. First, our paper (Vrugt et al. 2008) was not intended to explore different implementations of 1-day-ahead forecasting as Beven (2008) seems to believe, but just compares two different approaches for streamflow uncertainty estimation. The formal Bayesian approach requires an explicit expression for input, parameter, model structural and calibration data error. In our paper, we simply took one possible vanilla implementation of a formal Bayesian approach that used explicit information from the streamflow observations to quantify model structural error. Thus, our implementations of GLUE and formal Bayes were indeed different. Nevertheless, they both obtained fairly similar estimates of total predictive streamflow uncertainty. This is a rather unexpected result, which, we believe, speaks strongly in favor of the continued use of GLUE by practitioners, as discussed and highlighted on page 13, paragraph “If the interest is in estimating ...” of our paper.

Second, the goal of our paper was not to advocate which uncertainty estimation method is more appropriate and should be used, but rather (page 2, right column, lines 7–12 from top of our paper) to establish common ground between statistical and non-statistical methods for uncertainty estimation. At various places throughout the manuscript, we discussed the advantages and limitations of both approaches, starting from paragraph 2 to 3 of the

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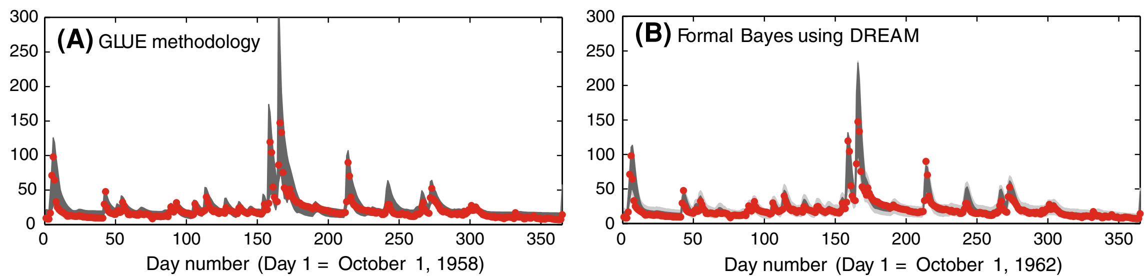

Fig. 1 Streamflow prediction uncertainty ranges derived with GLUE (*left panel*) and DREAM (*right panel*) for a representative portion of the evaluation period for the French Broad watershed. In contrast to Figure 7 in our original paper (Vrugt et al. 2008), both methods are now applied in simulation mode. For DREAM, the *dark gray region* represents the 95% confidence intervals of the output prediction due to parameter uncertainty, whereas the *light gray region* represents the additional 95% ranges of the prediction uncertainty. For GLUE the 95% prediction quantiles are presented. The *solid circles* denote the streamflow observations

introduction. We, therefore, find the comment by Beven (2008) "… A one-step ahead forecasting model beats a simulation model in predicting discharges is hardly a surprise" inappropriate. This comment reflects our formal Bayesian implementation, but is simply an incorrect reflection of what is presented in our paper. Thus, by honing in on the differences, Beven (2008) misses this take-home message of our paper.

In his Comment, Beven (2008) seems to express considerable concern that our paper has not been able to clearly convey how the formal Bayesian approach with DREAM was implemented. This Comment and our Reply serve to re-iterate our implementation. Perhaps, our specific implementation of using the streamflow observation at time $t - 1$ in predicting the error at time t was not described sufficiently clearly in our paper. However, to demonstrate that our findings also hold when using formal Bayes within simulation mode, consider Fig. 1, which presents streamflow prediction uncertainty ranges derived with GLUE (Fig. 1a) and formal Bayes (Fig. 1b) for a representative portion of the evaluation period for the French Broad watershed. Note that the streamflow uncertainty bounds derived with formal Bayes have increased a bit compared to what was originally presented in Figure 7 of our paper. However, the main thrust and findings of our original manuscript are left unaltered.

Finally, we agree that there are a number of challenging issues with the use of formal Bayes that require significant research and new thinking. The work presented in our paper provides possible directions to improve the utility and applicability of statistical approaches to hydrologic modeling and uncertainty estimation. Even though some of our assumptions may be open to criticism, we personally prefer to take this route instead of adopting informal approaches for which appropriate mathematical and statistical theory is lacking and needs to be developed. The inability of GLUE to separate individual error sources impairs our ability to better interrogate hydrologic systems to learn from our observations. This is what formal Bayes is trying to do, and thus it is key to identifying structural inadequacies in models, with the ultimate goal of improving hydrologic theory.

References

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