Comments on GLUE

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Abstract

An application of GLUE (Generalised Likelihood Uncertainty Estimation) methodology to the problem of estimating the uncertainty of predictions produced by environmental models is presented. The methodology is placed in a wider context of different approaches to inverse modelling and, in particular, a comparison is made with Bayesian estimation techniques. The role of a likelihood function and its different forms are explained in relation to different approaches to the estimation problem. The uncertainty in the choice of model structure is introduced by means of random sampling between two different models (e.g. statistical and mechanistic).

The Generalised Likelihood Uncertainty Estimation technique was introduced by Beven and Binley, (1992), partly to allow for the equifinality of parameter sets during the estimation of model parameters. The technique has been applied to a variety of environmental problems. Its popularity results from the very few assumptions that it requires and the informal approach. The statistical equivalent of GLUE was developed by Romanowicz *et al*. (1994). The idea was to explicitly derive the likelihood function based on the error between the observed outputs and those simulated by the model. This formal approach is equivalent to Bayesian statistical estimation: it requires independence of errors and an assumption about the statistical structure of the errors. We argue that any likelihood function, which uses the difference between the observed and simulated model output as a measure of model performance, involves some explicit (as in the case of Bayesian approach) or implicit (as popularly used in GLUE) assumptions about the structure of the model error.

The literature on this subject suggests that uncritical application of GLUE can lead to confusion about the nature and power of the results obtained (see Young and Romanowicz, 2003). This paper aims to clear up these misunderstandings through a comparison of informal and formal statistical numerical Bayesian techniques. This will shed some light on the limitations and advantages of both the informal GLUE and the more formal Bayesian approaches, and so aid further development of the GLUE methodology.

Although there are a number of possible measures of model performance that can be used in this kind of analysis, the formulation of the estimation problem should take into account both the goal of the modelling exercise (i.e. it should be application-oriented), as well as the existence of a feasible solution to the problem. An explicit statement of the assumptions used enables the appropriate methods of solution to be chosen (e.g. one can assume that the problem is deterministic or stochastic). In this paper, the implicitly assumed error models will be derived from the likelihood measures that are commonly applied by GLUE users. This will explain the methodology involved in the choice of error structures and corresponding measures of model performance (i.e. likelihood functions).

Using a simple example of a rainfall-flow model, we compare different evaluation measures and their influence on the prediction uncertainty and confidence limits. Also the influence of uncertainty in the observations of rainfall and flow variables on the confidence limits of model predictions will be analysed. In our approach we use both mechanistic and stochastic Data Based Mechanistic (DBM) rainfall-flow model (Young, 2002). The Monte Carlo sampling methodology applies Sampling Importance Resampling algorithm of Rubin, 1988.

References

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