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Hydrology and Earth System Sciences Discussions

Interactive comment on "A novel approach to parameter uncertainty analysis of hydrological models using neural networks" *by* D. L. Shrestha et al.

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We are very grateful to Dr. F. Fenicia for the valuable comments. We carefully studied the comments and our responses to them follow. We will revise our manuscript in accordance with his comments.

Our replies are in bold.

The paper presents a method to estimate prediction intervals produced by a hydrological model (HBV) through a neural network model. Provided that an ANN can accurately reproduce model results, the advantage of the approach would be a faster computation time.

While the approach can be of potential interest for flood forecasting, I find that the paper requires substantial revisions to really show the advantages and the novelty of the approach.

First of all, I think the paper is poorly referenced. The approach of simulating a higher order model through a lower order model is not new, and this has not been thoroughly discussed (see for example Young and Ratto, 2009, and references therein). Hence, I think that the authors should better demonstrate what is new in their approach in respect to what has been done before.

In the revised version, we will extend the literature review on uncertainty estimation techniques used in rainfall-runoff modeling especially.

To answer the comment on "simulating a higher order model through a lower order model" and on "what is new in their approach in respect to what has been done before"we would like to state the following.

Of course an approach when a complex model is emulated by a simpler model is not new; it is referred as surrogate, or meta-modelling, and we used it and published earlier on it as well. (We are not using however the nonlinear differential equations adopted in DBM, but the techniques coming from machine learning.) In the reported examples of using this approach, however, it is used to emulate the process (hydrological or other) models, or the complex data-driven models with an output related to some physical process (e.g., water flow).

In this paper we use data-driven (machine learning) model to emulate the probability distribution or its important characteristics (estimated by the MC process), and this model has the aggregated current and past hydrometeorological conditions as input. As far as we know this is quite different from what was done before.

The other important point, is that the authors compare a neural network model in forecast mode, to a HBV model in hindcast mode. In my opinion, in order to have an objective comparison, the HBV model should also be run in a forecast mode.

In this paper, we use ANN to estimate the pdf (or its quantiles) resulting from the Monte Carlo simulations. ANN model is also run in hindcast mode, i.e. it generates quantiles for the current momet, as HBV does. To make this clearer, we have updated the paper accordingly.

Furthermore, the authors should note that the HBV prediction intervals do not represent the probability of discharge falling within the intervals. Hence they should clarify their application in a veiw to flood forecasting.

This is correct; of course the prediction intervals estimated by Monte Carlo simulations do not necessarily enclose all the observed discharges, because the model could be inaccurate, not all sources of uncertainty are considered (like in this paper when only parameter uncertainty is considered), etc. The present study only considers the parametric uncertainty, however we have mentioned in the paper that this methodology can be also used to other sources of uncertainty.

It is not clear why we should "clarify the application in a view to flood forecasting". We have not mentioned flood forecasting (however the methodology can be used for this purpose as well). The presented use of the methodology is purely for simulation.

The authors show how Monte Carlo uniform sampling is an inefficient sampling strategy. There are more efficient sampling strategies such as Markov Chain Monte Carlo sampling, which are not taken into proper consideration by the authors.

We agree that there are other more efficient sampling techniques, and it is planned to use them in the future. We have mentioned in the conclusion that our method can be used to MCMC, Latin Hypercube sampling etc. In this paper we have only demonstrated its applicability to GLUE which uses traditional

sampling methods.

Furthermore, the authors do not mention that when the model is run in a forecast mode, there is no need to re-run the model for the whole past time series. Prediction intervals can be estimated in a Bayesian recursive estimation approach (Thiemann et al., 2001).

In this paper "re-running the model" does not mean for the "whole past time series", rather it is meant that even for one model simulation step it has to be run thousands of times as part of Monte Carlo process. We will reformulate the sentence to make it clear.

Finally, I think the paper would benefit from a comparison of the two approaches (HBV and ANN) using different lead times. It would be interesting to see if ANN, due to their difficulties of accounting for lag times within the system, have lower performance for higher lead times.

We have not done any forecast of the hydrological variables such as discharge either by HBV or ANN. Please note we are not using ANN for hydrological simulation so cannot compare it to HBV. Rather we used ANN to encapsulate the data generated by Monte Carlo simulations and forecast the quantiles or prediction intervals. Indeed if a hydrological is able to forecast, then the ANN uncertainty model will also be able to to forecast.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 6, 1677, 2009.