EGUsphere, author comment AC1
https://doi.org/10.5194/egusphere-2022-857-AC1, 2022

Reply on RC1

Simone Ulzega and Carlo Albert

Author comment on "Bayesian parameter inference in hydrological modelling using a Hamiltonian Monte Carlo approach with a stochastic rain model" by Simone Ulzega and Carlo Albert, EGUsphere, https://doi.org/10.5194/egusphere-2022-857-AC1, 2022

We are grateful for the positive comments and the very interesting remarks and questions, which give us the opportunity to clarify some important points. We answer the specific comments one by one below.

Specific comments.

- In Albert et al. (2016) we described a novel implementation of an HMC algorithm combined with a multiple time-scale integration for Bayesian parameter inference with nonlinear stochastic differential equation models, and we demonstrated the performance of the method using a simple rainfall-runoff toy model and synthetic data time-series. For purely didactic purposes, the rain input to the system was modeled using a smooth sinusoidal function.

  In the present work instead, we apply the HMC method with the time-scale separation approach from Albert et al. (2016) for the first time to a real-world case study in urban hydrology, using real time-series of observed rainfall and outflows. Moreover, in this work we carry out the inference process using intentionally inaccurate rainfall observations and demonstrate the ability of the algorithm to reconstruct with great accuracy the unknown true average rainfall over the catchment. The reconstructed precipitation is then used to infer the hydrological model parameters, which are thus protected from the corrupting effect of the uncertainty on the rainfall observations.

- This is indeed a very interesting point. We have run the HMC inference without rainfall data, obtaining both model parameter marginals and a predicted rainfall pattern that are substantially identical to those obtained with the inaccurate data of Sc2. Therefore, in Sc2 the HMC algorithm “learns” that the observed rain should be essentially ignored, thus producing results which are practically the same as if the inference was run without any rain data at all. However, in most applications the accuracy and reliability of the measured precipitation data is unknown a priori. We show here that in those

cases the rainfall observations can be safely used in the inference process, since the algorithm itself will assess its accuracy and possibly disregard it in favor of a more reliable reconstructed rainfall.

We believe that this result is interesting and worth a remark. Therefore, we will certainly be glad to add a comment on it in the next revision of the paper.

-

  This is also an interesting point. The inferred posterior distribution does not show any correlations between the parameters, e.g., lambda and gamma. Therefore, the problem of inferring them does not seem to be ill-posed.

  Instead, in Sc1 the HMC algorithm tunes the parameters of the rainfall potential transformation to match the (accurate) rainfall data. This is evident for the large precipitation peak near time = 60 min, as clearly visible in the lower halves of figures 5 and 6. The smaller value of the inferred parameter gamma in Sc1 reflects exactly this attempt of the algorithm to find a better fit to the rain observations, especially where precipitation values are large. The smaller observational error for the precipitation in Sc1 is also an obvious consequence of a better match of predictions and data. All other parameter marginals exhibit much smaller discrepancies between Sc1 and Sc2. We will discuss this point more clearly in the next paper revision.
- This work is intended to be a purely methodological study. Its main goal is to demonstrate that the HMC algorithm combined with a multiple time-scale integration presented in Albert et al. (2016) can be successfully applied to solve real-world hydrological inference problems with computationally expensive stochastic models. This method is especially very well-suited for cases, far from rare in hydrology, where the precipitation data is inaccurate and unreliable. It reduces considerably the bias in the inferred parameters by shielding them from the deteriorating effect of the rainfall data inaccuracy, thus leading to more reliable runoff predictions. The knowledge of all model parameters, including the groundwater flow and the retention time, is essential for making robust probabilistic predictions, which can certainly be useful in planning and policy making. This method is definitely a powerful and versatile tool for Bayesian inference with expensive stochastic models, whereas it might not be the optimal solution for real-time control of hydrological systems, where faster algorithms might be preferable. This topic, however, is not discussed in detail here since it goes beyond the scope of this study.

Technical comments

We thank the reviewer for pointing out these two technical issues. We will fix them in the next revision.