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Interactive comment on "Coupled hydrogeophysical parameter estimation using a sequential Bayesian approach" *by* J. Rings et al.

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This is an excellent paper that will make a strong contribution to HESS. To the best of my knowledge this is the first paper that applies Sequential Monte Carlo (SMC) sampling for solution of hydrogeophyiscal inverse problems. The proposed method is a classical vanilla SMC method that uses importance resampling to maintain sampling diversity and avoid collapse to a single realization.

Future work should focus on improving the efficiency of the method (the authors indicate this as well), yet initial results are very promising and show important insights into posterior tracking of model parameters, and what data constrain what hydrological and geophysical parameters. The paper is well written and provides a thoughtful numerical

experiment to demonstrate the advantages of SMC over classical batch Markov Chain Monte Carlo or other (non)-Bayesian approaches for full posterior inference. I only have a few small comments.

1. Eq. (2) is a classical measurement operator. Yet, I wonder whether the model parameters are actually needed to translate the model states to the model parameters? Classical textbooks of SMC use the authors formulation, but in many instances and practical applications only information about the new states at k+1 is required to derive the associated model output at k+1.

2. Eq. (3). I would suggest to use another symbol for the perturbation. Very close now to the model predictions used to confront the model. Also this parameter perturbation approach has been used previously in Moradkhani et al. (2005) and Salomon and Feyen (2009). Perhaps discuss this here. How is the size of the pertubation obtained? From the actual diversity at each analysis time, prior to the update? Note however, that the approach by Moradkhani et al. (2005) and Salomon and Feyen (2009) does not handle correlation between parameters. This is important especially with increasing dimensionality of the filtering problem.

3. Eq. (3) is rather inefficient. More efficient strategies would be to use Differential Evolution in a manner similar to the DREAM sampling scheme. This would explicitly consider parameter correlation through full-dimensional crossover of chain pairs. The authors have used this method previously.

4. Why do the authors use an effective sampling size of 0.8 to determine when to resample or not? Is this value determined by trial-and-error? I find this value to be very small. A standard value would be of 0.5 * N, where N denotes the number of particles. Would the filter work if a more standard value of 0.5N is used?

5. Why is importance resampling used? Did the authors try a different resampling method. I think that this might significantly increase the efficiency of the filter utilized herein. N > 3000 is significant, and similar results should be obtainable with much

small N (N = 100) but using MCMC or so for resampling.

6. Fig. 11 suggest a multimodal distribution. Is this true or the effect of resampling?

7. What about parallel computing. Section 3.1 does not say anything about this, but this might speed up the efficiency of the used filter considerably. Hence, each particle can easily be run on a different node. Or run a number of particles on different nodes, given that number of nodes will generally be smaller than N.

I enjoyed reading and studying this paper. Very nice work!

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