

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

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Thank you very much for your positive review. We will address each of your points below.

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 $k+1$.

In the way that we formulated our problem for the dike parameters, we apply the petrophysical parameters that relate water content and electrical resistivity only in the observation step. One could however formulate the state in terms of electrical resistivity, so that the petrophysical relation is included in the propagation step. This formulation would allow an observation model independent from any parameters.

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 perturbation 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.

We agree that the choice of the perturbation symbol should not be the next Greek letter following the noise terms of the propagation and observation models. We will change this to another letter in the revision. We have chosen to use only a static noise term with a variance of 0.02 times the mean of the parameter prior. This follows the method by Liu and West (2000). We are aware that a perturbation that shrinks with time (and width of the parameter distribution) is more appropriate. In our application, however, especially because of the rather small number of available time steps, we don't expect notable differences from this method.

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.

We have previously used DREAM in Huisman et al. (2009). The current study was a first investigation of particle filtering, so we chose to stay with a plain SIR filter to test if it is a worthwhile topic. As we are now confident that our results are promising, we're looking forward to combining the DREAM and particle filtering approach for a systematic and global parameter space exploration as a next step.

*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?*

We are not familiar with the criteria suggested here. Our definition of effective sample size is already normalized and cannot obtain values larger than 1. The value of 0.8 reported in the paper was confusing. We actually used an even larger value (0.95) to enforce resampling on a regular basis, which is necessary because of the limited number of filter updates. It should be noted that the computation time for the resampling is negligible compared to the model runs, which is a difference from "traditional" particle filter applications like signal processing, where filter variants like the auxiliary particle filter have been introduced to decrease computation time.

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.

We have based our choice of resampling on the recommendations of Douc et al.

(2005) who have compared 4 resampling schemes and have shown good performance of residual resampling. Again, the run time of the filter prevented comparisons of different schemes. For future work, the choice of resampling scheme and threshold should be systematically compared to find out whether the experience from the "traditional" particle filter application holds in hydrogeophysical, parameter estimation problems. If MCMC resampling can successfully be implemented, this problem may become obsolete.

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

This is only due to the resampling, and shows that the large number of particles is needed to achieve an appropriate coverage of the parameter space. We will add a sentence to the text addressing this issue.

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 .

For the numerical experiment, the run time was very fast, so there was no need to parallelize. For the dike experiment, we parallelized the filter as shortly described in section 4.1.

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