

## *Interactive comment on* "Covariance resampling for particle filter – state and parameter estimation for soil hydrology" *by* Daniel Berg et al.

## Anonymous Referee #1

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The paper introduces a new resampling method for particle filters, well suited to estimate both state variables and model parameters in a sequential DA approach. The well-known Universal Resampling Approach is modified by assigning new weights to the particles that should be duplicated, without actually duplicating the particles. These weights are proportional to the number of times the particles are selected in the universal resampling. To keep constant the ensemble size, new particles (states and parameters) are then generated by sampling from a multivariate Gaussian distribution having the same mean and covariance of the weighted particles. To avoid the degeneracy of the filter, the covariance is inflated using a multiplicative factor.

The proposed method is applied to a synthetic 1-d infiltration problem in a porous media constituted of two layers. Initial conditions and soil parameters (saturated hydraulic

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conductivity and two parameters of the Van-Genuchten equations, for both layers) are considered uncertain. The authors demonstrate that, in the considered example, the proposed pf well retrieves the state variables of the system and the soil parameters.

The paper is well written and the method is clear. At my knowledge, the proposed resampling technique is new and I really like it, since it gives the possibility to propagate realizations consistent with the model equations (a limitation of EnKF – see e.g., Pasetto et al. 2012) and, at the same time, the possibility of sampling new particles, which is fundamental to explore the parameter space.

The paper should be considered for publication in HESS since the topic is relevant to the hydrological community. However, there are some limitations that need to be considered, especially taking into account that the method is new and the results are presented for just a single application:

1) The paper does not present any result on the convergence of the filter with respect to the ensemble size: it would be important to show that at least the first and second moments of state and parameters converge toward the correct solution when N increases, and that the results are insensitive to the particular seed used. This analysis would also help justifying the choice of N=100.

2) In a similar way, the sensitivity of the filter to the multiplicative factor gamma for the parameters (selected to be 1.2) should be presented. Could the authors give an advice to the readers on how to choose gamma for a different problem?

3) A comparison of the results against the SIR using universal resampling (or the methodology proposed in Moradkhani et al. 2005) would help to understand if the proposed PF is retrieving the correct solution (in terms of both mean and covariance) and which are the practical advantages of the proposed resampling step.

With the addition of these results, this work would become an outstanding paper. Since these analyses are time-consuming, I am proposing major revisions to let the authors

more time for the required computations.

MINOR COMMENTS

Please revise the numbers and labels on the x and y axis for all figures. Probably there was an error with the software used to produce the figures.

L8, p1: 'With just 100 particles'. In large scale applications 100 particles are frequently adopted. However, in this 1-d scenario it is difficult to assess is 100 particles are 'small', especially without presenting a comparison with other approaches and/or the sensitivity of the results to the number of particles.

L8-10, p1: 'The estimated states and parameters are tested with a free run after the assimilation, which is found to be in good agreement with the synthetic truth'. PFs (and DA in general) are meant to assess not only the mean value of states and parameters, but also their covariance (if not all the pdf). To assess if the covariance computed is correct, a comparison with respect to other DA schemes would be required.

L20, p1: 'The EnKF based on Richards equation..'. EnKF is applied to Richards equation, not 'based on'. Please rephrase.

L23, p2: what does it mean 'without additional model evaluation'? This statement would be more relevant if the results of the proposed method are compared against more traditional PFs (e.g. SIR with a standard resampling).

L27,p2: missing point.

Section 3 and part of section 2: particle filters refer to a broad class of methods (see, e.g., Arulampalam 2002). The authors are mainly describing the Sequential Importance Resampling technique. Please clarify this point in the paper, so that readers familiar with PFs can easily understand which technique has been modified.

Fig1: Write evapotranspiration instead of evaporation.

Eq. 12, Page 5. I was expecting to see the weight w\_i in the summation. Please,

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provide a reference for the Bessel correction.

Lines 5-10, p9: it is not clear how the covariance matrix for the initial ensemble has been generated. Which matrices are multiplied in step 2? Is step one performed after step 2, to ensure zero correlation of the states across the two layers?

Page 13,L1: add 'of' after estimate

## REFERENCES

Arulampalam MS, Maskell S, Gordon N, Clapp T. A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. IEEE T. Signal Proces. 2002;50(2):174–88.

Moradkhani H, Hsu K-L, Gupta H., and Sorooshian, S.: Uncertainty assessment of hydrologic model states and parameters: Sequential data assimilation using the particle filter. Water Resour. Res., 2005; 41.

Pasetto D, Camporese M, Putti M. Ensemble Kalman filter versus particle filter for a physically-based coupled surface-subsurface model. Adv. Water Resour., 2012; 47(1), 1-13.

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