Interactive comment on "Parameter-state ensemble data assimilation using Approximate Bayesian Computing for short-term hydrological prediction" *by* Bruce Davison et al.

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hess-2017-482: Authors' responses to Reviewer Comments for "Parameter-state ensemble data assimilation using Approximate Bayesian Computing for short-term hydrological prediction"

Responses to RC3

1. Section 2.1: The first few sentences describe briefly how the P-SEDA filter works. States and parameters are drawn from some multivariate initial distribution - and then analyzed for use in a projection period. How is this analysis done? I think a Figure

may really help to communicate to readers how the P-SEDA method is implemented. The two sentences, "The analysis is completed and the process repeated for the next appropriate time-step in the continuous simulations" and "In this manner, both the parameters and states are drawn from the entire M simulations for the projection period". Not clear to me.

Author response: A figure will be added in section 2.1, which will now open with "The P-SEDA filter works in the following manner, as illustrated in Figure 1." We trust that this new figure, along with the second algorithm added to section 2.7 (as requested by the first reviewer), clarifies how the P-SEDA method is implemented.

2. Line 10: so you are talking here about the normalized weights. A particle filter uses three different weights: incremental weight (for current datum only), unnormalized weight (normalized weight prior to datum x incremental weight -> summarizes weight of entire trajectory) and normalized weights -> normalization of unnormalized weights before moving on to the next datum.

Author response: It is not clear that this comment requires a response or any changes to the paper. We do not plan to make any changes to the text accordingly.

3. Line 12: Resampling is the crux to an efficient implementation of the particle filter. Otherwise, many trajectories will receive a negligible weight and the PF does not approximate closely the target PDF.

Author response: It is not clear that this comment requires a response or any changes to the paper. We do not plan to make any changes to the text accordingly.

4. Line 14 - 16 "The approach presented here is the same, but without resampling and always returning to the original particles as updated by the model and assigning a weight of zero or one to each particle based on the filter (i.e. using a rectangular filter)." is unclear to me. This goes back to my earlier comment. From what is presented, I do not understand how the authors implement such approach. Thus, no resampling is

done? How do you return to the original particles. As with comment 1 above, can you give a detailed example, in text or in Figure that explains how this works. For example, at a time, t, we have the state forecast and associated parameter values + an incoming observation. What does the filter do then? How does it return to the original particles? How are the weights assigned? How is resampling avoided? etc.

Author response: We always return to the original particles by performing a continuous simulation of all of the particles. We trust that the addition of Figure 1 and Algorithm 2 makes the process more clear.

5. Algorithm 1: How is $s(y_i)$ computed? And how do you find the theta's from the k_m nearest neighbors of s_0?

Author response: In the pure form of ABC, $s(y_i)$ is simply a statistical property, such as mean or standard deviation, of the simulation. This is compared to the same statistical property of the observation (s_0). So if the mean were the statistical property being compared between the simulation and the observation, then the k_m nearest neighbors of s_0 would be the k simulations that have the mean that is closest to the observations. As with the response to the first major concern of reviewer one, we trust that the addition of Algorithm2 clarifies what is being done in this paper.

6. I do not understand where ABC comes in. Is this in the selection of s_0? and the s_y's? And how is the likelihood function formulated? This is done by simulation, yet, I miss the details necessary to understand and comprehend what has exactly been done.

Author response: All of algorithm 1 represents the ABC algorithm. In addition to the previous response, the likelihood function is approximated by the model. The additional text and figures added to the paper (in response to your concerns 1 and 8) should make it easier to understand and comprehend what has exactly been done.

7. Latin Hypercube sampling is argued as being highly inefficient. That is true if you want to approximate a target PDF, nevertheless, if you just want to sample the param-

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eter space, then this may be one of the best methods you can use.

Author response: As stated in the introduction, operational models are generally concerned with predictive ability and thus are more concerned with approximating a target PDF rather than sampling the parameter space. As such, future work in this area should consider methods other than LHS. No changes are planned to address this comment.

8. In Section 2.7 the authors describe how they construct the ensemble. None of the four approaches listed are described in detail. Hence, I do not understand what is being done. "minimized uncertainty filter". Need a detailed explanation, step by step how we go about initial states and parameters to a minimized uncertainty filter. Same holds for the other three listed methods. Without this the results in this paper will not be understood, nor are impossible to be reconstructed by the reader.

Author response: The following Figures will be added to Section 2.7 as Figures 4 to 7 in the transcript, but as Figures 2 to 5 in this response, which we expect will make the details of the various approaches more clear.
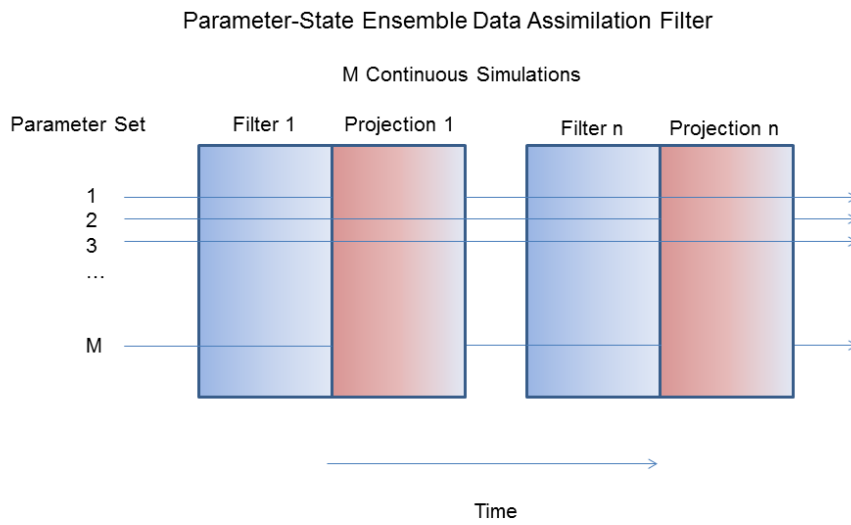
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Fig. 1. Schematic of the Parameter-State Ensemble Data Assimilation (P-SEDA) filter.
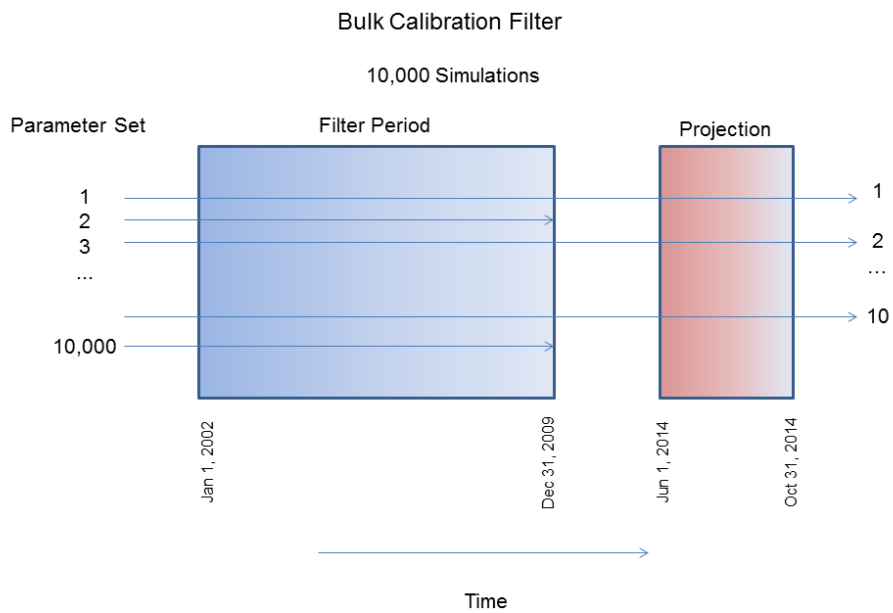
Fig. 2. Schematic of the Bulk Calibration Filter in which the top 10 simulations are selected from the filter (calibration) period of Jan 1, 2002 to Dec 31, 2009 and run for the projection (validati
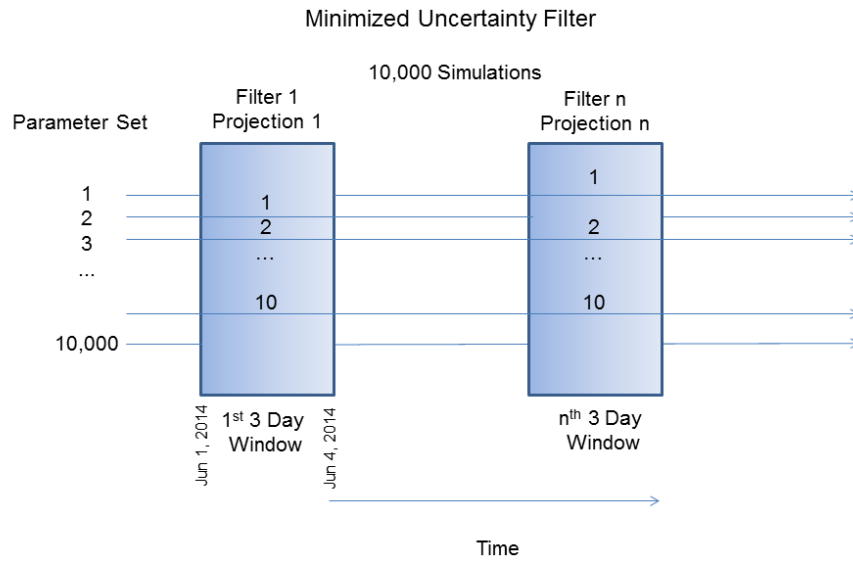
Minimized Uncertainty Filter

Fig. 3. Schematic of the Minimized Uncertainty Filter in which the 3-day filter and projection periods are the same for each window of time.
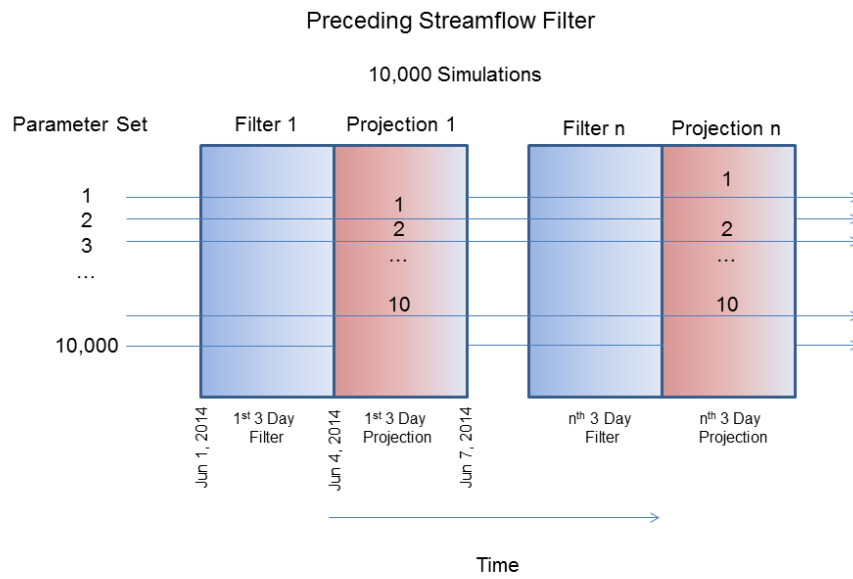
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Preceding Streamflow Filter

Fig. 4. Schematic of the Preceding Streamflow Filter in which each 3 day filter period is followed by a 3 day projection period.
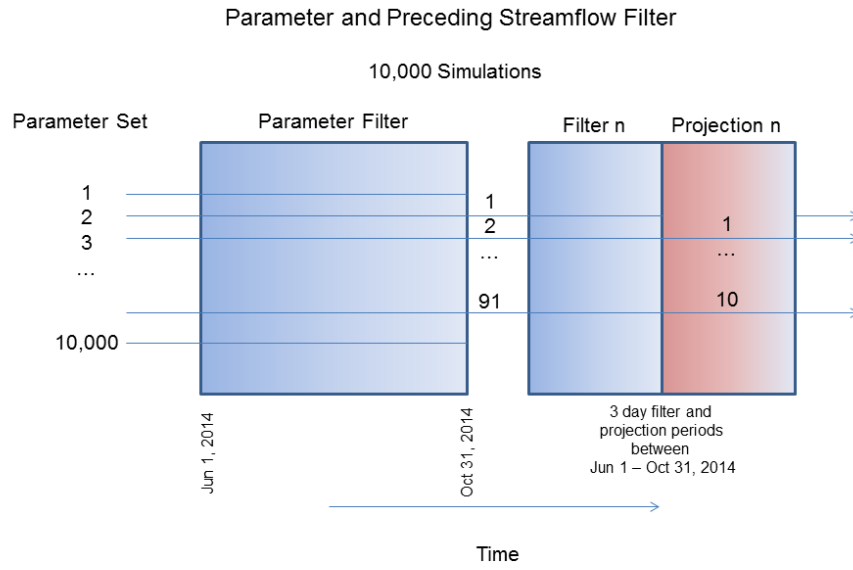
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Fig. 5. Schematic of the Parameter and Preceding Streamflow Filter. Note that the time period is re-run for the 3 day filter and projection periods after initially reducing the 10,000 parameter sets to 91.

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