Brief description of the modifications of the manuscript

The major modifications of our manuscript are

- More relevant literatures and explanations are added in the introduction to highlight the enhancement of our study.
- An additional scene with a series of wide prior parameter distribution cases are added in the revised manuscript. And more detailed discussions are added in section 4 to test the effects of prior distribution of parameters on the performance of estimation.
- Dual-parameter estimation cases are added to give more detailed discussions about multi-parameter estimation analyses.

Detailed responses

H. Moradkhani Referee

This paper presents another interesting implementation of the EnKF for state and parameter estimation in an Atmosphere-Vegetation Interaction Model using synthetic soil moisture data. The study examines the ability of the EnKF to estimate three soil moisture parameters individually and simultaneously. The paper concludes that in order to accurately perform simultaneous estimation of all three parameters in the AVIM model using the EnKF, a constraint based update must be used. While this paper presents an implementation of the novel approaches reported in previous studies, some justifications of the results and also major edits are required given pervasive grammatical errors and typos. Furthermore, not an appropriate literature review is provided to reflect the state of the art in the topical area. My evaluation is that the paper is publishable and could be a good contribution to data assimilation community (given the encouraging results provided), however, a moderate revision is needed while the following issues should be resolved for the paper to be fit for publication.

1. Page 1436 line 19 cites Vrugt et al. (2005) as using the EnKF for state and parameter estimation but this study used the EnKF for state estimation and SCEM-UA for parameter estimation.

A: We agree with this comment. There is our mistake in the manuscript to cite Vrugt et al. (2005) as an example of simultaneous state and parameter estimation approach. We removed this literature in our revised manuscript.

2. The listing of studies using the EnKF for state-parameter estimation is quite limited and should include Moradkhani et al., (2005a), Franssen and Kinzelbach (2008), Wang et al., (2009), DeChant and Moradkhani, (2010), Leisenring and Moradkhani, (2010), Montzka et al., (2011).

A: We thank for this comment. These literatures were added to section 1 of the revised manuscript. The new sentence is “In hydrologic field, the idea of state-parameter estimation was first introduced by Moradkhani et al. (2005a,b) using the EnKF and particle filter. The results were promising and almost all of the parameters were well estimated. Subsequently, this approach is widely used in many hydrological studies (Franssen and Kinzelbach, 2008; DeChant and Moradkhani, 2010; Leisenring and Moradkhani, 2010; Wang et al., 2009; Montzka et al., 2011)."

3. The idea of state-parameter estimation using the EnKF and also Particle Filtering (PF) in hydrologic modeling were first introduced by Moradkhani et al., (2005a and 2005b). Considering that the contribution of the current paper is exactly on the same topic but with the focus on soil moisture, the authors need to acknowledge the earlier research in this area that directly relates to their work. Particularly, the work by Moradkhani et al., (2005a) on state-parameter estimation using the EnKF is missing in the literature review provided by the authors. Given the similarity of some the fundamental equations (4-10) with those of Moradkhani's (2005a). The authors need to highlight the enhancement they have made in their work which distinguishes it from the others.

A: We agree with this comment. We acknowledged the researches of Moradkhani et al. (2005a,b) in the revised manuscript. Please see the revised manuscript for more details.

Comparing to earlier researches, firstly, our manuscript analyzed the capability of the EnKF in estimating LSM hydraulic parameters in two kinds of scenes: a series of narrow prior parameter distribution cases (meant our insufficient knowledge about first guess error of hydraulic parameter in LSM) and a series of wide prior parameter distribution cases (meant we knew enough about first guess error of hydraulic parameter in LSM). Secondly, we discussed the application of a new constrained parameter estimation procedure for simultaneous multi-parameter estimation in soil moisture data assimilation framework. In the earlier researches about constraint treatment methods in hydraulic field (Pan and Wood, 2006; Wang et al., 2009), inequality constraints were their points. In our manuscript, we focused on equality constraints between different hydraulic parameters. Please see the revised manuscript for more on this comment.

4. Similar to previous comment, in the context of soil moisture and state-parameter estimation, I suggest that the authors look at the recent work by Montzka et al., (2011). Although the particle filter was used in that work, the topic seems to be very relevant to the current work.

A: We thank for this comment. We acknowledged this research in our revised manuscript.

5. Page 1437 lines 5 through 8 explain that a constraint based EnKF is examined in this study but this was previously proposed by Wang et al. (2009). This previous work should be acknowledged. Also at the top of page 1444, it would be beneficial to this *paper to explain how the constraints in this paper differ from Wang et al. (2009).*

A: We thank for this comment. We acknowledged this work and explained the difference between the constraints in our paper and that of Wang et al. (2009). Please see the revised manuscript for more on this comment.

6. Page 1445 lines 20-24 explain that the ksat and b parameters converge faster than the Ψsat. This is used as justification to state that the Ψsat variable is more difficult to identify than the other parameters but I would argue that this is not necessarily true. The parameter converges quickly with the highest soil moisture observation values, which suggests that this parameter has a strong effect under high soil moisture values. Further, it is possible that the prior distribution of parameters affects the necessary time for convergence. There is little explanation of the reasoning for initial parameter distribution and how this may possibly affect the assimilation, but this is an important factor in the behavior of data assimilation techniques.

A: This is a good comment. We did not know that the prior distribution of parameters could be a problem. We make an additional scene with a series of wide prior parameter distribution cases motivated by this comment. In the revised manuscript, we added additional discussions in section 4 to test the effects of prior distribution of parameters on the performance of estimation. The results showed that the constrained parameter estimation procedure also had benefits to estimate all incorrect parameters simultaneously with a wide enough prior distribution of parameters. Please see the revised manuscript for more on this comment.

7. Figure 3 shows the RMSE of the "one-day-ahead" soil moisture prediction but it is unclear of how this is calculated. Is a set number of predictions and observations used to calculate this error? As the description stands, it seems that the error is only calculated for the one day prediction but I believe my understanding is incorrect.

A: the RMSE is calculated as follow equation:

$$\mathrm{RMSE}_t = \sqrt{\frac{1}{\mathrm{n}-1}\sum_{i=1}^{\mathrm{n}}(SM_t^{i-} - SM_t^{true})^2}$$

where the subscript "t" is the time (every day in the experiment period), the superscripts "–" refer to states in forecast step, n is the ensemble member, SM_t^{true} is the "true state" of soil moisture in time "t". We added this equation in the revised manuscript.

The RMSE is used to describe the errors in the soil moisture prediction comparing to the soil moisture "true state". As the assimilation interval was 1-day in Figure 3 of the first manuscript, the RMSE was for the one day prediction of soil moisture states.

8. Page 1447 describes the multi-parameter case and the reasons for using a *constrained filter. Line 13 attributes a lack of convergence to the increased dimensionality and explains that constraints must be used to overcome this problem. While the increased dimensionality makes the estimation more difficult, experiments with higher dimensionality have been performed and not required constraints (e.g. Moradkhani et al., 2005a & 2005b; Franssen and Kinzelbach, 2008; DeChant and Moradkhani, 2010; Leisenring and Moradkhani, 2010). What complicating factor in this study leads to a requirement of constraints in this study as opposed to previous studies? Have you examined the effects of creating a wider prior distribution of parameters? As it stands, your initial parameter distribution does not accurately reflect the uncertainty in theparameter.*

A: We summarize this comment in following items and answer below one by one:

8.1 While the increased dimensionality makes the estimation more difficult, experiments with higher dimensionality have been performed and not required constraints (e.g. Moradkhani et al., 2005a & 2005b; Franssen and Kinzelbach, 2008; DeChant and Moradkhani, 2010; Leisenring and Moradkhani, 2010). What complicating factor in this study leads to a requirement of constraints in this study as opposed to previous studies?

8.2 Have you examined the effects of creating a wider prior distribution of parameters?

8.1 While the increased dimensionality makes the estimation more difficult, experiments with higher dimensionality have been performed and not required constraints (e.g. Moradkhani et al., 2005a & 2005b; Franssen and Kinzelbach, 2008; DeChant and Moradkhani, 2010; Leisenring and Moradkhani, 2010). What complicating factor in this study leads to a requirement of constraints in this study as opposed to previous studies?

A: As the comment said, the increased dimensionality made the estimation more difficult in these previous studies. When the number of estimated parameters increased to a certain extent, most but not all of these parameters could converge to their “true” values. This means how to make all parameters to be estimated validly is still a challenge in the application of state-parameter estimation using data assimilation approach.

In our first manuscript, we used narrow prior distributions for all three estimated parameters, which represent our insufficient knowledge to get proper first guess hydraulic parameters in LSM (In most of the time this assumption might be valid, because we indeed did not know the true values of these parameters in nature). In this case, constraints as a new kind of information in addition to soil moisture observations were required to improve the multi-parameter estimation performance.

There was little discussion about the case of insufficient estimation of prior distribution of parameters in previous studies. In our revised manuscript, we gave corresponding analyses about this scene.

8.2 Have you examined the effects of creating a wider prior distribution of parameters?

A: We thank for this comment. We added additional discussions in section 4 according to this comment to test the effects of creating a wider prior distribution of parameters on the performance of estimation. Please see the revised manuscript for more on this comment.

9. Building on comment 6, lines 19 -22 of the conclusion attributes the failure of the multi-parameter estimation experiment to independent perturbations of the parameters but this is not completely proven in light of repeated results in previous studies. Why is it necessary for this specific application to use constraints while previous applications converged without constraints?

A: The independent perturbations of different parameters, a relative narrow initial parameter distribution, and different interaction relationships between state variable (soil moisture) and hydraulic parameters in different LSMs might be the reasons for the failure of the multi-parameter estimation in our study.

According to the analyses in the revised manuscript, when the number of estimated parameters increased, some of these incorrect parameters could be estimated effectively if the initial parameter distributions were wide enough. However, a wider initial parameter distribution could only improve the performance for some but not all of these parameters (the similar results could be seen in those previous studies). If all incorrect parameters were need to be estimated in multi-parameters estimation cases, using constraints between parameters might be an effective way to achieve this purpose. In our study, we wanted to estimate all incorrect parameters simultaneously. Therefore, constraints between parameters were needed to be used in the assimilation process. Please see the revised manuscript for more on this comment.

References:

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