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Title: Assimilating Shallow Soil Moisture Observations into Land Models with a Water Budget Constraint

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The authors highly appreciate the anonymous reviewer for his/her very helpful and insightful comments that lead to the considerable improvement of the quality of this manuscript. We have checked our work carefully according to these comments and made the requested changes.

Below we indicate the comments and use blue font for our responses. The corresponding revised texts are also used blue font in the revised version of our manuscript.

Reviewer #1

It is with great interest that I read this paper, which investigates a number of different approaches to improve the assimilation of near-surface soil moisture observations. Specifically, the authors use an Ensemble Kalman Filter (EnKF) data assimilation (DA) framework to investigate the effect of forecast error inflation, vertical localization, and a weak water balance constraint. They find that the forecast error inflation helps to reduce the analysis error in upper soil layers that are close to the assimilated observations, however, leads to large analysis errors in deeper soil layers. They conclude that the introduction of a vertical localization function can mitigate the increased analysis error in the deeper soil layers. Finally, the authors concluded that the introduction of a weak water constraint helped to reduce the water residual after the assimilation.

Overall, this is a well-written manuscript that presents a novel and scientifically valuable contribution to the field of land data assimilation. I have a few minor comments that I would invite the authors to address before the publication of this manuscript.

Response: [Thank you very much for your thorough reviewing and valuable comments.](#)

General comments:

1. One concern I have is the authors' choice not to implement any bias correction. The argument made is that the removing the model bias can lead to issues, but what is lacking is an argument for not implementing the (arguably more traditional) approach of bias correcting the observations to match the model's climatology. By not

addressing the bias between the observations and model, you are ultimately violating the assumptions of your DA framework and I would at the very least like to see a discussion on how this impacts the results.

Response: Thank you for your comments. Following it and the major comment of another reviewer, the bias-aware data assimilation proposed by Dee (2000) was applied to further correct the bias of the analysis states assimilated using WCEnKF-Inf-Loc. This scheme was named as WCEnKF-Inf-Loc-BA, and the corresponding results were added in Figures 5-6.

Figure 5 shows that, the spatial averaged root analysis error variances of WCEnKF-Inf-Loc and WCEnKF-Inf-Loc-BA were comparable (2.12% for the WCEnKF-Inf-Loc-BA and 2.16% for the WCEnKF-Inf-Loc) for the layers that are shallower than 36.6 cm. This could be due to that the observations are closer to the shallow layers and the vertical localization approach is reasonably effective to reduce the bias. However, for the layers that are deeper than 62.0 cm, the averaged root analysis error of the WCEnKF-Inf-Loc-BA (6.05%) was less than that of the WCEnKF-Inf-Loc (6.59%). This indicates that the bias correction is useful for this experiment, especially for the soil moistures in deeper layers. (Lines 420-428)

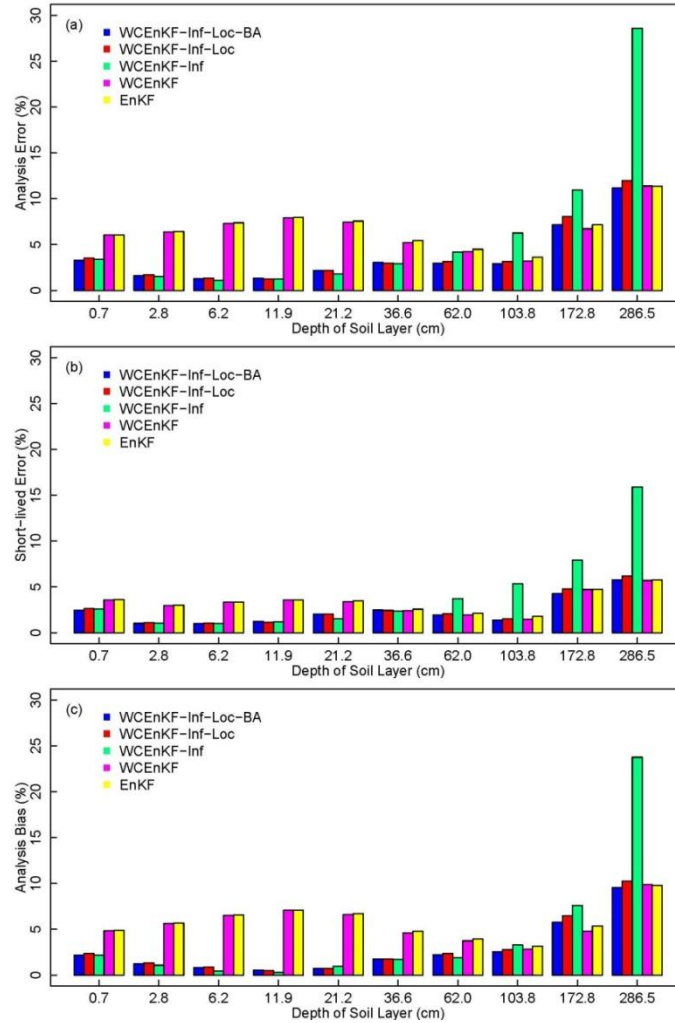


Figure 5. The assimilation results in each layer for the five schemes: a weakly constrained bias-aware ensemble Kalman filter with forecast error inflation and vertical localization (WCEnKF-Inf-Loc-BA), a weakly constrained ensemble Kalman filter with forecast error inflation and vertical localization (WCEnKF-Inf-Loc), a weakly constrained ensemble Kalman filter with forecast error inflation (WCEnKF-Inf), a weakly constrained ensemble Kalman filter (WCEnKF), and the traditional assimilation (EnKF). Graphic (a) is for spatial averaged analysis error of the soil moisture content, (b) is for the short-lived error and (c) is for the analysis bias.

A secondary effect of the lack of bias correction is that it probably aggravates the non-closure of the water balance. While assimilating bias-corrected observations can

still lead to a water imbalance, the effect would likely be reduced and requiring less ‘intervention’ by the water balance constraint introduced in the ‘WC’ experiments. In this context, it is also worth considering that the nature of observed and modeled soil moisture can be very different (see e.g. Koster et al. 2009), which further necessitates a bias correction step.

Koster, R.D., Guo, Z., Yang, R., Dirmeyer, P.A., Mitchell, K. and Puma, M.J., 2009. On the nature of soil moisture in land surface models. *Journal of Climate*, 22(16), pp.4322-4335.

Response: Thank you for your comments. In the revised version, the water budget residuals of different assimilation schemes were shown in Figure 6. The spatial average of the water balance residuals for WCEnKF-Inf-Loc-BA scheme was 0.0723 mm, which was slightly smaller than that for WCEnKF-Inf-Loc scheme (0.0737 mm). The small improvement on water balance residuals may be due to the small improvement on analysis bias by the additional bias-aware assimilation, but it suggests a tendency of the bias correction to further reduce the water balance budget. (Lines 442-445)

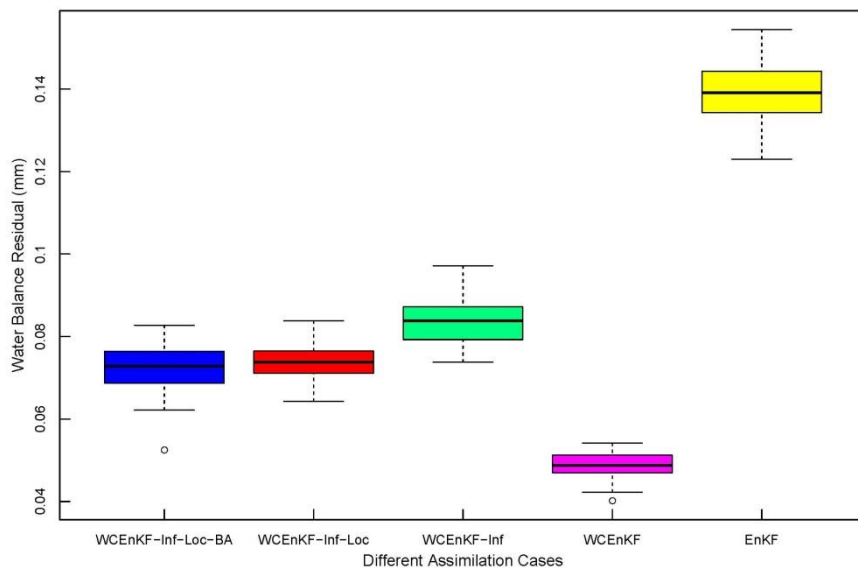


Figure 6. The box plot of the water balance residual in all 40 pixels for the WCEnKF-Inf-Loc-BA, WCEnKF-Inf-Loc, WCEnKF-Inf, WCEnKF and EnKF assimilation schemes.

2. I would like to see some discussion of the feasibility of the proposed approach for global data assimilation. As the authors discuss, in particular the vertical localization function can be strongly location dependent. I am wondering whether expanding to the global domain would require computing the localization function at each model grid cell and whether that would be computationally feasible? Or would you compute a localization function at a regional scale using soil texture or climate regimes to delineate different regions? Some discussion of the transferability of the presented approach to global scales would be valuable.

Response: Thank you for your suggestions. As you pointed out, the most computational cost in the assimilation system is on computing the localization function at each model grid cell. For the synthetic experiments with CoLM model and 40 grids, it takes about 24 hours running on the personal workstation. For global data assimilation with 2° resolution it could take about 3 months to finish if running on the personal workstation, but the super server and parallel computation can significantly shorten the computational time. We also agree with you that “a regional scale using soil texture or climate regimes can be used to delineate different regions”. By this way, the computational time of global data assimilation can be further reduced. (Lines 525-532)

Detailed Comments:

ll. 14-15: This sentence is somewhat redundant, I would recommend rephrasing it.

Response: We have revised this sentence to “Assimilating observations of shallow soil moisture content into land models is an important step in estimating soil moisture content.” (Line 14-15)

l. 28: ‘effectively reduces. . .’

Response: Revised.

l. 42. Actually, the sub-seasonal to seasonal time scale is probably the one where the land states have the largest impact, so I would mention it here.

Response: We have added “at sub-seasonal to seasonal time scale”.

l. 63: ‘land model predictions’

Response: Revised.

l. 67: ‘can successfully increase’ or ‘successfully increases’

Response: The sentence has been deleted following the next comment.

ll. 65-74: This paragraph focuses a lot on the assimilation of brightness temperatures, while your study is actually investigating methods to improve soil moisture assimilation. So I would include a discussion of soil moisture assimilation here or even a short discussion of soil moisture vs. brightness temperature assimilation.

Response: Thanks for your comment. This paragraph has been revised as follows.
(Lines 60-69)

Many studies indicated that a better approach to improving the estimates of soil moisture contents on regional scales is to constrain land model predictions by

assimilating surface soil moisture data (Crow and Loon 2006; Crow and Wood 2003; Reichle and Koster 2005). It can provide better estimates of the true soil moisture content column states than the model forecasts (Crow *et al.* 2017; Lu *et al.* 2012; Lu *et al.* 2015), and can further improve land surface model initial conditions for coupled short-term weather prediction (Chen *et al.* 2014; Santanello *et al.* 2016; Yang *et al.* 2016). Especially, surface soil moisture data can be provided by in-situ observations and passive microwave measurements (brightness temperatures) observed by remote sensing.

ll. 115-119: Please see general comment on bias correction of observations.

Response: Thanks for your comment. In the revised version, the sentence “Therefore in this study, we still use traditional bias-blind data assimilation framework.” was replaced as “However, bias can be detected by monitoring observation-minus-forecast statistics in the assimilation system (Dee and Todling 2000). Then a bias-aware assimilation method can be designed to estimate and correct the systematic errors sequentially with the model state variables (Dee 2005). Such bias correction method is adopted in this study to detect the performance among different assimilation schemes.” (Lines 109-114)

ll.128-130: I think you are making an argument here in favor of removing the bias between model and observations.

Response: Yes, we have added the bias correction schemes in the revised version.

ll.178-182: Just to clarify, the synthetic experiments are conducted over 40 pixels, whereas the real data are conducted only over the two ground station sites, correct?

Response: Yes.

II. 230-231: I am surprised to see that you are letting the assimilated soil moisture observations update the canopy water content directly, rather than only updating the soil moisture and letting your vegetation module transport the water into the vegetation layer. Is this approach also taken for the real data assimilation experiments, when you are assimilating in situ soil moisture?

Response: We agree that not update the canopy water content is an option. The approach in this study is adopted from Yilmaz *et al.* (2011; 2012) where the canopy water content was updated. This approach was also taken when we are assimilating in situ soil moistures at the two Mongolia stations.

I. 395: Do you mean ‘At each point..’?

Response: Yes, the words have been revised.

I. 415: When you say ‘the simulation case’, do you mean the open-loop?

Response: Yes it is open-loop. However, the results for the open-loop are not shown in Figures 5 and 6 in the revised version.

II. 446-449: This paragraph needs some language editing.

Response: We have removed the observation study in the revised version. This is because the paper is too long after adding the bias-aware data assimilation experiment, so we would like to shorten it. Also the observations are not available in all layers, and then it is more difficult to validate the proposed assimilation methods. Since these paragraphs were related to observation study, they were deleted in the revised version.

l. 511: 'threshold'

Response: The typo has been revised.

Again, thank you very much for your thorough reviewing and valuable comments.

The references in this reply are listed as follows, while some of them have already in the previous version of the manuscript.

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533: 266-276.

Yilmaz, M.T., Delsole, T. and Houser, P.R., 2011. Improving land data assimilation performance with a water budget constraint. *Journal of Hydrometeorology*, 12: 1040-1055.

Yilmaz, T.M., Delsole, T. and Houser, P.R., 2012. Reducing water imbalance in land data assimilation: Ensemble filtering without perturbed observations. *Journal of Hydrometeorology*, 13(1): 413-420.