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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 #2

The paper titled "Assimilating Shallow Soil Moisture Observations into Land Models with a Water Budget Constraint" presented several modifications to the EnKF data assimilation (DA) that potentially improve DA performance in soil moisture (SM) modeling using shallow-layer observations. A forecast error covariance matrix inflation approach to avoid filter divergence due to underestimated sampling and modeling errors is shown to improve modeling accuracy of SM in layers close to the observation, but leads to increased error in the deeper layers. A vertical localization method is applied to limit the updates to the deep layers to mitigate the errors introduced in the deeper layers. A weak constraint on water balance is able to reduce the water balance residual which is increased due to the forecast error covariance inflation at the price of small increase in the analysis error. Overall the results indicate potential usefulness of such modifications in improving soil moisture assimilation accuracy of surface soil moisture observations.

Response: Thank you very much for your thorough reviewing and valuable comments.

However, there is a major issue in the experiment design the raises my concern, i.e. the lack of observation bias-correction. I found the authors' reasoning behind adopting the "traditional bias-blind data assimilation framework" (line 112-117) unconvincing, as there is no evidence to support the "observations" are unbiased relative to the model background in both the synthetic and real-data experiments in this study. Also, it is well known that remotely sensed soil moisture (the intended application of the proposed modifications) and modeled soil moisture often exhibit different dynamic ranges which warrants the use of a "bias-aware" approach instead (see e.g. Kumar et al. 2012, doi:10.1029/2010WR010261).

Response: Thank you for your comment. Following it and the major comment of the other reviewer, the bias-aware data assimilation proposed by Dee (2005) 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. 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 indicated that the bias correction is useful for this experiment, especially for the soil moistures in deeper layers. (Lines 420-428)

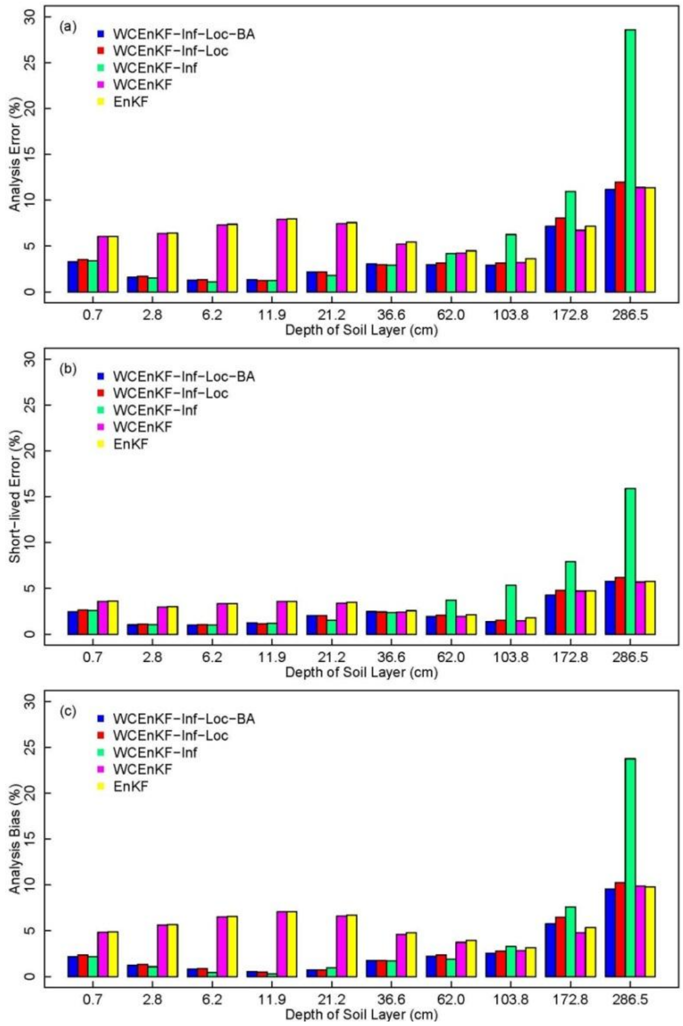

Figure 5. The assimilation results in each layer for the five schemes: a weakly constrained bias-aware ensemble Kalman filter with forecast error inflation and vertical localization (WCEnKF-Inf-Loc-BA), a weakly constrained ensemble Kalman filter with forecast error inflation and vertical localization (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.

In addition, there is an apparent misunderstanding of the Koster et al. (2009) and Reichle and Koster (2004) works where the authors stated that "A major objective of soil moisture data assimilation is to address biases in models and observations" (line 110-111). In fact, both publications indicated the importance of removing the bias in the statistical moments in the observations relative to the model background prior to data assimilation. The major objective of data assimilation is not to remove the bias in model states but to reduce the random, mean-zero noise in the model states, with the model state climatology respected. Even if the observations are considered unbiased, it is recommended that the observations be "scaled" to match the statistical moments of the model states (with long enough time-series). It is well known that directly assimilation of raw observations likely causes model integration to drift, i.e. introduce further bias to the model states. Therefore, the model water balance residual after the soil moisture update in the experiments in this study may be partly attributed to assimilating observations without bias-correction (relative to model), and the true effect of the weak water balance constraint is not accurately revealed.

I would like suggest that the DA experiments repeated with a more robust "bias-aware" approach, to rule out the impact of observation bias in the analysis errors so that the effects of the proposed modifications are better isolated.

Response: Thank you for your comments. We agree that the model state climatology should be respected and directly assimilation of raw observations likely causes model integration to drift. We also agree that a more robust "bias-aware" approach is necessary, because it respects the model state climatology and uses the estimated bias to prevent model integration to drift. In the revised version, the bias-aware data assimilation proposed by Dee (2005) was investigated.

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)

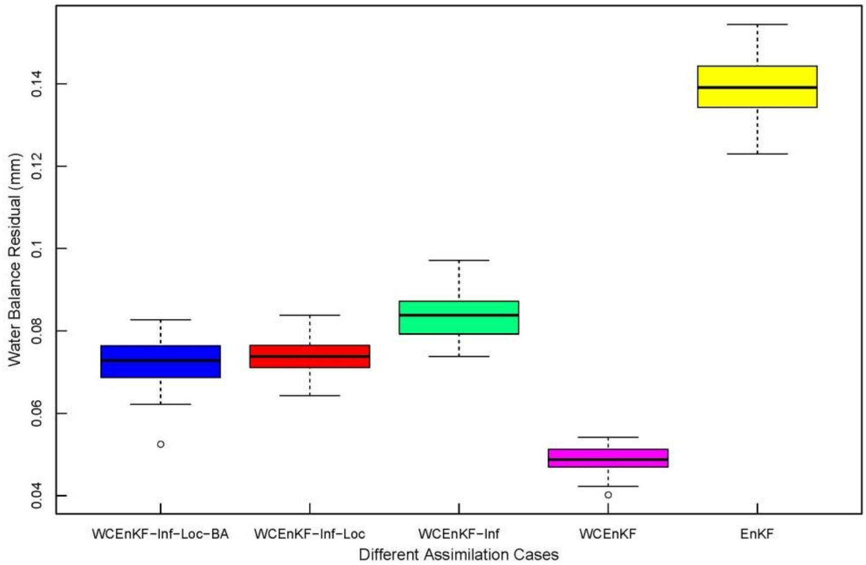

Figure 6. The box plot of the water balance residual in all 40 pixels for the WCEnKF-Inf-Loc-BA, WCEnKF-Inf-Loc,WCEnKF-Inf, WCEnKF and EnKF assimilation schemes.

Other minor comments:

Lines 65-74: irrelevant to the topic of the paper and should be removed.

Response: Thanks for the comment. Following it and the comment of the other reviewer, lines 65-74 were removed and the paragraph is revised as follows:

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. (Lines 60-69)

Line 229: why directly update canopy water content and snow water equivalent when these two variables are not regulated by near-surface soil moisture?

Response: We agree that not update the canopy water content and snow water equivalent is an option. The approach in this study is adopted from Yilmaz *et al*. (2011; 2012) where the canopy water content and snow water equivalent were updated.

Line 448: remove "the" following "cover"

Response: Revised.

Line 478: "the different experiments" –> "different cases"

Response: This paragraph was related to cases of the DGS and BTS stations, and was removed in the revised version.

Lines 479-480: for better understanding of the magnitude of improvement, use a percentage scale for water balance residuals

Response: Thank you for your suggestion. In the revised version, the real data experiments were deleted due to the length of the manuscript.

Line 494 "deflation «of» the water balance ..."; "plain" –>"plainly"

Response: Revised.

Line 511 "shreshould" –>"threshold"

Response: Revised.

Sec 7.2 Again, one should be careful to use data assimilation to achieve "bias correction" in model states. This is another example of misunderstanding the major objective of DA in this work. Seemingly reduced systematic bias in modeled soil moisture may be an artifact due to biased observation relative to model background.

Response: Thank you for your comment. We have added the experimentation with bias correction method. The results shows that the bias-ware assimilation schemes can further reduce the analysis error and water budget residuals.

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.

Chen, F., Crow, W.T. and Ryu, D., 2014. Dual Forcing and State Correction via Soil Moisture Assimilation for Improved Rainfall-Runoff Modeling. *Journal of Hydrometeorology*, 15(5): 1832-1848.

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Crow, W.T. and Loon, E.V., 2006. Impact of incorrect model error assumptions on the sequential assimilation of remotely sensed surface soil moisture. *Journal of Hydrometeorology*, 7: 421-432.

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Lu, H., Yang, K., Koike, T., Zhao, L. and Qin, J., 2015. An Improvement of the Radiative Transfer Model Component of a Land Data Assimilation System and Its Validation on Different Land Characteristics. *Remote Sensing*, 7(5): 6358-6379.

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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.