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# *Interactive comment on* "Satellite soil moisture data assimilation for improved operational continental water balance prediction" *by* Siyuan Tian et al.

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# Response to Anonymous Referee 3

January 21, 2021

The study "Satellite soil moisture data assimilation for improved operational continental water balance prediction" by Siyuan Tian et al. develops a data assimilation approach of remote-sensing soil-moisture information for improving the water-balance predictions of the BoM-based implementation of the hydrological AWRA-L model, which is extensively used in Australia for agricultural applications and risk assessment. The novelty of the paper does not lie in the modification of the hydrological model, but in the development of a data assimilation approach. Overall, I think that the paper is well written, and that the topic is relevant for the HESS readers. However, I believe that some critical points developed in the paper should be clarified.

We thank Reviewer 3 for the positive response and thoughtful comments. Particularly we are grateful for the suggestion on the use of EVI, which has led to the most widespread change to the manuscript. Our response to all of the reviewer's concerns are provided below.

The reviewer raises several items in Concern 1 below which we address sequentially in the following.

**Main concerns:**

(1) The proposed method very clearly improves the performance of the BoM-based operational AWRA-L model for the prediction of surface (0-10 cm depth) soil moisture, but I am not convinced that this methodology significantly improves the predictions of the model for the other components of the water balance: - Panels b, c and d of Figure 7 suggest that the tested data assimilation methods DA-TC and DA-TCAIR do not improve the open-loop model predictions for the 0-1 m soil moisture, evapotranspiration and streamflow data. Furthermore, in some cases (e.g., 0-1 m modeled soil moisture records for OzNet), the DA-TC and DA-TCAIR outcomes tend to reduce the performance of the original model.

On the improvements of other components of the water balance, we agree with the reviewer that the changes in model estimates with and without SM assimilation are marginal in comparison with in-situ observations. We have said as much in the Results, Discussion and Conclusion sections, specifically L235–L240, L260–L270, L334 – L238 and L359 – 360. We also suggest that the small number of in-situ validation sites (as shown in Fig. 1d) is one of main reasons we do not see significant improvements in these components of the model — which incidentally was the impetus of exploring indirect verification via vegetation index. We will further clarify this in L277 as follows:

*"The limited number of root-zone soil moisture monitoring sites and the large spatial disparity between in-situ measurements at point scale and modelling resolution (∼5-km grid cell) scale are the substantial limitations for wide-area evaluation of root-zone soil moisture estimates."*



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Nevertheless, changes in these components across the continent can be seen in Fig. 6, with clear difference in spatial pattern for Etot, Qtot and Ss after the assimilation and with mass redistribution. Similarly, Fig. 10 demonstrates the impacts of data assimilation on the prediction of Etot, Qtot and Ss are significant over western and central Australia.

In terms of the degradation of the root-zone soil moisture for some locations in OzNet, we noted this and discuss the potential reasons in L263. If the reviewer believe we place too strong an emphasis on 'improving' water balance modelling, we would consider removing it from the title of the manuscript — a decision we will leave to the discretion of the Editor.

The authors have included a plot showing the observed and modeled streamflow series of one example pixel (Fig. 8) of Australia to justify some of the improvements that the proposed DA-TCAIR methodology may produce in the modelled outputs of the other components of the water balance. In my opinion, this figure only indicates that both the original, model open-loop predictions and the "improved" DA-TCAIR predictions are very poor (i.e., strongly differ from the observed streamflow data) for this example pixel. This is certainly intriguing, since Fig. 7d suggests that, for a very large proportion of the modelled pixels in Australia, there should be a good correspondence between the observed and modelled streamflow data using any of the three tested methodologies (clearly, this is not the case for the Fig. 8 example). This also rises important concerns about the convenience of using the selected example as a representative pixel of the modelled dynamics.

We agree with the reviewer that Fig. 8 shows that both model open-loop and data assimilation results have large disparity with streamflow observations. The correlations between model results and in-situ observations for this selected site are 0.74 and

0.83 for open-loop and DA-TCAIR respectively, which are the average performance of the streamflow estimates from the model as pointed out by the reviewer (Fig. 7d). Nevertheless the model differences with streamflow observation suggests a need for model re-calibration for this catchment, but this is beyond the scope of the investigation. However we still maintain that while the change in correlation is small, the data assimilation does indeed correct model estimates in the right direction towards observations. As such we will add the following statement in the revised manuscript to clarify:

*"Although the change in streamflow estimation from soil moisture data assimilation is small compared to the disparity between model and observed streamflow, the adjustment is in the direction towards observations, highlighting the importance of accurate antecedent soil moisture conditions in the simulation of runoff response. The joint assimilation of gauge-measured streamflow and satellite soil moisture retrievals into AWRA-L is expected to improve significantly improve both soil water balance and streamflow simulation."*

The authors use remote-sensed greenness information (NDVI) of crop fields to justify the better performance of the proposed DA-TCAIR methodology for predicting the “root zone” (0-1 m soil profile) soil moisture. Fig. 9 shows an increased correlation between the crop biomass production (or greenness) and 0-1 m soil moisture for the proposed methodology, but I wonder whether this is an indirect effect of the better prediction of surface (0-10 cm) soil moisture for the proposed method, since (i) the 0-10 cm values are integrated within the modelled 0-1 soil moisture values, and (ii) crops typically concentrate a very large proportion of their roots in the surface (first 15 cm) of the soil profile (see Fan et al. 2016; Field Crops Research, 189: 68-74 for details). An exploration of the correlation between the vegetation greenness of the crops and the modeled surface (0-10 cm) soil moisture series, and between the modelled series of surface (0-10 cm) and “root zone” (0-1 m) soil moisture would be useful to clarify this point.

We thank reviewer for this comment. It is true that the improvement of S0 (0-10cm) will contribute to the improvement of the root-zone (0-1m). However, the surface water storage S0 (0-10cm) is only a small proportion of the volume in root-zone soil water storage (0-100cm). Guided by reviewer's suggestion, we calculated the correlation between S0, Ss and S0+Ss with NDVI. The averaged correlation over all cropland pixels is summarised in the Table 1 below. The results demonstrate that the correlation between Ss and vegetation index is higher than S0 (0.54 vs 0.42) from model open-loop which indicates a stronger correlation between Ss and vegetation index. And the correlation of the root-zone (S0+Ss) water storage with vegetation index mainly comes from Ss since the correlations for Ss layer are as same as root-zone soil storage (S0+Ss).

We also calculated the correlation between the monthly S0 and S0+Ss from model open-loop as suggested by the reviewer. The average correlation for all the cropland pixels is 0.68, which indicates a moderate linear relationship. This is expected since S0 is included in the root-zone soil water storage and soil moisture between two layers are coupled, but not strongly correlated.

Furthermore, our choice of definition of root-zone for the cropland areas was guided by several Australian studies. The first was that of Donohue et al (2012) who showed through hydro-climate data analysis that for vegetation in the highlighted region have on average an effective rooting depth of 30 – 60 cm (see Fig.13 in Donohue et al. (2012)). Moreover the predominate vegetation in the cropland areas is wheat (the so-called Australian wheatbelt) where several main varieties have been shown to have rooting depths varying from 30 – 80 cm (Incerti and O'Leary 1990; Figueroa-Bustos et al., 2018).

We will clarify this in the manuscript in L140 as below:

*"The choice of root-zone soil water storage at the 0-1 m depth is due to the average rooting depths varying from 30 - 80 cm over the cropland areas in Australia (Donohue et al., 2012; Incerti and O'Leary, 1990; Figueroa-Bustos et al., 2018)."*

| | NDVI | | EVI | |
|---|---|---|---|---|
| | Open-Loop | DA-TCAIR | Open-Loop | DA-TCAIR |
| S0 (0-10 cm) | 0.42 | 0.62 | 0.40 | 0.57 |
| Ss (10-100 cm) | 0.54 | 0.65 | 0.52 | 0.64 |
| S0+Ss (0-100 cm) | 0.54 | 0.65 | 0.52 | 0.64 |

**Table 1.** Summary of correlation between model S0 and Ss layers and NDVI/EVI time series.

(2) The proposed methodology is affected by a strong circularity. The authors apply a method of data assimilation based on the use of remote-sensed surface soil moisture estimations to improve the modeled hydrological components of the water balance of the AWRA-L model, impacting mainly in the outcomes of the surface soil moisture predictions.

We understand reviewer's concern, however, as the previous reviewers have noted that use of satellite SM time series in TC method to first characterise observation error and then use the estimated error to assimilate the SM observation is standard practice.

**Other comments:**

(1) The authors apply MODIS NDVI data as a proxy of the vegetation dynamics in the crop fields for some of the analyses. Although NDVI has been very extensively used



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as a proxy of vegetation cover and production within the last 4 decades, numerous studies indicate that this VI shows considerable limitations to represent accurately the dynamics of vegetation, particularly in drylands. For example, NDVI is strongly influenced by the spatiotemporal variations in soil background reflectance in moderate and low cover areas. In addition, this VI typically shows saturation effects in high biomass areas and is also notably affected by the presence of atmospheric aerosols. Other MODIS VIs (e.g., EVI) may show a better performance for characterizing the vegetation dynamics of the crop fields.

We thank reviewer for their fascinating insight and suggestion into the use of EVI. We have re-calculated our results using EVI, but found the overall similar performance compared to NDVI as shown in the Table 1 and Figure 1. We can only speculate that since we have aggregated the data to monthly time steps, that the suggested benefits of EVI over NDVI have been suppressed. Nevertheless we will take reviewer's suggestion of using EVI in the revised manuscript and modify the text accordingly.

Specifically we will modify the description of the data set in L137 as below:

*"The 0.05-degree monthly Enhanced Vegetation Index (EVI) from Moderate Resolution Imaging Spectroradiometer (MODIS, MYD13C2 v6) were used to evaluate estimates of monthly root-zone soil water storage (the sum of water storage in surface-layer* $(S0)$ *and shallow-layer* $(Ss)$ *within the AWRA-L soil column) over cropland regions of the continent. The EVI is used here to characterize vegetation dynamics since it is not as influences of atmospheric effects and canopy background noise, and has a greater dynamic range (i.e., less likely to saturate) in areas of dense vegetation compared to the Normalized Difference Vegetation Index (NDVI)."*

The Figure 1 below will replace Figure 9 in the revised manuscript based on the suggestions from both Reviewer 2 and Reviewer 3. In the revised figure, subplot (a) shows the improved correlation of root-zone soil water storage from DA-TCAIR with EVI compared against model open-loop; subplot (b) shows the relative change (%) in correlation between DA-TCAIR and DA-TC and the location of a selected 15km x 15km cropland area; subplot (c) shows the time series between modelled water storage and EVI.

The description of the results for this figure will be changed as below from L277:

*"A limited number of root-zone soil moisture monitoring sites as well as the large spatial disparity between the point-scale in-situ measurements and modelling resolution (∼5 km grid cell) represent substantial limitations for wide-area evaluation of root-zone soil moisture estimates. An indirect verification of AWRA-L simulations of root-zone soil moisture was based on a comparisons against satellite-derived EVI. This provided an independent, albeit indirect, way of evaluating the impact of data assimilation over larger areas. We calculated the correlation between time series of monthly average AWRA-L root-zone soil moisture estimates from OL, DA-TC and DA-TCAIR against EVI for cropland across Australia from 2015 to 2018. Cropland cover type was selected based on the rooting depths of the dominant grass species and wheat varieties in the area that have been shown to have rooting depths spanning at least half the combined soil depths (0-1m) of the surface- and shallow-layer soil water storage in AWRA-L. Figure 9a shows the relative change in correlation between root-zone soil water storage simulations from DA-TCAIR and those from model OL against EVI data for cropland areas of Australia. Significant improvements were found after the data assimilation and mass redistribution for the vast majority of model grid cells (Fig. 9a). The averaged correlation with EVI is 0.64 from DA-TCAIR compared to 0.52 for model open-loop. The root-zone soil water storage estimates after the mass*







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*redistribution are significantly improved over the cropland in Western Australia and southern Australia with more than 20% increase in correlation comparing to DA-TC without mass redistribution (Fig. 9b). Fig. 9c shows time series of an averaged AWRA-L root-zone soil water storage and EVI for a 15km x 15km farmland area in Victoria (origin: -36.25, 142.15). The correlations are 0.49, 0.70 and 0.77 for the model OL, DA-TC and DA-TCAIR, respectively. This demonstrates that enforcing mass balances as part of the soil moisture data assimilation at each time step is essential to improving the simulation of root-zone soil water balance. Limited difference between DA-TC and DA-TCAIR were found over cropland regions over southeastern Australia, likely due to the overall good performance of AWRA-L OL root-zone soil moisture estimates in those areas (Fig. 7b). The improved consistency with EVI after data assimilation highlights the potential of improving agricultural planning with more accurate information of root-zone soil water availability."*

(2) Fig. 7 lacks statistics. Without statistical testing the authors cannot claim whether there are any differences in the performance of the compared methodologies for soil moisture, evapotranspiration and streamflow prediction.

Thank you for this comment. We believe that the statistical significance of the S0 improvements in Fig.7a are evident in the little or no overlap distribution of $r$ . Similarly, Fig.7 b-d show no significant change as we mentioned in L260-L270. We can modify the figure to scatter plots with confidence level plotted in dashed line as shown in our response to Reviewer 1. However, we believe having boxplots showing the distribution of the correlations for each in-situ network is neater than having overlapping dots for each network.

**Reference**

*Donohue, R. J., Roderick, M. L., McVicar, T. R. (2012). Roots, storms and soil pores: Incorporating key ecohydrological processes into Budyko's hydrological model. Journal of Hydrology, 436, 35-50.*

*Incerti, M., O'Leary, G. J. (1990). Rooting depth of wheat in the Victorian Mallee. Australian Journal of Experimental Agriculture, 30(6), 817-824.*

*Figueroa-Bustos, V., Palta, J. A., Chen, Y., Siddique, K. H. (2018). Characterization of root and shoot traits in wheat cultivars with putative differences in root system size. Agronomy, 8(7), 109.*

**Figure Caption:**

**Figure 1:** Comparison of vegetation index, EVI, with modelled root-zone SM over cropland: (a) changes in correlations after data assimilation (DA-TCAIR) compared to model OL; (b) changes in correlations between DA-TC and DA-TCAIR; (c) time series of EVI and root-zone soil water storage of the farmland area identified in the inset of subfigure (b).

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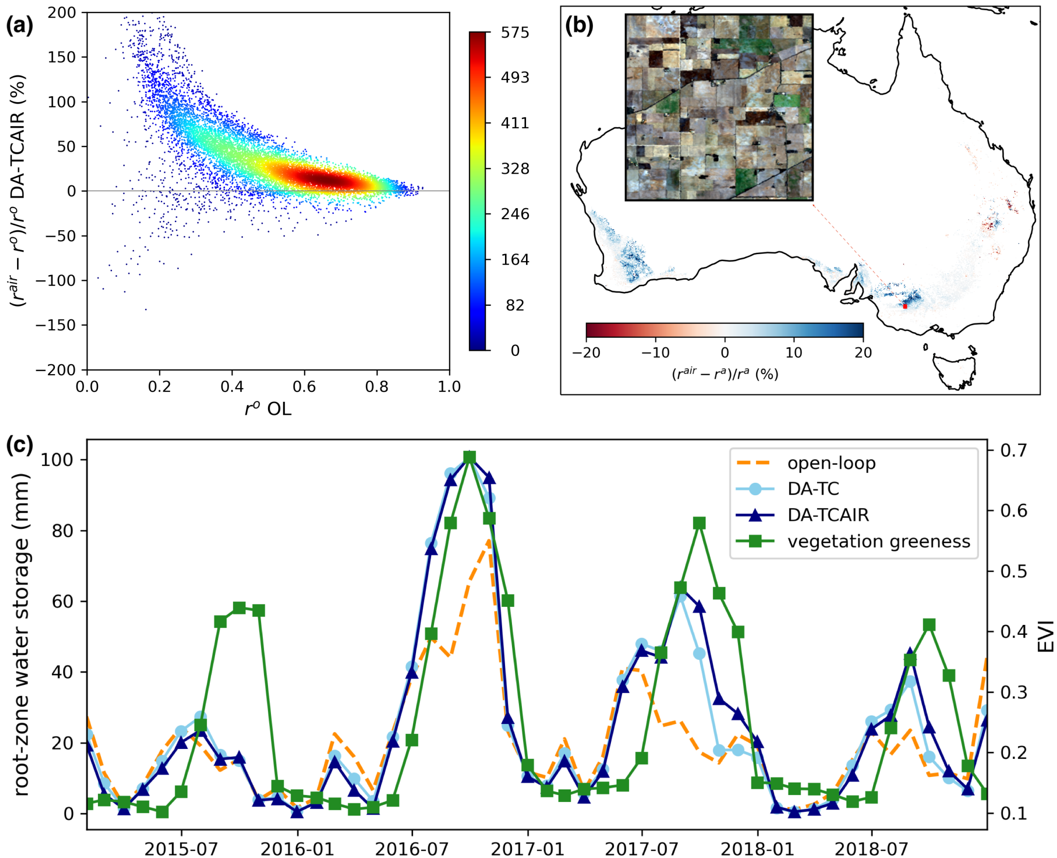


**Fig. 1.** Comparison of vegetation index, EVI, with modelled root-zone soil moisture over cropland



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