Response (Referee #2 comment)

Ms. Ref. No.: hess-2022-379

Title: Improving predictions of land-atmosphere interactions based on a hybrid data assimilation and machine learning method

This study investigates the performance of the advanced WRF model in the HRB based on the coupled data assimilation and machine learning framework. Also, the authors assessed the impact of the hybrid framework on near-surface air conditions and land-atmosphere interactions in this region. The paper is readable and easy to follow. However, the manuscript still needs moderate revisions. Please find my comments below:

We gratefully thank the reviewers for their review, which we believe has led to significant improvement on the original manuscript. The original reviewers' comments are reproduced below in black text and the corresponding response is shown in blue text.

(1) Although the description of the manuscript is clear, I am still confused about why the authors did not directly assimilate the Soil Moisture Active Passive (SMAP) soil moisture observations. The advantages of the machine learning-based soil moisture surrogate model need to be enhanced.

Thank you for your good comment. The advantages of the SM-based surrogate model will be added to section 3.2: "Compared with the direct assimilation of coarse-resolution remotely sensed SM, this method can improve the estimation of SM and ET on the heterogeneous land surface. This is because *in situ* SM profile observations are used to construct an ML-based surrogate model to improve SM and ET estimation on complex underlying surfaces."

(2) It is not clear which soil moisture data are used for training and which data are used for validation. Independent soil moisture validation data are required.

Thanks for your comment. In this study, soil moisture profile observations from 19 automatic weather stations and SMAP SM products in the Heihe River Basin are used to train and test the soil moisture surrogate model (machine learning model). The global ten-fold testing was adopted to examine the performance of each machine learning method. This is mentioned in our manuscript (Line 186-188): "A ten-fold testing method is employed to examine the performance of each ML method. In each fold, 90% of the training samples are used to train the model, and the remaining 10% of the data is used to test the model."

In addition, soil moisture observations from the ecohydrological wireless sensor networks (WATERNET) in the up- and midstream of the HRB are used as an independent validation to evaluate the results of the WRF (DA-ML) simulations.

To address the reviewer's comment, the sentence is revised in section 2: "In this study, SM observations from the ecohydrological wireless sensor networks (WATERNET) in the up- and midstream of the HRB are used as an independent validation to evaluate the SM estimates from the WRF (DA-ML)."

(3) Line 114: The observation elements of the automatic weather stations need to be briefly described.

Thanks for your comment. The following paragraph will be added to section 2: "The AWS variables at each station include the wind speed/direction, air temperature/humidity, precipitation, air pressure, four-component radiation, photosynthetically active radiation, infrared radiation temperature, soil heat flux, and soil temperature/moisture profile (Liu et al., 2018b)."

(4) Line 132: ETMap is also uncertain and affected by assumptions. Explain why it can be used as a reference.

The following paragraph will be added to section 2: "The retrieved ET from the ETMap agrees well with the LAS observations. The multi-site averaged R^2, root mean square error (RMSE), and mean absolute percentage error (MAPE) values are 0.68, 0.85 mm day^{-1}, and 20.27%, respectively. These results confirm that the ETMap can effectively validate watershed ET simulations."

(5) Line 195: The structure diagram can provide a clear description of the coupled land-atmosphere framework.

To address the reviewer's comment, the flowchart of the hybrid model coupled with the WRF is added to the Figure 2.

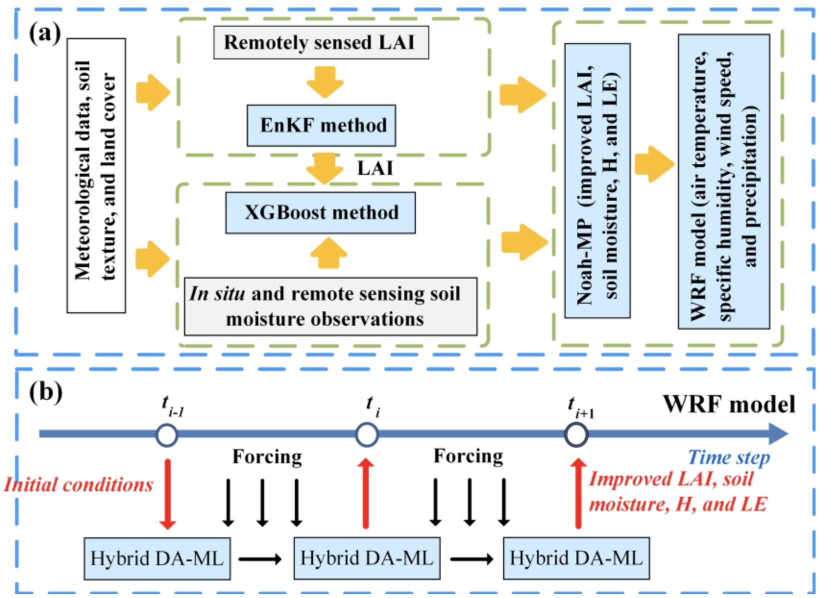

Figure 2: (a) Details of the hybrid DA and ML method, and (b) flowchart of the coupling with the WRF model.

(6) Line 202: The details of the statistical metrics need to be listed.

To address the reviewer's comment, the following paragraph will be added to section 3.2: "The root mean square deviation (RMSD) and coefficient of determination (R^2) statistical metrics were used to evaluate the performance of the WRF (DA-ML) model,

$$\mathrm{RMSD} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{1}$$

$$\mathrm{R}^2 = \frac{[\sum_{i=1}^{n}(P_i-\overline{P})(O_i-\overline{O})]^2}{\sum_{i=1}^{n}(P_i-\overline{P})^2\sum_{i=1}^{n}(O_i-\overline{O})^2} \tag{2}$$

where P_i and O_i are the predicted and observed values at time step i, respectively. $\overline{P}$ and $\overline{O}$ represents the mean values of P_i and O_i."

(7) In Figure 2, the WRF (DA-ML) LAI value is still higher than GLASS products in cropland. Please explain the specific reasons.
Thanks for your comment. The following paragraph will be added to section 4.1: "The results also show that the WRF (DA-ML) systematically overestimates the LAI, especially in the cropland. This is because, in addition to LAI assimilation, the integration of multi-source SM observations also affects the LAI dynamics."

(8) Line 235: "The maps of estimated LAI and SM from the DA-ML method consistently resembled the rainfall, vegetation cover, irrigation event, and shallow groundwater table features". Please explain why.
Thanks for your comment. The following paragraph will be added to section 4.1: "The precipitation in the upstream mountains, irrigation in the midstream oasis, and shallow groundwater in the downstream oasis enhance SM and provide the necessary water supply for vegetation growth (Li et al., 2022)."

(9) In Figure 5, the spatial distribution of ET estimates from the WRF (OL) and WRF (DA-ML) is more consistent in the upstream of the HRB. The authors need to explain whether the improvement of the WRF (DA-ML) is related to the original performance of the WRF (OL). Compared to ETMap, ET estimated from the WRF (OL) is underestimated in the downstream oasis, please explain more.
Thanks for your comment. The following paragraph will be added to section 4.2: "The improvement of the WRF (DA-ML) model is related to the performance of the WRF (OL). The estimation of ET in the WRF (OL) is sensitive to SM and vegetation dynamics, especially in semi-arid regions. Therefore, the WRF (DA-ML) model will produce more improvements in the mid- and downstream oasis regions compared to the WRF (OL) model."

The following paragraph will be added to section 4.2: "In addition, the higher surface heterogeneity and complex hydrological processes in the downstream oasis affect the training accuracy of the ML method, which further affects the performance of the WRF (DA-ML) model (He et al., 2022)."

References:

He, X., Liu, S., Xu, T., Yu, K., Gentine, P., Zhang, Z., Xu, Z., Jiao, D., Wu, D., 2022. Improving predictions of evapotranspiration by integrating multi-source observations and land surface model. Agric. Water Manag. 272, 107827. https://doi.org/10.1016/j.agwat.2022.107827.

Li, Xin, Cheng, G., Fu, B., Xia, J., Zhang, L., Yang, D., Zheng, C., Liu, S., Li, Xiubin, Song, C., Kang, S., Li, Xiaoyan, Che, T., Zheng, Y., Zhou, Y., Wang, H., Ran, Y., 2022. Linking Critical Zone With Watershed Science: The Example of the Heihe River Basin. Earth's Future, 10. https://doi.org/10.1029/2022EF002966.

Liu, S., Li, X., Xu, Z., Che, T., Xiao, Q., Ma, M., Liu, Q., Jin, R., Guo, J., Wang, L., Wang, W., Qi, Y., Li, H., Xu, T., Ran, Y., Hu, X., Shi, S., Zhu, Z., Tan, J., Zhang, Y., Ren, Z., 2018. The Heihe Integrated Observatory Network: A Basin-Scale Land Surface Processes Observatory in China. Vadose Zone J. 17, 180072. https://doi.org/10.2136/vzj2018.04.0072.