Reply to comments:

We would like to thank the Associate Editor and the reviewers for the valuable feedback to the preprint Discussion.

Please note:

- ✔ Modifications have been marked by red color.

#Reviewer1

General comments:

This study provides valuable insights on how to optimally merge remotely sensed observations with a widely used land surface model (Noah-MP) using an irrigation scheme to improve simulated irrigation and effected hydrologic states and fluxes. The study concluded that the evaluated data assimilation system is largely affected by errors in simulated irrigation. The authors pose that inclusion of dynamic crop information and the assimilation of backscatter data per orbit can improve the results presented in this study. A very interesting aspect of this study is the assimilation of backscatter (rather than soil moisture) which allows assimilation to be performed in the observation space. It would be helpful for the authors to elaborate on this decision and if they think there would be degraded performance if SM was assimilated instead. Specific comments and questions are included below.

- R: We would like to thank the reviewer for this comment and for the interest in the manuscript. In particular, the rationale behind the decision of assimilating Level-1 observation (i.e., backscatter) instead of retrievals (i.e., soil moisture) was partly explained from lines 80 to 86 of the Introduction section. But we agree with the Reviewer that this aspect needs more elaboration. Based on the work by Modanesi et al. (2021), assimilating retrievals (i.e. soil moisture rather than MW brightness temperature or backscatter measurements) can be problematic as the retrievals may have been produced with ancillary data that are inconsistent with those used in the LSM (De Lannoy et al., 2016). This is particularly true for passive MW retrievals, while active MW retrievals generally rely on change detection methods that lack land-specific ancillary information. Directly assimilating MW observations and equipping the LSM with an observation operator that links the land surface variables of interest (e.g. soil moisture and vegetation) with remote sensing data allows to obtain consistent parameters and to reduce the chance of cross-correlated errors between model states and corresponding satellite retrievals. We will elaborate more on this aspect in the manuscript.

  Specific comments are addressed in the following answers.

  REFERENCE

De Lannoy, G. J. M. and Reichle, R. H.: Assimilation of SMOS brightness temperatures or soil moisture retrievals into a land surface model, Hydrol. Earth Syst. Sci., 20, 4895–4911, https://doi.org/10.5194/hess-20-4895-2016, 2016.

Modanesi, S., Massari, C., Gruber, A., Lievens, H., Tarpanelli, A., Morbidelli, R., De Lannoy, G.J.M., 2021. Optimizing a backscatter forward operator using Sentinel-1 data over irrigated land. Hydrology and Earth System Sciences 25, 6283–6307. https://doi.org/10.5194/hess-25-6283-2021

Specific comments:

C1: Were any bias correction methods employed (e.g., LSM calibration)? If not were there any steps taken to check if there are systematic biases between the observed and modeled backscatter that could violate the Kalman filter assumption (i.e., line 236). It seems it would be useful to run an open loop Noah-MP simulation forced with precipitation + known irrigation to see if simulated backscatter errors are truly random relative to the observations.

- R1: Thank you for this comment. The bias between observations (Sentinel-1) and simulations (WCM) is minimized by calibrating the WCM as forward operator (explained in Section 2.4). The procedure to minimize the long-term bias and to obtain calibrated WCM parameters over irrigated areas was investigated in a previous work, in preparation for the DA analysis (Modanesi et al., 2021). Results highlighted that coupling the LSM with an irrigation scheme, together with the use of a Bayesian objective function are required "ingredients" to obtain an unbiased DA system, which is an essential assumption of Kalman filtering techniques. We do not remove any interannual, seasonal or short-term bias via the WCM calibration, meaning that remaining biases can still be present.
  A sentence to clarify this concept will be added in Section 2.4:

  "As a final note, the WCM calibration procedure acts as a climatological bias correction method addressing to meet the assumption of unbiased observations and simulations in a DA system. It is worth mentioning that after the calibration step an interannual, seasonal or shorter-term bias correction was not performed, meaning that possible remaining biases may still be present."

  A simulation using precipitation plus known irrigation is an interesting experiment for future research. We will mention it as an additional potential simulation in the discussion section. However, it should be noted that running this experiment could be non-trivial due to the absence of gridded high quality/evaluated irrigation products. Indeed, benchmark irrigation data have a different spatial and temporal resolution compared to Noah-MP grid cells, and MERRA2 forcing; this could introduce additional uncertainties to the analysis. We will add the following sentence at line 508:

  "To test the goodness of the EnKF assumptions over the study areas, future research could benefit from an experiment using precipitation plus known irrigation as modified input forcing. However, such an experiment implies a non-trivial design effort due to the lack of gridded high quality and already evaluated irrigation products together with the necessity to develop solutions able to deal with the different spatial (and temporal) resolution between benchmark irrigation, the LIS grid and MERRA-2 forcing."

  REFERENCE

  Modanesi, S., Massari, C., Gruber, A., Lievens, H., Tarpanelli, A., Morbidelli, R., De Lannoy, G.J.M., 2021. Optimizing a backscatter forward operator using Sentinel-1 data over irrigated land. Hydrology and Earth System Sciences 25, 6283–6307. https://doi.org/10.5194/hess-25-6283-2021

C2: The relationship between Noah-MP simulated soil moisture and vegetation with the assimilated variable, backscatter, is vitally important to this analysis. It would be very beneficial to include equations that show how backscatter is related to these variables, and then how the assimilation is used to 'correct' each state. What assumptions are made within these steps that can affect irrigation estimates?

- R2: We would like to thank the reviewer for this comment. We will include detailed WCM equations of both the direct vegetation and the soil-related backscatter terms in an Appendix section where we will assess the following equations. In summary, these equations are the same or similar to the the previous work by Modanesi et al (2021):

$$\gamma^0_{tot} = \gamma^0_{veg} + t^2\gamma^0_{soil} \tag{2}$$

where:

$$\gamma^0_{veg} = AV_1 cos\theta(1 - t^2_{pq}) \tag{3}$$

$$t^2 = exp(\frac{-2BV_2}{cos\theta}) \tag{4}$$

$$\gamma^0_{soil} = C + \mathrm{D} \cdot SSM \tag{5}$$

In equations 3 and 4 V_1=V_2 are two bulk vegetation descriptors (accounting for the direct vegetation γ^0 and the attenuation respectively), here represented by the LAI. In this study, as compared to Modanesi et al. (2021), the incidence angle θ was set to zero, considering that the γ^0 terrain-flattened version does not include this information. Equation 4 describes the soil-related term which can be described, in a simple linear approach, as a function of the SSM.
Equations 3-4-5 should help to better understand the relation between SSM and LAI obtained from Noah-MP and the backscatter predictions. The calibrated WCM is the observation operator that maps Noah-MP SSM and LAI into backscatter predictions and, conversely, maps observation-minus-forecast backscatter residuals back to updates in SSM and LAI through the Kalman Gain of the Ensemble Kalman filter (EnKF). The reviewer can refer to Section 2.5 for additional details. Considering that the optimal calibration of the WCM is obtained using Open Loop run simulations from Noah-MP equipped with the irrigation scheme (i.e., SSM and LAI input already include a signal of irrigation), SSM and LAI increments will update model state and consequently correct the simulated irrigation signal. In other words, increments will correct for over- or underestimation of irrigation.

C3: The EnKF is a commonly used data assimilation algorithm and certainly has proven useful. However, from a mass-balance perspective, particle assimilation algorithms (e.g., Abolafia-Rosenzweig et al., 2019) may be more appropriate. For instance, in particle DA algorithms, all model states are corrected in a physically consistent manner (e.g., rather than choosing to only update surface soil moisture or empirically decide how to update states and fluxes related to the observation). Can you discuss why the EnKF was used and potential limitations of this data assimilation strategy in the context of irrigation quantification and simulating irrigation signals? In future steps that seek to employ the lessons of this study, considering other DA algorithms can also be beneficial.

Reference:

Abolafiaâ Rosenzweig, R., Livneh, B., Small, E.E., Kumar, S.V., 2019. Soil Moisture Data Assimilation to Estimate Irrigation Water Use. J. Adv. Model. Earth Syst. 11, 3670–3690. https://doi.org/10.1029/2019MS001797

- R3: We agree and we thank the reviewer for giving us the opportunity to explain this aspect. One of the novelties of this study is the implementation of an additional observation operator in the LIS framework, being the WCM. We assume that starting from a widely investigated solution (i.e. Kalman filtering) is beneficial to better control an innovative DA system where we directly ingest backscatter observation to improve irrigation estimates. In particular, the EnKF is a popular technique, widely used in literature also for non-linear dynamics (Reichle et al. 2002; De Lannoy and Reichle, 2016a, Kumar et al. 2019, 2020; De Santis et al., 2020) and main limitations are related to highly non-linear problems. However, in future studies we plan to investigate additional DA algorithms, including Particle Filtering techniques.

  We plan to add the following specification at line 100 in the Introduction section:

  "The ensemble Kalman Filter (EnKF; Evensen 1994) algorithm is selected to perform the DA analysis. The EnKF was optimally used in previous studies for non-linear dynamics and it is popular in hydrological and land surface modeling studies (Reichle et al. 2002; De Lannoy and Reichle, 2016a, Kumar et al. 2019, 2020; De Santis et al., 2020 to cite a few works). It uses an ensemble of model trajectories to represent the background error covariance at each time of an update."

  In the discussion section, we will acknowledge the potential benefit of using particle filtering:

  *"*As a final note, future research should also focus on investigating different DA techniques. In particular, the DA analysis could benefit from the use of Particle Filtering (PF) which has proven useful from a mass-balance perspective, also for irrigation applications (Abolafia-Rosenzweig et al. 2019).*"*

  REF.

  De Lannoy, G.J., Reichle, R.H., 2016a. Assimilation of SMOS brightness temperatures or soil moisture retrievals into a land surface model. Hydrology and Earth System Sciences 20, 4895–4911.

  De Santis, D., Biondi, D., Crow, W.T., Camici, S., Modanesi, S., Brocca, L., Massari, C. Assimilation of Satellite Soil Moisture Products for River Flow Prediction: An Extensive Experiment in Over 700 Catchments Throughout Europe Water Resour. Res., 57, (6), Article e2021WR029643, https://doi.org/10.1029/2021WR029643, 2021.

  Kumar, S.V., Holmes, T.R., Bindlish, R., Jeu, R. de, Peters-Lidard, C., 2020. Assimilation of vegetation optical depth retrievals from passive microwave radiometry. Hydrology and Earth System Sciences 24, 3431–3450.

  Kumar, S. V., Mocko, D. M., Wang, S., Peters-Lidard, C. D., Borak, J., 2019: Assimilation of remotely sensed Leaf Area Index into the Noah-MP land surface model: Impacts on water and carbon fluxes and states over the Continental U.S., Journal of Hydrometeorology, doi:10.1175/JHM-D-18-0237.1.

  Reichle, R.H., McLaughlin, D.B., Entekhabi, D., 2002. Hydrologic data assimilation with the ensemble Kalman filter. Monthly Weather Review 130, 103–114.

C4: The timing of irrigation (e.g., continuous vs. applied only during morning hours) can greatly affect the amount of irrigation required to achieve a specified (or observed) soil and vegetation moistness. Is the irrigation timing assumed from Noah-MP reasonable, or is this likely to introduce errors? If so, are 'corrected' errors from DA a sign of skill or are they compensating for other errors?

- R4: We thank the reviewer for this comment. In Noah-MP sprinkler irrigation is only applied between 06:00 to 10:00 am local time. We accept this assumption considering that sub-daily irrigation data are not available and that irrigation applications do not rely on unlimited water resources. Farmer's irrigation decisions are generally dependent on water regulations, climate, and resource availability (Massari et al., 2021) and additionally, the time window 06:00-10:00 am is typically chosen by farmers to reduce evaporative losses (Ozdogan et al., 2010). However, we are aware that there are limitations in the DA system that are due to the performance of the irrigation scheme and we mentioned them with the shortcomings of the system (Section 4.2, lines 522-525):

  "The main reason is that the irrigation model does not necessarily produce the best irrigation estimates for the best estimates of land surface state variables at the test sites. Thus, in line with the suggestions by Lawston et al. (2017), besides optimizing the DA itself, future research should also focus on improving the irrigation model to optimally use the observational information contained in the Sentinel-1 γ^0"

  Massari, C., Modanesi, S., Dari, J., Gruber, A., De Lannoy, G.J., Girotto, M., Quintana-Seguí, P., Le Page, M., Jarlan, L., Zribi, M., 2021. A review of irrigation information retrievals from space and their utility for users. Remote Sensing 13, 4112.

  Ozdogan, M., Rodell, M., Beaudoing, H.K., Toll, D.L., 2010. Simulating the effects of irrigation over the United States in a land surface model based on satellite-derived agricultural data. Journal of Hydrometeorology 11, 171–184.

C5: What is the footprint of irrigation at the study sites relative to the observed footprint? How could this affect the amount of information provided to the LSM via observations?

- R5: We thank the reviewer for this comment. In Section 2.7 we discuss the extent of each test site. In Italy, the Budrio farm is composed of five small fields (0.4 ha each) and to reduce the spatial mismatch, we averaged irrigation data over the five fields. However, a non-negligible difference between the benchmark irrigation footprint (representative of an area of 2 ha) and the Sentinel-1 observations (0.01° spatial resolution) still remains. For the fields of Faenza (290 ha [i.e., 2.9 km^2] and 760 ha [i.e., 7.6 km^2] respectively) this effect is less relevant, considering that irrigation benchmark data refer to an area extending from 3 to 8 Sentinel-1 (or model) pixels (see analysis at Figure 7). For the Germany site (including 49 small fields), we pre-processed irrigation benchmark data in order to reduce the footprint/scale effect. We will add in Section 2.1 the extent of the 49 German fields as it was not previously mentioned:

  "The test site is composed of 49 fields (ranging from 1.3 ha to 30 ha)".

  Additionally, we plan to add a sentence at line 310 to better explain how the irrigation benchmark pre-processing was performed:

  "Second, the German pilot site is composed of 49 fields, covering 24 LIS pixels. The irrigation data of the fields falling within each grid cell were averaged, assigning a weight to each time series based on the percentage area of the field falling within the LIS pixel. By considering only pixels with a percentage of irrigated area larger than 25%, 8 irrigated pixels of the 24 pixels were retained. For these 8 pixels, statistical distributions of the skill metrics could be obtained"

  This step reduced the scale effect and increased the performance of the DA run, especially in terms of temporal dynamics (i.e., Pearson-R).

As a final note, in the submitted version of the manuscript we already discussed the limitation of the system in providing irrigation information at plot scale. The reviewer can refer to Sections 3.2.1 (lines 419-422) and 4.2. (lines 531-534) for additional details on the effects of footprint differences.

C6: Why use ASCAT to evaluate Noah-MP surface soil moisture instead of finer resolution data such as SMAP-S1 (which has been shown to have irrigation signals in Jalilvand et al., 2021) or SMAP which was shown to have irrigation signals in Lawston et al. (2017) and provide more reliable data than ASCAT (Kumar et al., 2018)?

References:

Kumar, S.V., Dirmeyer, P.A., Peters-Lidard, C.D., Bindlish, R., Bolten, J., 2018. Information theoretic evaluation of satellite soil moisture retrievals. Remote Sens. Environ. 204, 392–400. https://doi.org/10.1016/j.rse.2017.10.016

Kumar, S.V., Peters-Lidard, C.D., Santanello, J.A., Reichle, R.H., Draper, C.S., Koster, R.D., Nearing, G., Jasinski, M.F., 2015. Evaluating the utility of satellite soil moisture retrievals over irrigated areas and the ability of land data assimilation methods to correct for unmodeled processes. Hydrol. Earth Syst. Sci. 19, 4463–4478. https://doi.org/10.5194/hess-19-4463-2015

Lawston, P.M., Santanello, J.A., Kumar, S.V., 2017. Irrigation Signals Detected From SMAP Soil Moisture Retrievals: Irrigation Signals Detected From SMAP. Geophys. Res. Lett. 44, 11,860-11,867. https://doi.org/10.1002/2017GL075733

- R6: We thank the reviewer for this comment. Like SMAP, ASCAT was also already used with success in previous studies for modeled/remote sensing soil moisture evaluation over Europe (Modanesi et al. 2021; Bauer Marschalliger et al. 2018). A Sentinel-1 derived product (i.e., SMAP-Sentinel1) would not provide an independent evaluation considering that Sentinel-1 backscatter is ingested in the system. The 36-km Level 2 SMAP data have a somewhat coarser resolution than ASCAT, and the SMAP L2 Enhanced 9-km SM product could be considered. However, to have sufficient data, we should relax the recommended flags on the SMAP data over the Po river valley (see Modanesi et al., 2021). In short, we do not think that any one product is better suited than another for our purpose. If the reviewer would suggest, we are willing to change the evaluation to another product, although we do not expect changes in our findings.

Bauer-Marschallinger, B., Freeman, V., Cao, S., Paulik, C., Schaufler, S., Stachl, T., Modanesi, S., Massari, C., Ciabatta, L., Brocca, L., 2018. Toward global soil moisture monitoring with Sentinel-1: Harnessing assets and overcoming obstacles. IEEE Transactions on Geoscience and Remote Sensing 57, 520–539.

Modanesi, S., Massari, C., Gruber, A., Lievens, H., Tarpanelli, A., Morbidelli, R., De Lannoy, G.J.M., 2021. Optimizing a backscatter forward operator using Sentinel-1 data over irrigated land. Hydrology and Earth System Sciences 25, 6283–6307. https://doi.org/10.5194/hess-25-6283-2021

C7: The paragraph from lines 75-86 (or the following paragraph) could benefit from discussion of Abolafia-Rosenzweig et al. (2019) which designed a system to assimilation remotely sensed soil moisture with land surface models to quantify irrigation water use as well as Jalilvand et al. (2021)

which compliments Lawston et al. (2017) by evaluating irrigation signals from SMAP-S1 soil moisture retrievals (i.e., from Das et al., 2019).

References:

Abolafiaâ Rosenzweig, R., Livneh, B., Small, E.E., Kumar, S.V., 2019. Soil Moisture Data Assimilation to Estimate Irrigation Water Use. J. Adv. Model. Earth Syst. 11, 3670–3690. https://doi.org/10.1029/2019MS001797

Das, N.N., Entekhabi, D., Dunbar, R.S., Chaubell, M.J., Colliander, A., Yueh, S., Jagdhuber, T., Chen, F., Crow, W., O'Neill, P.E., Walker, J.P., Berg, A., Bosch, D.D., Caldwell, T., Cosh, M.H., Collins, C.H., Lopez-Baeza, E., Thibeault, M., 2019. The SMAP and Copernicus Sentinel 1A/B microwave active-passive high resolution surface soil moisture product. Remote Sens. Environ. 233, 111380. https://doi.org/10.1016/j.rse.2019.111380

Jalilvand, E., Abolafia-Rosenzweig, R., Tajrishy, M., Das, N.N., 2021. Evaluation of SMAP-Sentinel1 High-Resolution Soil Moisture Data to Detect Irrigation over Agricultural Domain. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 1–1. https://doi.org/10.1109/JSTARS.2021.3119228

- R7: We would like to thank the reviewer for this suggestion. Jalivand et al. (2021) will be added at line 77 when irrigation detection through MW remote sensing is discussed:

  "The optimal integration of fine-scale modelling and satellite observations using DA in LSMs could be a promising solution to account for anthropogenic activities and alongside improve the estimation of irrigation amounts and model predictions. Lawston et al. (2017) as well as Jalivand et al. (2021) suggested the use of MW surface soil moisture (i.e., SMAP or the SMAP-Sentinel 1 product respectively) to incorporate the irrigation signal into models via DA."

  Additionally we will add a sentence to discuss the work by Abolafia-Rosenzweig et al. (2019):

  "Lawston et al. (2017) as well as Jalivand et al. (2021) suggested the use of MW surface soil moisture (i.e., SMAP or the SMAP-Sentinel 1 product respectively) to incorporate the irrigation signal into models via DA. In this context, recently Abolafia-Rosenzweig et al. (2019) designed an innovative system to assimilate RS-based soil moisture into the VIC model through a particle batch smoother in order to improve irrigation estimates. Further studies investigated the use of surface soil moisture retrievals and vegetation indices such as leaf area index (LAI) or vegetation optical depth to improve model predictions (Albergel et al., 2018; De Lannoy and Reichle, 2016; Kumar et al., 2020)"

C8: Please reference the following when introducing NASA's LIS:

- R8: We thank the reviewer for this suggestion. We will add the references in the Introduction section at line 52.

Kumar, S., Peters-Lidard, C., Tian, Y., Houser, P., Geiger, J., Olden, S., Lighty, L., Eastman, J., Doty, B., Dirmeyer, P. Land information system: An interoperable framework for high resolution land surface modeling. Environmental Modelling & Software 21, 1402–1415. https://doi.org/10.1016/j.envsoft.2005.07.004 (2006).

Peters-Lidard, C.D., Houser, P.R., Tian, Y., Kumar, S.V., Geiger, J., Olden, S., Lighty, L., Doty, B., Dirmeyer, P., Adams, J., Mitchell, K., Wood, E.F., Sheffield, J. High-performance Earth system modeling with NASA/GSFC's Land Information System. Innov. Syst. Softw. Eng. 3, 157–165. https://doi.org/10.1007/s11334-007-0028-x (2007).