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 in the text have been marked by red color.

#Editor

The authors need to add references for the SMAP-Sentinel1 product (https://doi.org/10.1016/j.rse.2019.111380) mentioned in the text. There are few other examples of using SMAP-Sentinel1 product for irrigation detection, such as recently published in IEEE JSTARS (DOI: 10.1109/JSTARS.2021.3119228). These references should also go in the manuscript in the introduction while discussing the potential of using Sentinel-1 based observations/retrievals for agriculture irrigation detection and quantification.

The authors have responded to reviewer's comments well and have addressed most of the comments.

- R: We thank the Editor for this comment. We cited Das et al. (2019) as a reference for the SMAP/Sentinel-1 product in the Introduction section. We additionally mentioned the work by Jalilvand et al. (2021) to highlight the potential of Sentinel-1 based observations in agriculture and for Data Assimilation (DA) studies.
  Line 75-76:

  "A recent study by Jalilvand et al. (2021) has highlighted the potential of high-resolution Sentinel-1 based soil moisture data, such as the 1-km SMAP/Sentinel-1 product (Das et al., 2019) to detect the irrigation signal over agricultural areas."

  Line 82-83:

  "Lawston et al. (2017) and Jalilvand et al. (2021) suggested the use of MW-based surface soil moisture retrievals from SMAP or SMAP/Sentinel-1 respectively, to incorporate the irrigation signal into models via DA."

  Please note that we found a small bug in our script and the Pearson-R values, only in terms of irrigation, are very slightly deteriorated over Budrio (i.e. 0.76 vs the old value 0.78 for the OL run; 0.62 vs the old value 0.65 for the DA run VV pol; 0.51 vs the old value 0.55 for the DA run VH pol). We have corrected the values where needed in Table 3, in the title of Figure 6e (and S5e) and in the bar plots of Figure 7. Note that this does not impact the overall conclusions on the Budrio test site.

#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 thank the reviewer for this comment and for the interest in the manuscript. We agree to elaborate our earlier (L. 80-86) rationale behind the decision of assimilating Level-1 observation (i.e., backscatter) instead of retrievals (i.e., soil moisture) as follows (L. 87-97):

  "However, MW-based retrievals could also add unreliable information into LSM systems due to the RS observation pre-processing and the retrieval algorithm. More specifically, passive MW retrievals are produced with ancillary data that might be inconsistent with those used in the LSM (De Lannoy et al., 2016a), and active MW retrieval products based on change detection methods often rely on a climatological approximation of the vegetation signal (Wagner et al., 1999). To avoid this limitation, previous studies investigated the direct assimilation of MW observations, such as brightness temperature (Tb) derived from Soil Moisture and Ocean Salinity (SMOS) or Soil Moisture Active Passive (SMAP) missions (De Lannoy and Reichle, 2016a, 2016b; Reichle et al., 2019), radar backscatter from the Advanced Scatterometer (ASCAT; Lievens et al., 2017a), or the joint assimilation of Sentinel-1 backscatter and SMAP Tb (Lievens et al., 2017b), through the use of calibrated observation operators. The assimilation of Level-1 observations has the potential to limit inconsistencies in the DA system and to address the climatological bias correction through the observation operator calibration, as compared to classical soil moisture bias correction techniques (i.e., CDF matching)."

  Specific comments are addressed in the following answers.

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 systematic interannual, seasonal or short-term observation-minus-forecast differences via the WCM calibration, meaning that some remaining biases could still be present, and they are treated as random error.

A sentence to clarify this concept has been added in Section 2.4 at lines 239 to 242:

"As a final note, the WCM calibration procedure acts as a climatological bias correction method to meet the assumption of unbiased observations and simulations in a DA system. It is worth mentioning that after the calibration step, no further interannual, seasonal or shorter-term bias correction was performed."

A simulation using precipitation plus known irrigation is an interesting experiment for future research. We have mentioned it as an additional potential simulation in the discussion section. However, it should be noted that running this experiment would not lead to definitely conclusive results, because gridded high quality/evaluated irrigation products are missing. 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 have added the following sentence at lines 576-579:

"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, high quality gridded irrigation products are not yet available, and the difference between the spatial resolution of MERRA-2 forcings and irrigation input will complicate such an experiment."

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 have included more detailed WCM equations of both the direct vegetation and the soil-related backscatter terms in an Appendix section (Appendix) where we have assessed the following equations. In summary, these equations are the same or similar to the previous work by Modanesi et al (2021):

$$\gamma^0_{tot} = \gamma^0_{veg} + t^2\gamma^0_{soil} \qquad (2)$$

where:

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

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

$$\gamma^0_{soil} = C + D \cdot SSM \qquad (5)$$

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 contrast to

Modanesi et al. (2021), the incidence angle θ was set to zero here, considering that the γ^0 terrain-flattened data do 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.
In the following it is reported the specific text added in the Appendix (L. 629):

This Appendix section has the objective to describe more in detail the WCM equation, stated in Section 2.4. The γ^0 is described as the sum of the backscatter from the vegetation (γ^0_{veg}) and from the bare soil (γ^0_{soil}), attenuated by a t^2 coefficient representing the two-way attenuation from the vegetation layer:

$$\gamma^0 = \gamma^0_{veg} + t^2\gamma^0_{soil} \quad \text{(A1)}$$

where:

$$\gamma^0_{veg} = \mathrm{A}V_1 cos\theta(1 - t^2) \quad \text{(A2)}$$

$$t^2 = exp(\frac{-2BV_2}{cos\theta}) \quad \text{(A3)}$$

$$\gamma^0_{soil} = \mathrm{C} + \mathrm{D} \cdot SSM \quad \text{(A4)}$$

Equations A2 and A3 refer to the vegetation-related terms. In particular, V_1 and V_2 represent two bulk vegetation descriptors, the first one accounting for the direct vegetation γ^0, and the second one representing the attenuation. We assume $V_1 = V_2 =$ LAI following previous studies (Modanesi et al., 2022; Lievens et al, 2017; Baghdadi et al. 2017). A[-] and B[-] are the two fitting parameters related to direct vegetation and attenuation respectively, while θ represents the incidence angle, here set to zero considering that the γ^0 terrain-flattened version does not include this information. Equation A2, as well as equation A1 are computed in linear scale.

Equation A4 accounts for the soil-related term which is described in a simple linear approach, as a function of SSM, following the work by Lievens et al. (2017). The C and D parameters are fitted in dB and dB/m^3/m^3, respectively, but γ^0_{soil} is transformed back to linear scale in Equation A1. Those parameters, as well as A[-] and B [-], are calibrated separately for each polarization and for each grid cell.

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 simply started from our expertise with the Kalman filter to better control our innovative DA system where we directly ingest backscatter observations 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 indeed plan to investigate additional DA algorithms, including Particle Filtering techniques.

  We have added the following specification at lines 111-114 in the Introduction section:

  "The ensemble Kalman Filter (EnKF; Evensen 1994) algorithm is selected to perform the DA analysis. The EnKF was 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). It uses an ensemble of model trajectories to represent the background error covariance at each time of an update."

  In the discussion section, we have additionally acknowledged the potential benefit of using particle filtering at lines 579-581:

  "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 which has proven useful from a mass-balance perspective, also for irrigation applications (Abolafia-Rosenzweig et al. 2019)."

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 as potential shortcomings of the system (Section 4.2, lines 554-558):

> "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. In addition, if the soil moisture is updated to wetter conditions to include irrigation before the model would forecast it, then the irrigation simulation will be skipped or delayed in the DA results. 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. "

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: 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 km2] and 760 ha [i.e., 7.6 km2] 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 have added 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 added a sentence at lines 331-333 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 and 4.2. 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 one, we are willing to change the evaluation to another product, although we do not expect changes in our findings

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. Jalilvand et al. (2021) was added in the introduction section.

  Lines 75-77:

"A recent study by Jalilvand et al. (2021) has highlighted the potential of high-resolution Sentinel-1 based observations, such as the 1-km SMAP/Sentinel-1 product (Das et al., 2019) to detect the irrigation signal over agricultural areas."

Lines 82-83:

"Lawston et al. (2017) and Jalilvand et al. (2021) suggested the use of MW-based surface soil moisture retrievals from SMAP or SMAP/Sentinel-1 respectively, to incorporate the irrigation signal into models via DA."

Additionally, we added a sentence to discuss the work by Abolafia-Rosenzweig et al. (2019) at lines 82-87:

"Lawston et al. (2017) and Jalivand et al. (2021) suggested the use of MW-based surface soil moisture retrievals from SMAP or SMAP/Sentinel-1 respectively, to incorporate the irrigation signal into models via DA. In light of this, 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:

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).

- R8: We thank the reviewer for this suggestion. We have added the references in the Introduction section at line 53-54.

REFERENCE

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.

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, https://doi.org/10.5194/hess-20-4895-2016.

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.

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.

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

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.

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

#Reviewer2

General comments:

The study idea is to explore the possibility of improving the irrigation water use simulation by direct assimilation of sentinel1 backscatter in co- or cross-polarization, which contains both soil moisture and vegetation information, with the Noah MP land surface model. The results suggested that assimilating Sentinel 1 backscatters data can slightly improve irrigation simulation over some test sites (especially the VH polarization DA). Still, poor parametrization of the Noah-MP irrigation module does not allow the DA to improve the irrigation simulation significantly. This study and the previous study (Modanesi et al., 2021) provide valuable insights into the limitations and benefits of assimilating Sentinel-1 backscatter with the land surface model for improving irrigation simulation. However, I have some concerns regarding the improvement in accumulated irrigation after DA, the spatial mismatch between the model and the test sites scale, and the accuracy of the benchmark datasets used for the validation. Please see my comments for details.

- R. We thank the reviewer for articulating the relevance of the study and for the valuable comment. We will improve the manuscript based on the specific comments below, addressing the concerns that are highlighted in the General comment.

Specific comments:

C1 - L65: I think studies that focused on calculating the Evapotranspiration through the energy balance algorithm should also be mentioned here as examples for consumptive water use estimation using optical and thermal sensors.

- R1: We thank the reviewer for this recommendation. We have added references for the suggested approach at lines 65-69 and in the Reference section:

  "For instance, visible and near-infrared measurements were mainly used in previous studies for developing irrigation mapping techniques (Ambika et al., 2016; Ozdogan and Gutman, 2008; Peña-Arancibia et al., 2014; Salmon et al., 2015) and, in recent years, optical data were also combined with microwave (MW) observations (Ferrant et al., 2019) or with thermal sensor data (i.e., land surface temperature data) via energy and water balance models (van Eekelen et al., 2015; Olivera-Guerra et al., 2020; Brombacher et al., 2022), to investigate advantages of multi-sensor approaches."

C2- L77: Consider the following study along with Lawston et al., 2017 that shows the more recent and high-resolution SMAP-Sentinel1 SM product also contains the irrigation signal.

Jalilvand, R. Abolafia-Rosenzweig, M. Tajrishy, and N. N. Das, "Evaluation of SMAP/Sentinel 1 High-Resolution Soil Moisture Data to Detect Irrigation Over Agricultural Domain," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 10733-10747, 2021, DOI: 10.1109/JSTARS.2021.3119228.

- R2: We edited the text as follows.

  Lines 75-77:

  "A recent study by Jalilvand et al. (2021) has highlighted the potential of high-resolution Sentinel-1 based observations, such as the 1-km SMAP/Sentinel-1 product (Das et al., 2019) to detect the irrigation signal over agricultural areas."

  Lines 82-83:

  "Lawston et al. (2017) and Jalilvand et al. (2021) suggested the use of MW-based surface soil moisture retrievals from SMAP or SMAP/Sentinel-1 respectively, to incorporate the irrigation signal into models via DA."

C3- L97: The irrigation module of the Noah-MP model calculates the ideal IRR needed for the crop to avoid water stress which is different from the actual irrigation (the farmer might over or under irrigate the fields). How do you account for that?

- R3: We thank the reviewer for remarking this critical point. In this context, there are two important aspects that need to be highlighted: i) accurate information on farmer's decisions related to quantities and timing of irrigation applications are often not available for public use or, if available, they are limited to small areas; on the other hand ii) irrigation schemes cannot deal with farmer's decision or water availability and policies (Massari et al., 2021).

  These are the main reasons which pushed us to apply satellite DA, that is the method used to correct model inaccuracies. DA can theoretically improve model predictions accounting for farmer's applications (see lines 64 to 78 in the submitted manuscript). In this context, we added the following specifications at lines 111-114:

  "The ensemble Kalman Filter (EnKF; Evensen 1994) algorithm is selected to perform the DA analysis. The EnKF was 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). It uses an ensemble of model trajectories to represent the background error covariance at each time of an update."

  However, future studies could benefit additional DA algorithms. In the discussion section, we have acknowledged the potential benefit of using particle filtering at lines 579-581:

"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 which has proven useful from a mass-balance perspective, also for irrigation applications (Abolafia-Rosenzweig et al. 2019)."

Additionally, as irrigation timing is often driven by the stakeholders' permissions to withdraw water or by water availability (i.e., rather than by the moisture conditions), the comparisons between simulated observed irrigation were carried out by aggregating the data at a 15-days time window (L. 398). In other words, the aggregation should partly soften our hypothesis about irrigation.

C4- L179: Here, you are talking about the time and location of irrigation. I think GVF looks a little out of context here; some explanation regarding where GVF is used in the Noah MP model is needed.

- R4: The reviewer is right; this aspect needs to be better addressed. The GVF is used in the Noah-MP model to define the growing season. We have changed the text as follows at line 190:

"In order to identify the irrigation season, timing and location of irrigation …"

C5- L250: typo, de Kalman should be changed to the Kalman

- R5: We corrected the text accordingly at line 269.

C6- L378: [Major] I can't entirely agree with this statement that the accumulated irrigation has improved compared to the OL run. Looking closely at Figure 6e, the DA underestimation of irrigation during the mid-summer months of 2015 and 2017 resulted in the overall lower accumulated irrigation (the OL run simulation during the same period closely matched the observed irrigation). In other words, the underestimation during these months compensated for overestimations in other months (e.g., the late summer months of 2016 and 2017), and the right result is obtained here for the wrong reasons! Please comment on this.

- R6: We thank the reviewer for this comment. It is not easy to assess the results in terms of quantity of irrigation but the reviewer is right, there are specific periods in which the DA underestimates. However, if the model is able to improve the bias and the amount of yearly irrigation we can assume this is a good result, considering the current status of research on this topic. Looking at the table below you can read the amount of yearly irrigation for benchmark irrigation (IRR OBS), the OL and DA runs for Figure 6. The final two columns show differences in the amount of irrigation between the OBS and OL or DA runs. The DA run improves the amount of irrigation in 2016 and 2017:

YEAR	IRR OBS [mm]	IRR OL [mm]	IRR DA [mm]	IRR OBS-IRR OL [mm]	IRR OBS-IRR DA [mm]
2015	344.6282	418.8873	220.5123	-74.2591	124.1159
2016	223.0424	356.4250	306.7947	-133.3827	-83.7523
2017	349.5000	444.7400	315.1728	-95.2400	34.3272

Overall, while absolute long-term bias seems to be reduced, it can occur that absolute annual bias increases. We have edited the sentence in order to better frame this aspect and to compare yearly estimates of irrigation at lines 400-408:

"The observed irrigation amounts in the years 2015, 2016, 2017 are about 345, 223, 350 mm, respectively. The corresponding OL and DA estimates are 419 and 220 mm in 2015, 356 and 306 mm in 2016 and finally 445 and 315 mm in 2017. This indicates that the DA reduces the bias in some years (2016, 2017), but in other years DA might worsen the irrigation estimate (2015) increasing the annual bias. This could be related to the lower number of assimilated observations during the year 2015, due to the solely acquisition from Sentinel-1A. However, the lack of benchmark irrigation data for this year over other test sites makes it difficult to test this hypothesis. An inset of Figure 6 for the period March 2017-November 2017 was added in the Supplementary (Figure S4), with the objective to help the visualization of the irrigation quantification improvement due to DA during the irrigation season."

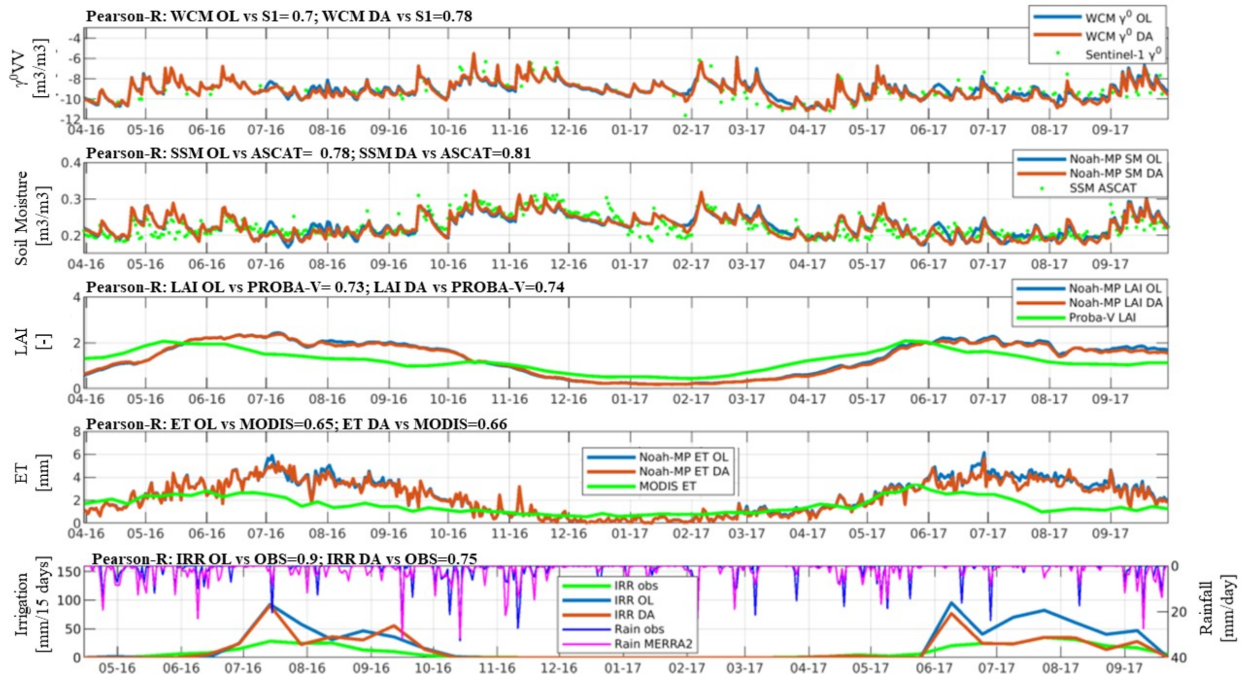
C7- L383: The most considerable overestimation by the DA run relative to the observed irrigation occurred in July 2016 (Figure 6e), which is right after a significant precipitation underestimation by MERRA2. This contrasts with what is mentioned at the end of this paragraph.

- R7: The reviewer is right; the sentence is not properly assessed. During July 2016 both the OL and DA runs have strong overestimation due to the small amount of rain in MERRA-2. The DA provides a negligible correction for missing rain in MERRA-2, slightly reducing the higher and lower peaks. We have changed the sentence as follows (L. 409-411):

  "Although a good agreement is observed between MERRA-2 and gauge-rainfall in terms of Pearson-R (0.78), it is worth noting that the precipitation from MERRA-2 during the summer is typically less than in situ rainfall and this aspect could also contribute to create overestimation in irrigation simulation, which is only slightly corrected by the Sentinel-1 γ^0 VV DA"

C8- L385: The size of the Budrio site is much smaller than your benchmark soil moisture product spatial resolution (ASCAT 12.5 km); the other Italian site or the German site would be a better choice for the SSM time series comparison shown in this figure.

- R8: We thank the reviewer for this comment. We selected the Budrio farm considering that this is the only test site where three years of irrigation data are available (i.e., it is challenging to collect longer time series) and this is an added value to evaluate the DA system. To give a complete overview of the Italian test sites, we had already added the evaluation results Table 3. For an example figure over the Faenza San Silvestro field (270 ha and 3 LIS pixels), the reviewer can refer to the figure below (Sentinel-1 backscatter VV experiment). The Pearson R between ASCAT and SSM OL run is 0.78 while the Pearson R between ASCAT and SSM DA run is 0.81. This figure was already added in the first version of the Supplementary material (now Figures S6 and S7 of the Supplement).



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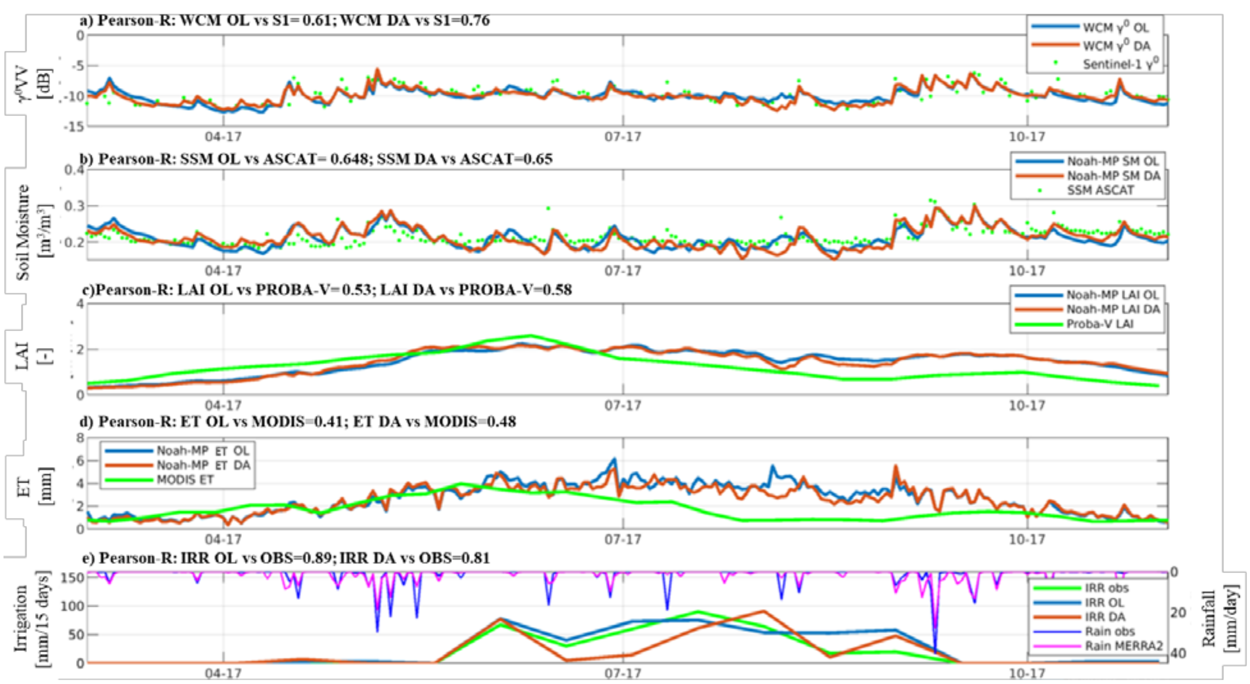
C9- Figure 6) It is difficult to compare the 3 time series in Figure 6 as it shows 3 years of data. As the study focuses on irrigation, adding an inset (or possibly another figure) that focuses on one irrigation season can give the readers a better idea of how DA improves or degrades different parameter simulations during the irrigation season.

- R9: We thank the reviewer for this comment. The figure displayed below is an inset of Figure 6 for the irrigation season 2017:



As mentioned in R8, Figure 6 allows an analysis over a longer time frame. Instead of replacing Figure 6 or adding an inset in Figure 6 (which could result cumbersome), we have added this inset in the Supplementary material (now Figure S4) and we have included additional discussion based on it (see reply to comment 6 – R6).

C10 - L425 and L478: The same result is reported on the benefits of LAI DA relative to the SSM DA in this very recent study by Nie et al. 2022, which can be discussed here.

Nie, W., Kumar, S. V., Arsenault, K. R., Peters-Lidard, C. D., Mladenova, I. E., Bergaoui, K., Hazra, A., Zaitchik, . F., Mahanama, S. P., McDonnell, R., Mocko, D. M., and Navari, M.: Towards Effective Drought Monitoring in the Middle East and North Africa (MENA) Region: Implications from Assimilating Leaf Area Index and Soil Moisture into the Noah-MP Land Surface Model for Morocco, Hydrol. Earth Syst. Sci. Discuss. [preprint], https://doi.org/10.5194/hess-2021-263, in review, 2021.

- R10: We thank the reviewer for this suggestion. We have added the following text in the discussion section, at lines 512-514:

  "Similar conclusions were obtained by Nie et al. (2022) over Morocco. This recent study showed how the assimilation of MODIS LAI into Noah-MP v.4.0.1, with and without activating irrigation, provides critical information to improve the root-zone soil moisture and more generally water-energy-carbon fluxes."

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