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.

#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 will add references for the suggested approach at line 66 and in the References 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 (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."

Brombacher, J., de Oliveira Silva, I. R., Degen, J., Pelgrum, H. 2022. A novel evapotranspiration based irrigation quantification method using the hydrological similar pixels algorithm, Agricultural Water Management, 267, 107602, https://doi.org/10.1016/j.agwat.2022.107602.

Olivera-Guerra, L., Merlin, O., Er-Raki, S. 2020. Irrigation retrieval from Landsat optical/thermal data integrated into a crop water balance model: A case study over winter wheat fields in a semi-arid region. Remote Sens. Environ. 239, 111627.

Van Eekelen, M.W., Bastiaanssen, W.G., Jarmain, C., Jackson, B., Ferreira, F., Van der Zaag, P., Okello, A.S., Bosch, J., Dye, P., Boastidas-Obando, E., et al. 2015 A novel approach to estimate direct and indirect water withdrawals from satellite measurements: A case study from the Incomati basin.Agric. Ecosyst. Environ. 200, 126–142.

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 will edit the text as follows at line 77:

  "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."

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 60 to 74 in the submitted manuscript). In particular, we applied the EnKF which 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). In this context, we will add the following specifications at line 100:

  "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."

However, future studies could benefit additional DA algorithms. In the discussion section, we will acknowledge the potential benefit of using particle filtering:

*"*As a final note, a future study 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).*"*

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. In other words, the aggregation should partly soften our hypothesis about irrigation.

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.

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.

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. So, timing here was additionally intended for the start and end of the irrigation season. We will change the text as follows:

"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 will correct the text accordingly.

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/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 will certainly edit the sentence in order to better frame this aspect, and will include the following sentence to compare yearly estimates of irrigation:

"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 due 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 verify our hypothesis."

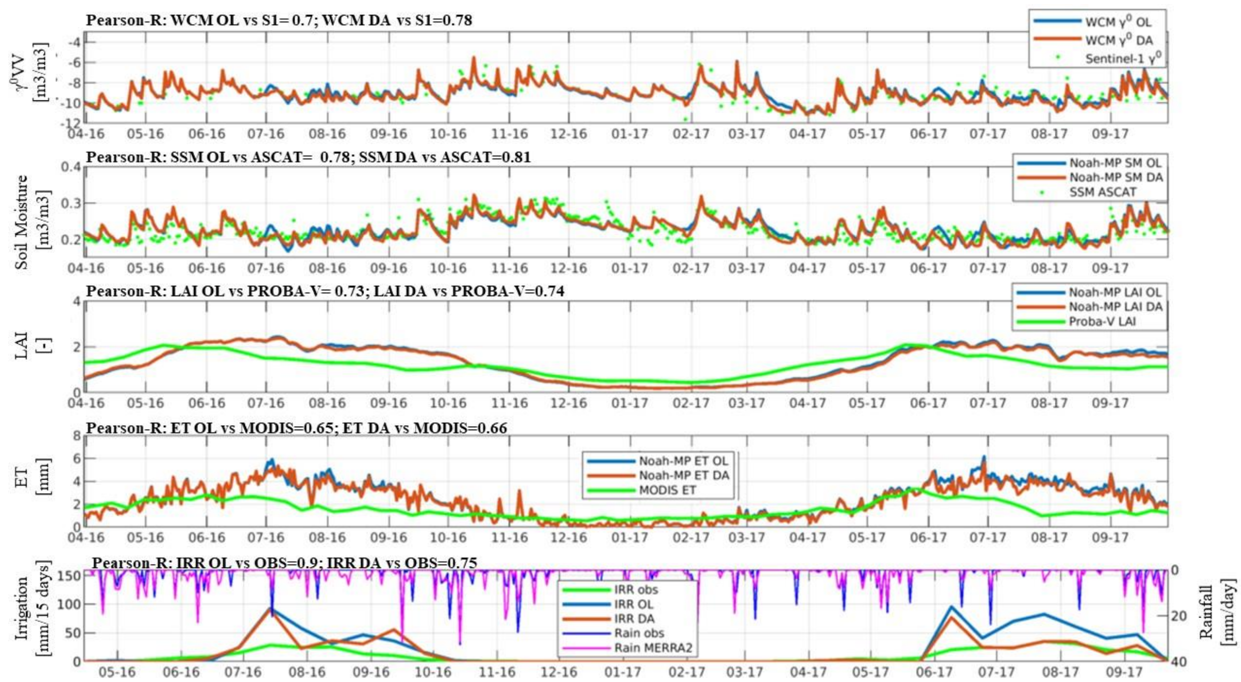
C7- L383: The most considerable overestimation by the DA run relative to the observed irrigation occurred in July 2016 (Figure 6e), which is right after a significant precipitation underestimation by MERRA2. This contrasts with what is mentioned at the end of this paragraph.

- 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 will change the sentence as follows:

  “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 overestimations in irrigation simulation, which is only slightly corrected by the Sentinel-1 γ^0 VV DA”

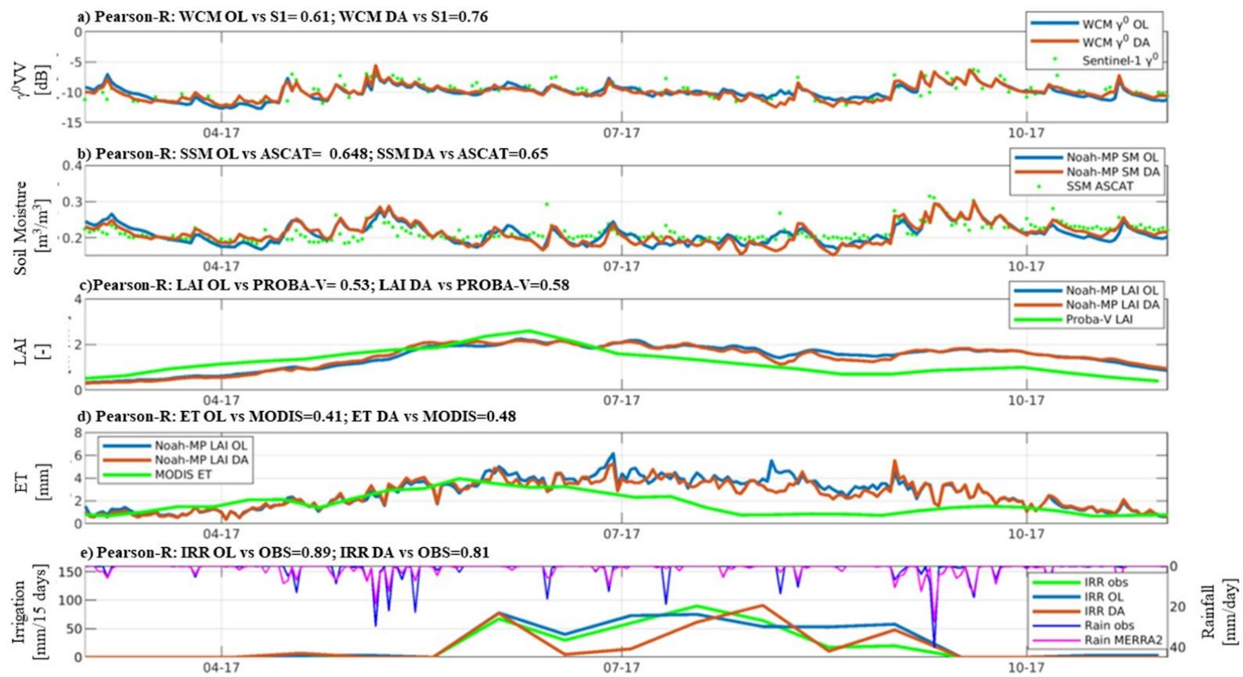
C8- L385: The size of the Budrio site is much smaller than your benchmark soil moisture product spatial resolution (ASCAT 12.5 km); the other Italian site or the German site would be a better choice for the SSM time series comparison shown in this figure.

- 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 (Figures S5 and S6).



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. If the Reviewer agrees, instead of replacing Figure 6 or adding an inset in Figure 6 (which could result cumbersome), we would add this inset in the Supplementary material and include additional discussion based on it.

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 will add the reference in the discussion section.