Reviewer#1 Evaluation and comments

General Comment:

Modeling irrigation in earth system models is facing different sources of uncertainties and utilizing satellite products via data assimilation could be an effective way to constrain and improve irrigation simulation and its effects on the terrestrial water, carbon, and energy cycles. This study evaluates the irrigation simulation in Noah-MP, identifies the potential of Sentinel-1 observations in containing irrigation signals and discusses the potential of assimilating this observation into Noah-MP in improving irrigation simulation. I found the study interesting and valuable as the exploration of high-resolution remote sensing products in improving model representation of agricultural activities could be valuable in improving modeling of hydrological and carbon cycles under human regulation and in providing info for water management in the future. However, I do think there are some sections need to be improved and clarified, and further discussion is needed regarding revealing the benefits of assimilating the observations into the model. Please see my specific comments below:

Reply. We thank the reviewer for having caught the relevance of the study and for the valuable comments. We will improve the manuscript based on the specific comments below.

Specific comments:

(1) I found the abstract a bit misleading as the study is only exploring the potential of Sentinel-1 sigma-0 observations in containing irrigation signals and providing evaluations in preparation for data assimilation instead of a data assimilation paper. For instance, it is difficult to connect WCM calibration with optimizing Noah-MP by reading only the abstract. I would suggest the authors to reorganize the second paragraph of the abstract to avoid vague statement of the scientific goal and the content of the study.

Reply. We thank the reviewer for this valuable comment. This work indeed does not address the data assimilation of Sentinel-1 itself but the preparation for an optimal data assimilation system which needs an optimal calibration of the observation operator (i.e., the WCM in our case). In this context, optimizing the land modelling system means optimizing a coupled system that includes the Noah-MP LSM and the WCM (used to simulate backscatter predictions). We do agree that the second paragraph needs reorganization to better focus on the content of the study and thus we will improve it in the revised manuscript.

(2)L 49-51: I didn't get the logistics using "either…or…". Are the authors trying to say one of the shortcomings of irrigation parameterization in existing studies is not specifying the source water (Ozdogan et al. 2010b, Evans and Zaitchik, 2008), and even if source water partitioning is considered in Nie et. al. (2018), it only includes groundwater irrigation, instead of dividing the source into different parts? Please clarify and rephrase.

Reply. Thanks for this comment. The meaning of this sentence is exactly the one highlighted by the reviewer. In the LIS public source code, it is possible to simulate irrigation without specifying the source of water or, as in Nie et al. (2018), to extract water from a simplified modelled groundwater such as in Noah-MP. In our specific case, this second option is not optimal considering that in the Po river valley the majority of irrigation water comes from surface water (i.e., Po river). We will edit the text in the revised manuscript to better clarify this concept.

(3) Why assuming a spatially distributed parameter sets (A, B, C, D) instead of a uniform distribution? I wonder whether the authors analyze the spatial pattern of the parameter distribution

and is there any obvious patterns or stratifications of the parameters relating to soil types, climate types, or anything else? Showing this would help audience understand better the meaning of those parameters and relate that to why Natural and Irrigation runs lead to different calibration performance.

Reply. Thank you for this comment. Note that the final objective of the WCM calibration is to reduce the long-term bias between Sentinel-1 and the simulated backscatter signal grid cell by grid cell, for future data assimilation experiments. Following previous works (Lievens et al. 2017; De Lannoy et al. 2013; De Lannoy et al., 2014) we implemented a grid-based calibration instead of using a uniform distribution in order to take into account the spatial differences between observed and modelled backscatter caused by the model parameterization of soil and vegetation, and specific features in the observed footprint. This will be better clarified in the revised manuscript.

We also analyzed the spatial pattern of the parameters and found a certain connection with land uses and soil texture as shown in Figure 2 of the manuscript. An example of parameter maps is reported in Figure R1 for the J-VV Natural and J-VV Irrigation experiments. Generally, the activation of the irrigation scheme seems to reduce the dependency of the vegetation parameters to the soil texture (the reviewer can refer for instance to the low A-values on the triangle structure at the eastern side of the study area in the Natural experiment --Figure R1 a --, which do not appear in the Irrigation experiment --Figure R1 e). On the other hand, the C and D parameters, which refer to the bare soil backscatter, seem to be more dependent on the soil texture in the Irrigation experiment (Figures R1g and R1h). Here, the big central triangle structure is highlighted as compared to the Natural experiment (lower C values and higher D values). In this area the sandy-loamy soil allows more irrigation water as compared to the less permeable silty-loam texture of the eastern triangle structure. We agree that showing maps of parameters can result in a better understanding of the different calibration experiments. We will point this out in the revised manuscript and add a specific paragraph for discussing this issue.

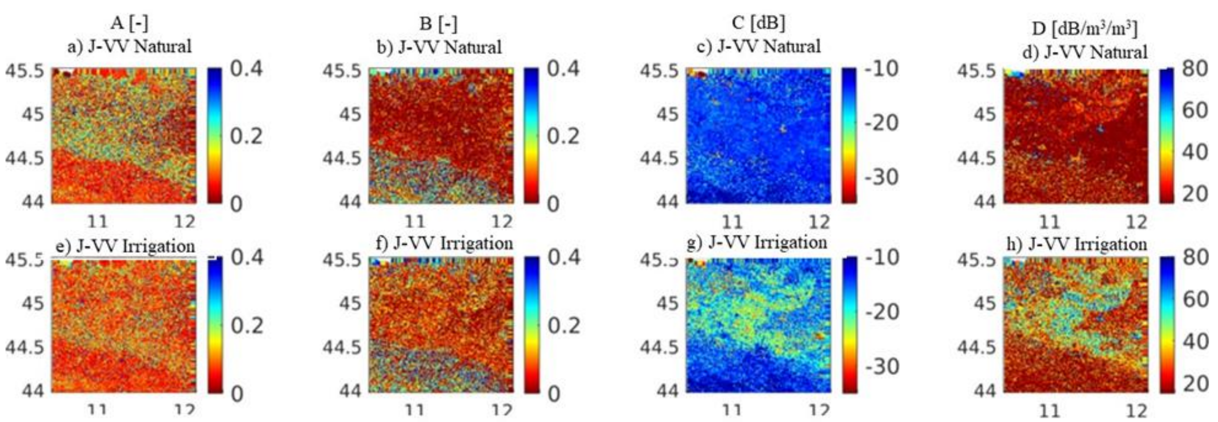

Figure R1. Maps of: a) A parameter; b) B parameter; c) C parameter; d) D parameter for the *J-VV Natural* calibration experiment. Maps of: e) A parameter; f) B parameter; g) C parameter; h) D parameter for the *J-VV Irrigation* calibration experiment.

(4) Irrigation affects SSM and LAI, leading to different parameter distribution in WCM calibration process. However, there are mixed results when evaluating against observed SSM and LAI products. For instance, Irrigation run provides improved estimation of LAI magnitude, while degradation in LAI temporal variability. I wonder whether the authors can calibrate the WCM model using the observed SSM and LAI product, and compare the difference in parameter distribution. How does that look like and what could be the uncertainties in retrieving these parameters purely depending on Noah-MP or depending on observations? In other words, could the authors elaborate the

discussion on the uncertainty of the calibrated parameters and for example quantify how capturing the LAI magnitude vs. LAI temporal variation would contribute to the calibration of WCM?

Reply. Thanks for pointing this out. The optimal calibration of WCM is indeed a challenging task and can be implemented by following different strategies depending on the final target. In this particular case, our goal is to build an observation operator tuned on model inputs, for future data assimilation experiments so, theoretically, model-based SSM and LAI should be used. On the other hand, while using observed 1km-SSM is practically unfeasible (as these data are normally not available at this resolution but from backscatter, e.g., from S1) the use of PROBA-V-based LAI can be a valuable alternative to model-based LAI. This would allow us to overcome the problem of the mismatch of the temporal dynamic between the true and modelled vegetation caused by the model parameterization of irrigation. However, a preliminary assessment shows very different LAI time series from different satellite sensors and missing data due to cloud cover, and after all, it is not LAI per se but the water in the vegetation which is needed for backscatter simulation. Imposing the use of an observed LAI product can therefore also introduce additional bias in the backscatter model simulations, undermining the optimality of the data assimilation experiments. We will add some text to discuss this aspect in the revised version of the manuscript.

(5) L349-352: I didn't quite understand the rationale of "minimizing the impact of the irrigation signal already contained in sigma-0 observations". Why activating irrigation can minimize this impact? And if the impact is minimized, how you can utilize the irrigation related info in data assimilation if detectable in sigma-0 observations? Please clarify.

Reply. Thanks for this comment. As discussed in the introduction at lines 115-119 if the WCM inputs (SSM and LAI from Noah-MP) miss crucial processes such as irrigation, then the WCM calibration (tuned on Sentinel-1, which theoretically contains the irrigation signal) will compensate for this bias providing correlated errors between the WCM and observations in the future data assimilation experiments. Activating the irrigation scheme reduces this risk as SSM and LAI inputs from Noah-MP contain the irrigation signal and the calibration system will not be "forced" to correct for unmodelled processes. We will make this point clearer in the revised version of the manuscript.

(6) The simulation is performed at 0.01 deg while part of the evaluation is conducted at field level, the area of which is much smaller than the model space. Could the authors discuss the uncertainties that might be associated with this evaluation due to the scale mismatch?

Reply. Thanks for this comment. We think that the reviewer has highlighted a crucial point, especially when modelling human activities such as irrigation. One of the most critical aspects of irrigation validation is given by the lack of irrigation benchmark data (Foster et al., 2020). In this specific case, we decided to not exclude the Budrio test site considering the reliability of the data over the fields. The second aspect is that we realized evaluations at different scales: 1) regional (the entire study area); 2) small-district (Faenza test site); and 3) plot scale (Budrio fields). Indeed, while the Budrio test site is composed by plots of about 0.4 hectares, the analysis over the Faenza test site (see Figure 10) refers to an area of 270 ha which is comparable with the model estimates. Finally, it has to be noted that we have selected an intensively irrigated area. Maps such as the Global Rainfed Irrigation Paddy Areas (GRIPC; Salmon et al., 2015) confirm that the Po river valley is almost entirely irrigated, thus reducing the risk to find non-irrigated fields within the 1-km LIS grid. We are aware that there are limitations in our approach but we think that 0.01° spatial resolution is a good compromise between analysis on a regional, small-district and plot scale. We will add a small section to better clarify this point in the revised version of the manuscript.

(7) Figure 7 (a): could the authors elaborate a bit why simulated soil moisture can be directly compared to the VV and VH data, and what might be the difference between the VV and VH data

regarding the detection of soil moisture? What might be the reason for negative correlation between simulated SSM and VH for both Natural and Irrigation runs?

Reply. Thanks for highlighting this aspect. VV polarization of radar backscatter is more strictly linked to SSM information than VH signal though both of them include information on soil properties (see Gruber et al., 2013; Wagner et al., 2013; Bauer-Marschallinger et al., 2018). For instance, Baghdadi et al. (2017) found that the soil's contribution to total backscattering coefficient is lower in VH than in VV because VH is more sensitive to vegetation cover and that, the use of VH alone to retrieve soil moisture, is suboptimal when vegetation cover is well developed. In this context, the cross-polarization backscatter (i.e., HV and VH signals) was found to be well related to vegetation in previous studies (i.e., Ferrazzoli et al., 1992; Macelloni et al., 2001). Based on that, we compared soil moisture directly with VV (and to VH to understand the soil contribution to it) and CR with LAI. This also provides insights about the potential of VV and VH to update soil moisture and vegetation. We will clarify this aspect in the revised version of the manuscript.

(8) L462-463: It is encouraging to see that the CR has a strong relation to the vegetation signal and could be potentially used to correct the simulated vegetation phenology. However, I was confused how exactly this calibration framework could be introduced to Noah-MP DA? Are you suggesting approximating CR to LAI and directly assimilating CR into the model? Or if you are using calibrated parameter to assimilate into Noah-MP, how does the CR information is going to be ingested? I would suggest the authors to clarify and provide more in detail how the current study is connected to assimilating sigma-0 observations into Noah-MP as I found it is unclear throughout the text.

Reply. Thank you for this comment. Firstly, we plan to couple the WCM with Noah-MP in LIS. The WCM is our observation operator, which means that the parameters obtained from the calibration will be used to simulate observation predictions (σ^{0}-VV and σ^{0}-VH) in LIS using the WCM. We plan to implement different experiments (i.e., assimilate VV to update SSM, VH to update LAI, or both VV and VH to update SSM and LAI simultaneously for instance). Another option, indeed, could be to directly assimilate the CR to update LAI. This is a future step which will be discussed in the following work focusing on ingestion of Sentinel-1 backscatter to improve irrigation quantification. We will introduce this clarification in the Discussion section of the revised manuscript.

(9) L486-491: Why a more uniform distributed C and D is more realistic? If so, why the calibrated parameters are designed to be spatially distributed?

Reply. Thanks for this comment. We agree with the reviewer that this aspect needs more clarification. We meant that the Natural experiment provided parameters values more squeezed towards the lower/upper defined boundaries. This means that the parameters are not well constrained and optimized while the Irrigation experiment shows a higher spread in the parameters. In this context, as suggested by the reviewer we will also add a spatial analysis of the results showing that the C and D parameters are more influenced by the soil moisture dynamics in the Irrigation experiments. We will clarify this aspect in the text and we will remove the term "uniform".

(10) What is the benefit of assimilating sigma-0 observations instead of directly assimilating LAI or SSM products? I think the authors should discuss and highlight the benefit of assimilating sigma-0 observations in both introduction section and results section.

Reply. Thanks for this comment. We partly discussed this methodological choice in the introduction section at lines 96 to 104. As reported in De Lannoy et al. (2016), a critical aspect in directly assimilating SSM retrievals is that potentially inconsistent ancillary data are used in the assimilation system and in the retrieval algorithm that generates SSM observations. Furthermore, active MW retrievals typically use change detection methods (Wagner et al., 2013; Bauer-Marshallinger et al., 2018) which lack land-specific information. This means that the 'error

management' within the data assimilation system is theoretically more transparent when assimilating backscatter observations. Using microwave retrievals allows us to have consistent parameters between the LSM and the radiative transfer model (in our case the WCM) and to avoid cross-correlated errors.

Technical corrections:

L57: remove “to” after “from”.
Reply. Thanks for this comment. We will correct the text.

L102: “focussed” -> “focused”.
Reply. Thanks for this comment. We will correct the text.

L195: Add a space between and “observations”
Reply. Thanks for this comment. We will correct the text.

L528 & L530: “Table 3” should be “Table 2”?
Reply. Thanks for this comment. We will correct the text.

References

- Bauer-Marschallinger, B., Freeman, V., Cao, S., Paulik, C., Schaufler, S., Stachl, T., Modanesi, S., Massari, C., Ciabatta, L., Brocca, L. and Wagner, W., (2018). Toward Global Soil Moisture Monitoring With Sentinel-1: Harnessing Assets and Overcoming Obstacles. IEEE
- De Lannoy, G.J.M., Reichle, R.H. Assimilation of SMOS brightness temperatures or soil moisture retrievals into a land surface model Hydrol. Earth Syst. Sci., doi:10.5194/hess-2016-414, 2016
- De Lannoy, G.J.M., Reichle, R.H., Vrugt, J.A.: Uncertainty quantification of GEOS-5 L-band radiative transfer model parameters using Bayesian inference and SMOS observations Remote Sens. Environ., 148, pp. 146-157, doi:/10.1016/j.rse.2014.03.030, 2014.
- De Lannoy, G.J.M., Reichle, R., Pauwels, V.: Global calibration of the GEOS-5 L-band microwave radiative transfer model over non-frozen land using SMOS observations, Journal of Hydrometeorology, 14, 765–785, doi:/10.1175/JHM-D-12-092., 2013.
- Ferrazzoli, P.; Paloscia, S.; Pampaloni, P.; Schiavon, G.; Solimini, D.; Coppo, P. Sensitivity of microwave measurements to vegetation biomass and soil moisture content: A case study. IEEE Trans. Geosci. Remote Sens. 1992, 30, 750–756.
- Foster, T.; Mieno, T.; Brozovic, N. Satellite-based monitoring of irrigation water use: assessing measurement errors and their implications for agricultural water management policy. Water Resour. Res. 2020, 56, 10.1029/2020WR028378
- Gruber, A.; Wagner, W.; Hegyiova, A.; Greifeneder, F.; Schlaffer, S. Potential of Sentinel-1 for high-resolution soil moisture monitoring. In 2013 IEEE International Geoscience and Remote Sensing Symposium-IGARSS; IEEE: Melbourne, Australia, 2013; pp. 4030–4033
- Lievens, H., Martens, B., Verhoest, N. E. C., Hahn, S., Reichle, R. H., Miralles, D. G.: Assimilation of global radar backscatter and radiometer brightness temperature observations to improve soil moisture and land evaporation estimates, Remote Sens. Environ., 189, 194–210, doi: 10.1016/j.rse.2016.11.022, 2017
- Macelloni, G.; Paloscia, S.; Pampaloni, P.; Marliani, F.; Gai, M. The relationship between the backscattering coefficient and the biomass of narrow and broad leaf crops. IEEE Trans. Geosci. Remote Sens. 2001, 39, 873–884.
- Salmon, J. M., Friedl, M. A., Frolking, S., Wisser, D.: Global rain-fed, irrigated, and paddy croplands: A new high resolution map derived from remote sensing, crop inventories and climate data, International Journal of Applied Earth Observation and Geoinformation, 38, 321–334, doi:/10.1016/j.jag.2015.01.014 , 2015.
- Wagner, W., Hahn, S., Kidd, R., Melzer, T., Bartalis, Z., Hasenauer, S., Figa-Saldaña, J., de Rosnay, P., Jann, A., Schneider, S., Komma, J., Kubu, G., Brugger, K., Aubrecht, C., Züger, J., Gangkofner, U., Kienberger, S., Brocca,

L., Wang, Y., Blöschl, G., Eitzinger, J., and Steinnocher, K.: The ASCAT soil moisture product: A review of its specifications, validation results, and emerging applications, Meteorol. Z., 22, 5–33, 2013