Response to the Comments of Referee #1

Dear Referee #1:

We are particularly grateful for your careful reading, and for giving us many constructive comments of this work!

According to the comments and suggestions, we have tried our best to improve the previous manuscript essd-2020-353 (SGD-SM: Generating Seamless Global Daily AMSR2 Soil Moisture Long-term Productions (2013–2019)). An item-by-item response follows.

Once again, we are particularly grateful for your careful reading and constructive comments. Thanks very much for your time.

Best regards,

Qiang Zhang

General comments:

In this manuscript, authors generated a seamless global daily soil moisture dataset from 2013 to 2019. The incomplete daily global AMSR-2 soil moisture productions indeed exist the coverage problem, due to the satellite orbit coverage and the limitations of soil moisture retrieving algorithms. Overall, the proposed 3D spatio-temporal deep learning model is novelty for reconstructing the invalid soil moisture area, to solve the above coverage issue in AMSR-2 global daily products. In addition, three validation programs are employed in this manuscript to ensure the reliability of the seamless global daily soil moisture dataset. Several suggestions may be helpful to better improve this meaningful work.

Response: We are particularly grateful to the reviewer for his/her detailed suggestions! According to the comments, we have tried our best to improve the previous manuscript. An item-by-item response to each constructive comment follows.

Major comments:

Q1.1: ***How to deal with the unique mutations for the proposed reconstructing model, such as precipitation or snowfall in single day? It seems that this work relies on the sequential time-series redundancy for generating seamless global daily AMSR-2 soil moisture products.***

Response: Thanks for this issue. As the referee stated, this work relies on the sequential time-series redundancy for generating SGD-SM products. For unique mutations, it also influences the latter days due to the inertial effects. Therefore, we take the T-4 to T+4 date SM as the input data, to utilize the continuity property of time-series values. In our future work, we will introduce multi-source information fusion into the proposed model, such as precipitation and snowfall.

Q1.2: ***In the testing stage of Fig. 3, the convergence of the training spatio-temporal 3-D reconstructing model is vital for subsequent processing. Therefore, descriptions of this convergence condition must be illustrated in this manuscript.***

Response: Thanks for this meaningful suggestion. The convergence condition denotes that the loss of the proposed model gradually decreases, and finally maintains smooth in training procedure. We have supplemented this description in the revised manuscript.

Q1.3: ***Why authors use 3D partial convolutional neural network, rather than common convolutional neural network, for the soil moisture gap-filling task in missing area? Besides, the intentions for mask updating operation in the reconstructing model should be given.***

Response: Thanks for this issue. it should be highlighted that the valid and invalid SM simultaneously exist especially around the coast regions and gap regions. The common CNN ignores the location information of invalid or valid pixels in soil moisture data, which cannot eliminate the invalid information. Therefore, to solve this negative effect, we develop the partial 3D-CNN to ignore the invalid information in the proposed reconstructing model. the partial convolutional output is only decided by the valid soil moisture pixels of input, rather than the invalid soil moisture pixels. Through the mask, we can effectively exclude the interference information of invalid soil moisture pixels such as marine regions and gap regions. Then the scaling divisor in Eq. (2) further adjusts for the variational number of valid soil moisture pixels. If the partial convolution can generate at least one valid value of the output result, then we mark this location as valid value in the new masks. We have added these explanations into the revised version.

Q1.4: ***Authors employed both local and global soil moisture information to optimize the network. The distinction and connection between local and global information need to provide the explanations and effects.***

Response: Thanks for this comment. Euclidean loss function only pays attention to the holistic information bias for network optimization. It ignores the soil moisture particularity of the local areas, especially in local coastal, mountain, and hinterland regions. However, this particularity is extremely significant for invalid regions gap-filling, because of the spatial heterogeneity in soil moisture products. Therefore, to take both the global consistency and local soil moisture particularity into consideration, the global land mask and current mask in date T are both employed after the final layer. Through this way, we can simultaneously ensure the global consistency and distinguish the local particularity. We have supplemented these descriptions in the revised manuscript.

Q1.5: ***In the time-series validation, most of the soil moisture time-series scatters can obviously reveal the annual periodic variations in Fig. 8. Authors should take advantage of these annual periodic variations to better verify the rationality of the daily SM products.***

Response: Thanks for mentioning this issue. As depicted in Fig. 8(a)-(f), most of the soil moisture time-series scatters can obviously reveal the annual periodic variations. The reconstructed soil moisture results generally behave fine temporal consistency with the original soil moisture results in different areas. Related low soil moisture values mostly existed in the droughty season of winter with the frozen lands such as in Fig. 8(d). Related high soil moisture values mainly generated in the moist season of summer with more rainy days, especially in Fig. 8 (b), (d) and (f).

Overall, compared with the whole original variation tendency between 2013 to 2019, the generated seamless global daily AMSR2 soil moisture long-term products can steadily reflect the temporal consistency and variation. It is significant for time-series applications and analysis. This daily time-series validation also demonstrates the robustness of the presented method and the availability of the established seamless global daily products. We have emphasized these annual periodic variations in the revised manuscript, for better verifying the rationality of the daily products.

Q1.6: ***In the simulated missing regions validation, the spatial continuity is also important for the reconstructed seamless soil moisture productions. To better distinguish the spatial details of reconstructed soil moisture, authors selected some enlarged patches in Fig. 10. More descriptions should be introduced to investigate this key point for spatial consistency between the reconstructing and adjacent regions.***

Response: Many thanks for this suggestion! To better distinguish the spatial details of reconstructed soil moisture, we select four enlarged patches in simulated regions in Fig. 10. It can be clearly observed that the reconstructed patches perform the high consistency with the original patches, as displayed in Fig. 10. The reconstructed invalid regions are consecutive between the original valid regions. And in the simulated missing patches, the spatial texture information is also continuous without obvious boundary reconstructing effects. These descriptions have been introduced into the revised version.

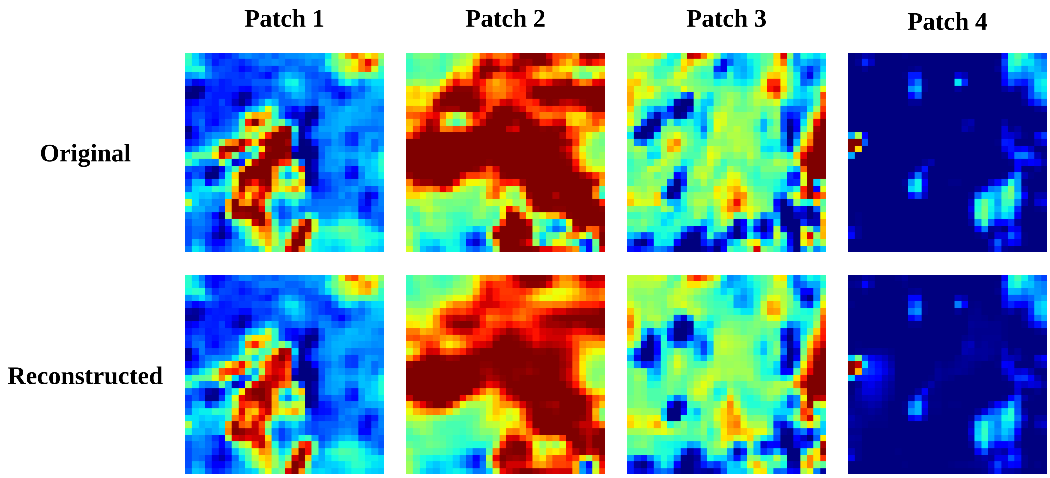

Fig. 10. Detailed original/reconstructed spatial information of four simulated patches in 2015.7.25