Response to the Comments of Referee #2

Dear Referee #2:

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:

Soil moisture information from remote sensing is of great value to understand the interactions between the land and the atmosphere, drought evaluation, ecosystems, hydrology, and water resources. Data gaps of remotely sensed surface soil moisture due to orbits and other sensor and environmental factors in space and time hinder our understanding of these important phenomena, studies, and applications. To address this important issue, the authors have proposed an approach that wisely utilizes 3D spatiotemporal partial convolutional neural network, to exact both spatial and temporal information for global daily soil moisture product gap-filling. Moreover, the experimental results and related validation have been fully examined and implemented, making the results and quality of the generated data sets convincing. Overall, this work is interesting and significant for generating seamless global daily (SGD) soil moisture products that could be valuable in a broad range of research and applications. I recommend acceptance of this manuscript into the prestigious journal of ESSD after addressing issues as follows.

Response: We are particularly grateful to the reviewer for his/her approval and 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:

Q2.1: ***The authors also need to emphasize the unique aspects of daily soil moisture products, compared with monthly/annual average soil moisture results at lower temporal resolution. The high temporal resolution and the global scale are the most important attributes and contributions of the generated SGD long-term soil moisture in this work. This is valuable in hydrology and climate communities.***

Response: Thanks for this significant suggestion. For most applications and spatial analysis, the incomplete soil moisture products are overall averaged as the monthly/quarterly/yearly results to generate the complete products. This operation can effectively improve the spatial soil moisture coverage. However, it distinctly sacrifices the high-frequency temporal resolution as low-frequency temporal resolution, which also severely reduces the data utilization. Besides, it ignores the unique spatial distribution of single day and loses the dense time-series changing information.

From these perspectives, a novel 3-D partial convolutional neural network is proposed for AMSR2 soil moisture products gap-filling. By means of the proposed method, we can effectively break through the above-mentioned limitations. And finally, this work generates the seamless global daily AMSR2 soil moisture long-term products from 2013 to 2019.

Q2.2: ***In Fig. 3, how did the authors design the patch selecting and mask simulating operations in the training procedure? In addition, in the testing procedure, it seems that the proposed model just uses 8-day soil moisture products. Why not use 16-day or 30-day products for gap-filling?***

Response: Thanks for these comments. Detailed descriptions are listed below:

1) In the patch selecting step, we traverse the global regions in date T to select the complete soil moisture patch label, whose local land regions are undamaged. It should be noted the rest incomplete patches in date T are excluded because they cannot participate in the supervised learning. The corresponding time-series soil moisture patches of this selected patch between date T-4 to T+4, is set as the spatio-temporal data patch groups. And their corresponding masks between date T-4 to T+4 is set as the spatio-temporal mask patch groups. After traversing the original products from 2013 to 2019, we finally establish the spatio-temporal data and mask patch groups with the number of 276488 patches. The soil moisture patch size is fixed as 40×40 for patch selecting.

2) In the mask simulating step, 10000 patch masks of the size 40×40 are chosen from the

global AMSR2 soil moisture masks from 2013 to 2019. The missing ratio range of these masks is set as [0.3, 0.7]. Then these patch masks are randomly selected for label patches use within the spatio-temporal data and mask patch groups. The complete patch in date T (label) is simulated as the incomplete patch (data) through the above mask. And the original corresponding mask of this patch needs also to be replaced. After traversing and building the label-data spatio-temporal patch groups, this dataset is set as the training samples for the usage of reconstructing network.

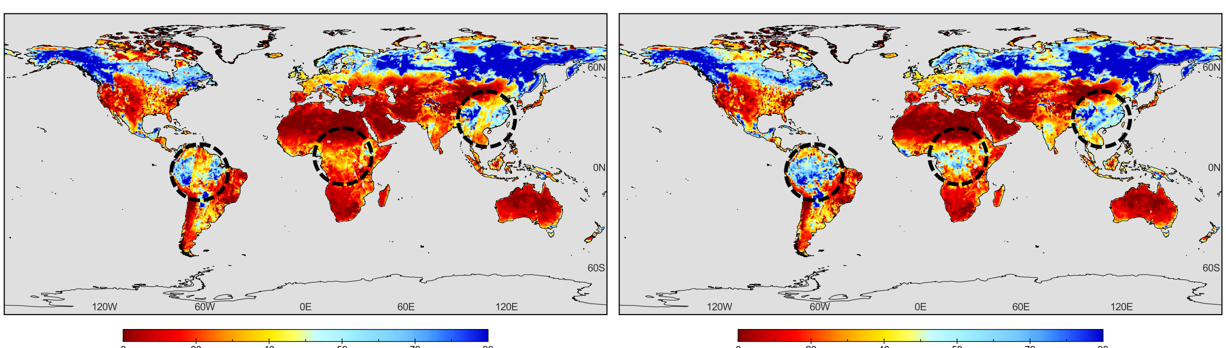
3) In terms of using 8-day soil moisture products not 16-day or 30-day for gap-filling, we mainly consider the adjacent rule. Generally, 8-day products have the most highly correlated relation, compared with 16-day or 30-day products. Therefore, we choose the 8-day products from the reliability and accuracy prospects.

Q2.3: ***In the validation section, the authors employed three validation approaches to test out the effectiveness of the SGD soil moisture production between 2013 to 2019: 1) In-situ validation; 2) Time-series validation; 3) Simulated missing regions validation. More explanations may need to be supplemented for these validations from both the spatial and temporal prospects.***

Response: Thanks for this issue. In-situ validation is utilized to compare the reconstructed soil moisture with original AMSR2 soil moisture through the selected in situ sites from the spatial prospect. In-situ shallow-depth soil moisture sites can be employed as the ground-truth to validate the reconstructing satellite soil moisture products. Time-series validation is employed for evaluating the time-series continuity from the temporal prospect. Soil moisture time-series scatters can obviously reveal the annual periodic variations for time-series validation. Simulated missing regions validation is used to testify the soil moisture consistency from the spatial prospect. It can verify the spatial consistency between the valid and invalid soil moisture regions. We have added these explanations into the revised manuscript.

Q2.4: ***In the discussion section, the authors claimed that time-series averaging strategy has the obvious "boundary difference effect". And the contrast experiments are performed in Fig. 12 (b) and (c). What is the fundamental reason if better describing this common phenomenon, especially for monthly/annual average soil moisture products?***

Response: Thanks for this meaningful query. The time-series averaging strategy ignores the unique spatial distribution of single day and loses the dense time-series changing information. In other word, the monthly/quarterly/yearly soil moisture data averaging operations damage the initial information on both spatial and temporal dimension. The time-series averaging strategy cannot use the 2D-spatial information and neglects these temporal differences. Therefore, it reflects the obvious "boundary difference effect", as shown in Fig. 12(a). This also reveals the limitations and shortages of the time-series averaging method. On the contrary, the proposed method jointly utilizes both spatial and temporal information of these time-series soil moisture products. Further, the proposed method can better richly exploit the deep spatio-temporal feature for soil moisture data reconstructing, as shown in Fig. 12(b). We have supplemented these reasons in the revised version.



(a) Time-series averaging (b) Proposed

Figure 12. Original/time-series averaging/proposed global soil moisture results in 2016.9.10

Minor comments:

Q2.5: ***Line 70: "for AMSR2 soil moisture productions gap-filling" may be better presented as "for global daily AMSR2 soil moisture productions gap-filling".***

Response: We have revised this sentence as the referee's suggestion.

Q2.6: ***Line 114: "part" may be better written as "a portion of".***

Response: We have revised this sentence as the referee's suggestion.

Q2.7: ***Line 232: "ignore the regions of" may be written as "ignore the coverage of".***

Response: We have revised this sentence as the referee's suggestion.

Q2.8: ***Line 243: "soil moisture stations (0 10cm)" lacks "-" in this sentence.***

Response: We have added "-" into this sentence.

Q2.9: ***Line 266: "daily time-series date between 2013 to 2019" may be written as "daily time-series date between Jan 1 2013 to Dec 31 2019."***

Response: We have revised this sentence as the referee's suggestion.

Q2.10: ***Line 305: In Table 3, the best statistical metrics such as R, RMSE, and MAE could be highlighted, to better demonstrate the superiority compared with the time-series averaging method.***

Response: We have highlighted the best statistical metrics in Table 3 as follow:

Table 3. Evaluation index comparisons between the time-series averaging and proposed method

Method	Evaluation index		
	R	RMSE	MAE
Time-series averaging	0.635	0.124	0.093
Proposed	**0.708**	**0.085**	**0.066**