Response to the Comments of Referee #3

Dear Referee #3:

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

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:

The complete satellite-based soil moisture products in space and in long time series can be assimilated to land surface models to generate spatiotemporal soil moisture at the global scale for climate/weather predictions and surface physical property retrieval. In this paper, the author generated the seamless Global Daily Advanced Microwave Scanning Radiometer 2 (AMSR2) Soil Moisture (SGD-SM) products by using the developed 3D spatiotemporal partial convolutional neural network (CNN), which filled the gap of AMSR2 soil moisture products due to limitations of satellite orbit coverage and soil moisture retrieval algorithms. Assessing the quality of SGD-SM products was carried out by means of in-situ validation, time-series validation and the validation in selected missing regions. Furthermore, it showed that the SGD-SM products had improved R and RMSE by comparisons to those based on the time-series averaging. Although it is enough to understand what 'went on', the scientific and English expressions are poor. Authors need to first go through the whole manuscript and make it readable. Meanwhile, the literature review is not very related to the deep learning method that the authors mentioned and used in this paper. The methodology part is not clear enough to follow. Considering the important applications of the complete products at the global scale, this review suggests to reconsider the paper after major revisions.

Major and minor comments are listed in blow and others please find them in the attachment.

Response: We are particularly grateful to the referee for his/her careful reading and detailed suggestions! For the language clarity, we have revised the whole manuscript sentence by sentence in the updated version. The literature review of this work has been rewritten in Q3.6. 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:

Q3.1: ***Please revise the title. See the attachment.***

Response: Thanks for this significant suggestion. We have revised the title as: 'Generating Seamless Global Daily AMSR2 Soil Moisture (SGD-SM) Long-term Products 2013-2019'.

Q3.2: ***Please give the definition of 'context information' and 'context consistency' used in this paper.***

Response: Thanks for this comment. For avoiding understanding in this work, we have revised these two expressions 'context information' and 'context consistency', as 'original information' and 'spatial consistency', respectively.

Q3.3: ***In lines 44-45, please explain who is "the best observed value". Please confirm "a best single-point" or "best single-points".***

Response: Thanks for this issue. We have corrected these problematic descriptions in multi-temporal soil moisture data synthesizing. 'the best observed value' has been replaced with 'the valid value'. 'best single-point' has been revised as 'valid single-point'.

Q3.4: ***In line 51, please give the definition of 'invalid land regions'.***

Response: Thanks for this suggestion. The 'invalid land regions' refers to the gap or information missing area. We have supplemented this definition in current manuscript.

Q3.5: ***In lines 55-58, please briefly introduce the advantage/weakness of the mentioned methods in the reference for fillings gaps of soil moisture products. The current literature review is just like a list and not informative to induce the developed method that you used in your study.***

Response: Thanks for this beneficial comment. We have introduced the advantage/weakness of the mentioned methods in the reference for fillings gaps of soil moisture products as follow:

'Overall, these methods can effectively fill the gaps of soil moisture products. However, these methods cannot simultaneously take both spatial and temporal information into consideration. In addition, the daily soil moisture products in global scale have not been exploited up to now.'

Q3.6: ***In lines 64-69, information like 'a new strategy to solve incomplete... obtain the global gap-filling' express the same meaning. The content in a), b) and c) sounds casual and is not concise in the scientific meaning. Most importantly, please state the reason why do you use the current deep learning method, although we know it is a hot topic. Since you mentioned deep learning, can authors give a literature review of soil moisture product gap-filling? I suggest to rewrite lines 48-65 to present a better literature review and the motivation of your work.***

Response: We are very grateful for these significant suggestions on literature review! To better demonstrate the motivation of this work, we have rewritten the literature review for oil moisture products gap-filling as follow:

'To overcome above-mentioned limitations, some missing values reconstruction methods have been developed especially on multi-temporal images thick cloud removal and deadline gap-filling (Zhang et al., 2020a). For example, Zhu et al. (2011) proposed the multi-temporal neighboring homologous value padding method for thick cloud removal. Chen et al. (2011) presented an effective interpolating algorithm for recovering the invalid regions in Landsat images. Zhang et al. (2018a) built an integrative spatio-temporal-spectral network for missing data reconstruction in multiple tasks.

In terms of the soil moisture products gap-filling, several methods have also been proposed to address this issue. Wang et al. (2012) presented a penalized least square regression-based approach for global satellite soil moisture gap filling observation. Fang et al. (2017) introduced a long short-term memory network to generate spatial complete overlay SMAP in U.S. Long et al. (2019) fused multi-resolution soil moisture products, which can produce daily fine-resolution data in local regions. Llamas et al. (2020) used geostatistical techniques and multiple regression strategy to get spatial complete results of satellite-derived products. Overall, there are few works for soil moisture productions reconstructing on global and daily scale.

In spatial dimension, the invalid land areas and adjacent valid land areas exist the spatial consistency and spatial correlation on daily soil moisture products (Long et al., 2020). In temporal dimension, daily time-series changing curve of the same point natively appears with the continuous and smooth peculiarities (Chan et al., 2018). Overall, these methods can effectively fill the gaps of soil moisture products. However, these methods cannot simultaneously take both spatial and temporal information into consideration. In addition, the daily soil moisture products in global scale have not been exploited up to now.

Therefore, how about simultaneously extracting both spatial and temporal features for seamless global daily soil moisture products gap-filling? Recently, deep learning has gradually revealed the potential for remote sensing products processing (Chen et al., 2021). In consideration of the powerful feature expression ability via deep learning, can we utilize spatio-temporal information to generate long-term soil moisture products?'

Q3.7: ***In line 70, please explain why the AMSR2 soil moisture products are focused, such as its availability in long time series compared to other satellite soil moisture products.***

Response: Thanks for this comment. The reason why the AMSR2 soil moisture products are focused in this work is discribed as follow:

'In consideration of the global coverage, temporal-resolution, and current availability, we select AMSR2 soil moisture products as the focused object.' In our future work, we will consider more soil moisture products such as AMSR-E, SMOS-IC, SMAP and so on.This explanation has been supplemented in the revised manuscript.

Q3.8: ***In lines 70-83, it seems that 'a novel 3-D spatiotemporal partial convolutional neural network, global-local loss function' appears suddenly. I suggest to briefly explain them a bit when they are first mentioned. Meanwhile, the objective part presents the content in the Conclusions. They are different, please revise.***

Response: Thanks for this helpful suggestion! We have revised these sentences as 'a novel 3-D spatio-temporal deep learning framework is proposed for AMSR2 soil moisture products gap-filling.' and 'To optimize the proposed network, we develop a global-local loss function for excluding the invalid information.'

In addition, we have also rewritten the conclusions part to keep consistent with the objective part as follow:

'In this work, aiming at the spatial incompleteness and temporal incontinuity, we generate a seamless global daily (SGD) AMSR2 soil moisture long-term products from 2013 to 2019. To jointly utilize spatial and temporal information, a novel spatio-temporal partial CNN is proposed for AMSR2 soil moisture products gap-filling. The partial 3D-CNN and global-local loss function are developed for better extracting valid region features and ignoring invalid regions through data and mask information. Three validation strategies are employed to testify the precision of our seamless global daily products as follows: 1) In-situ validation; 2) Time-series validation; And 3) simulated missing regions validation. Evaluating results demonstrate that the seamless global daily AMSR2 soil moisture dataset shows high accuracy, reliability, and robustness.'

Q3.9: ***In line 97, please specify the uncertainty of soil moisture. What do you really refer to? Is it the uncertainty from the soil moisture retrieval algorithm or others?***

Response: Thanks for this query. The uncertainty of soil moisture refers to the LPRM-AMSR2 data variable "soil_moisture_c1_error". This uncertainty is generated by LPRM retrieval algorithm in daily soil moisture products. We have added this explanation into the updated manuscript.

Q3.10: ***In line 114, please give the spatial distribution of (the used) in-situ soil moisture networks.***

Response: Thanks for this helpful comment. The spatial distribution of the used in-situ sites is depicted as below:

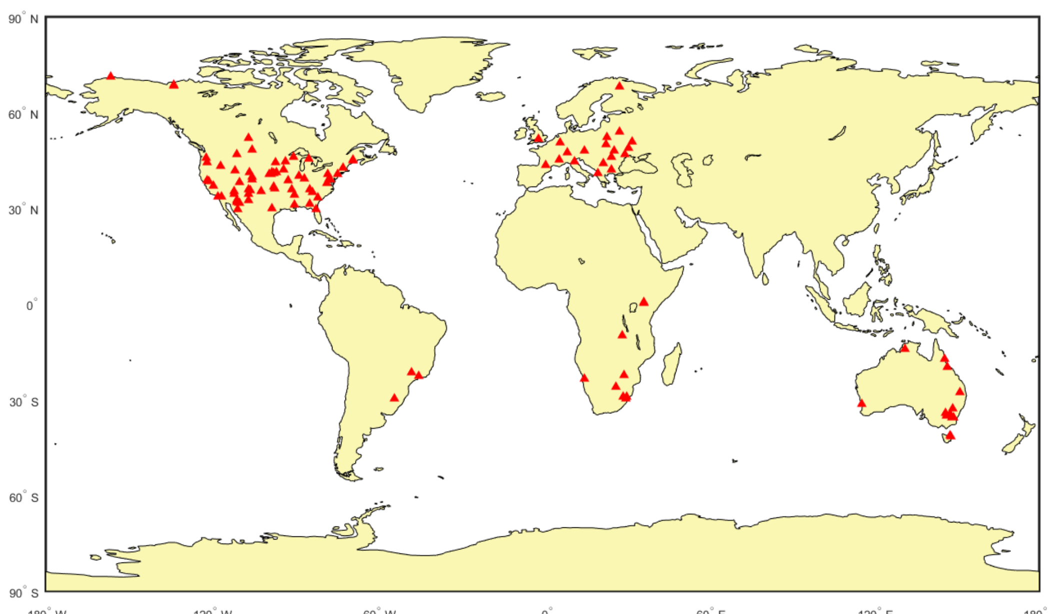


Figure A. The spatial distribution of the used in-situ sites.

Q3.11: ***In line 117, please do you mean descending and ascending data for 'neighboring in-situ hourly values'?***

Response: Thanks for this query. 'neighboring in-situ hourly values' means that to validate the proposed SGD-SM products through in-situ validation, we must match the remote-sensing SM data with in-situ data nearly at the same time. Because in-situ values are the hourly data, we cannot obtain the coincident in-situ data for current date AMSR2 descending SM. Therefore, we select the two neighboring in-situ hourly SM values of AMSR2 SM (e.g., AMSR2 Descending data at 01:20, the neighboring in-situs are selected at 1:00 and 2:00). Then the two neighboring in-situ hourly values are averaged as the ultimate result of current date.

Q3.12: ***The Methodology part is not clear and neat. In line 125, what is 'the loss convergent model'. It appears also suddenly. I suggest to rewrite the overall descriptions of the method, and clearly explain every step and their relations in a logical way. Please present the following sections in a clearer way. There are lots of numbers mentioned, like T-4, T+4, 3*3*3 (what does 3 mean?), 11 layers, 90, 0.1 during the training procedure, 128, 300, 0.001, etc. I question their rationalities, please give the reason for each. In line 190, I am not sure about the relation between loss function and learning parameters? By the way, who is the learning parameter in this study? In line 208, "After building up this unified loss function, the presented reconstructing model employs Adam algorithm as the gradient descent strategy, the number of batch size in this model is fixed as 128 for network training. The total epochs and initial learning rate are determined as 300 and 0.001, respectively. Starting every 30 epochs, the learning rate is degraded through decay coefficient 0.5." Please explain a bit in a clear way, it is very difficult for laymen to understand 'epochs, Adam algorithms and the gradient descent strategy'.***

Response: Many thanks for these meaningful suggestions! Deep learning allows computational models that are composed of multiple processing layers, to learn representations of data with multiple levels of abstraction. The forward-propagation and back-propagation are employed for optimizing the trainable parameters in neural network. I suggest referee can read the classical article (Yann LeCun et al., Deep Learning, *Nature*, 2015), to further understand more concepts in deep learning. Detailed explanations are listed as follows:

1) What is 'the loss convergent model': The loss convergence model 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.

2) Overall descriptions of the method: We have rewritten the overall descriptions of the method, and clearly explain every step and their relations in a logical way.

3) Reason for each number: 'T' stands for current daily date. '$3\times3\times3$' refers to the kernel size of 3D convolutional cube filter. '11 layers' represents the depth of the proposed deep neural network. '90' is the feature map number in CNN. '0.1' denotes the balancing factor to adjust the local loss and global loss in Eq. (6). '128' stands for the batch size in deep learning model. '0.001' refers to the learning rate for the training procedure.

4) Relation between loss function and learning parameters: In deep learning theory, the loss function is the 'baton' of the whole network, which guides the network parameters learning through the error back-propagation between the predicted sample and the original sample. In terms of the learning parameters, they represent the weighted and bias parameters in all the layers.

5) How to understand 'epochs, Adam algorithms and the gradient descent strategy': One 'Epoch' represents that the network goes through all the training data. 'Adam algorithms' is a gradient descent method in back-propagation step, to optimize the whole network parameters. 'gradient descent' denotes the partial differentiation and then updates the variation for each network parameter, which obeys the chain rule in deep neural network.

Q3.13: ***At the beginning of section 4, please put the doi related content in the section of'Data availability'. Additionally, please remove the duplicate information that is already mentioned in the Method. Please only present your results in the Result section.***

Response: Thanks for this comment. We have supplemented the doi related content at the beginning of section 4 as follow. Additionally, the duplicate information has been removed in section 4.

"It should be highlighted that this dataset can be directly downloaded at https://doi.org/10.5281/zenodo.4417458 for free use."

Q3.14: ***Figure 10, the original patch shows almost the same as the reconstructed. Do you mean the original patch is missing here? I am sorry if I misunderstand.***

Response: Thanks for this question. In the simulated missing regions validation, six simulated square missing patches are performed in six continents based on the original soil moisture products (As the referee supposed that the original patch is missing). Through this way, we can easily compare the reconstructed SM regions with original SM regions, to validate the 2D spatial continuity of the proposed SGD-SM products. Detailed original and reconstructed spatial information of four simulated patches in 2015.7.25 are displayed in Fig. 10.

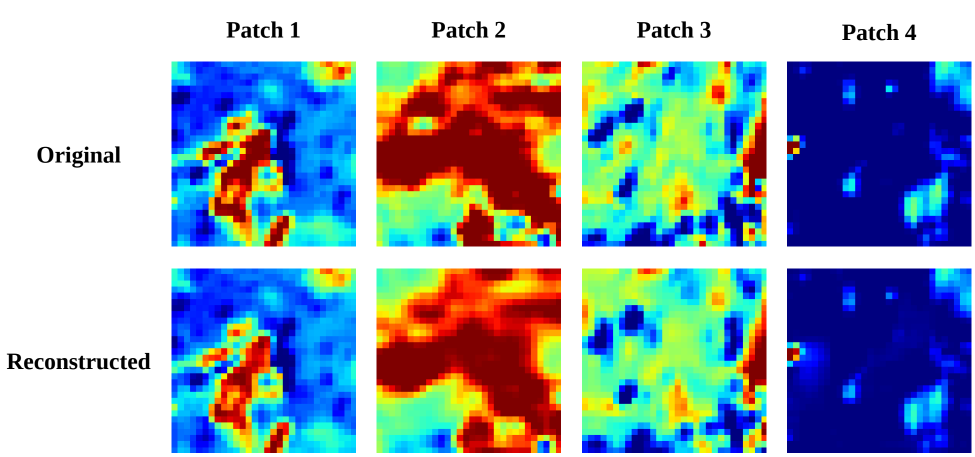
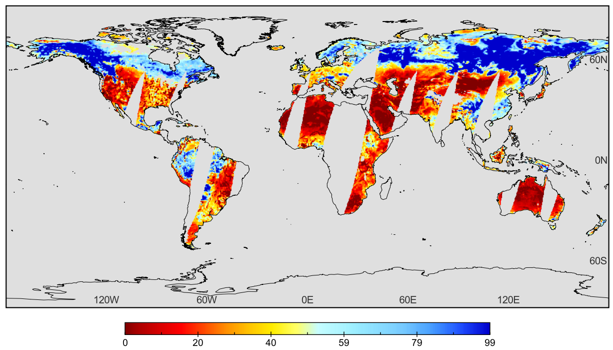


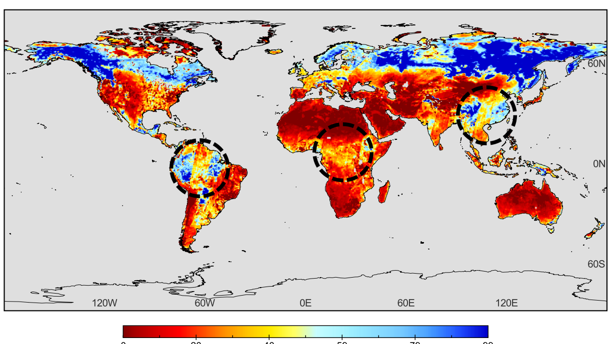
Fig. 10. Detailed original/reconstructed spatial information of four simulated patches in 2015.7.25

Q3.15: ***Figure 12, no black circles.***

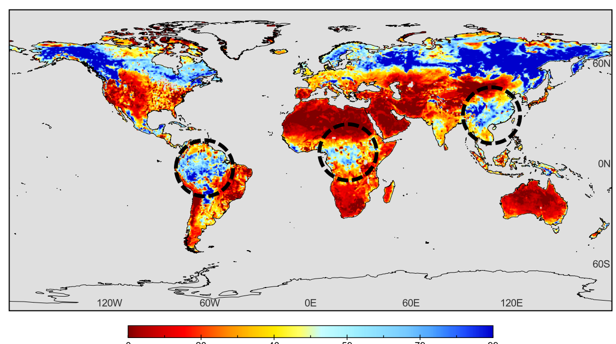
Response: Thanks for this issue. We have appended the black circles in Fig. 12(b) and (c), as shown below:



(a) Original



(b) Time-series averaging



(c) Proposed

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

Q3.16: ***Please describe uncertainties in this generated SGD-SM product.***

Response: Thanks for this significant comment. The uncertainties in this generated SGD-SM product can be classified as three types: 1) The errors of original AMSR2 SM product; 2) The meteorological factors such as precipitation and snowfall; 3) The generalization of proposed reconstructing model. Detailed descriptions of these three uncertainties are listed as follows:

1) The errors of original AMSR2 SM product: The proposed SGD-SM product is generated based on original AMSR2 SM product. While this original AMSR2 SM product also exists errors, due to the satellite sensor imaging and SM retrieval algorithm. As shown in Table 1, the R, RMSE, and MAE evaluation indexes of the original AMSR2 SM product are 0.687, 0.095, and 0.078, respectively. These errors are also inevitably transmitted into the generated SGD-SM product.

2) The meteorological factors: SGD-SM relies on the temporal continuity and spatial consistency for daily SM gap-filling. Nevertheless, if the unusual meteorologic occurs in single day such as precipitation and snowfall, it may destroy above assumption and influence the reconstructing effects. This uncertainty can be noticed in time-series validation, especially for rainy season.

3) The generalization of proposed reconstructing model: In this work, we train the proposed network through selecting complete soil moisture patches. In addition, the simulated masks are also chosen from the daily soil moisture products. However, it still exists the differences between the training data and testing data, such as land covering type, mask size, and so on. This uncertainty may disturb the generalization of proposed reconstructing model, to some degree.

Table 1. Comparisons between original and reconstructed soil moisture products

Soil Moisture Productions	Evaluation index		
	R	RMSE	MAE
Original	0.687	0.095	0.078
Reconstructed	0.683	0.099	0.081

Minor comments:

Q3.17: ***Please follow the "ESSD Manuscript composition (https://www.earth-system-science-data.net/submission.html/#manuscriptcomposition)" to make all related, e.g., Data availability as a separate section and use Sect accord with regulations.***

Response: Thanks for these suggestions. According to the manuscript composition, we have made all related parts (such as data availability, code availability, and author contributions) as the separate sections. The abbreviation 'Sect.' is also employed in our revised manuscript.

Q3.18: ***Use 'besides' too many times in a scientific paper.***

Response: Thanks for this issue. We have rewritten the whole manuscript and removed most worthless 'besides' words.

Q3.19: ***In line 20, I do not think ESA CCI is a sensor. Please revise.***

Response: Many thanks for pointing out this mistake! We have corrected this sentence and deleted 'ESA CCI is a sensor' in the revised version.

Q3.20: ***'Products' not 'Production'***

Response: Thanks for this comment. We have replaced all the 'productions' with 'products' in our revised manuscript.