Response to the Comments of Referee #4

Dear Referee #4:

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-2022-80 (SGD-SM 2.0: An Improved Seamless Global Daily Soil Moisture Long-term Dataset From 2002 to 2022). 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:

This paper addresses the emergent need to increase soil moisture information access, quality, and quantity for multiple users and applications. The authors present an interesting study about reporting a new data version of a seamless global soil moisture product that increases both the quality and accuracy of the previous version of this product. The methods are sound and novel, particularly the development of a deep learning algorithm to fill daily gaps in soil moisture estimates. The authors compare the old and new versions of the datasets, and they provide a robust quantitative accuracy benchmark between versions.

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:

Q4.1: ***The paper is generally well written. However, from the narrative, I feel that there are missing technical details. For example, the use and role of the three passive microwave sensors in modeled soil moisture values in the presence of the precipitation dataset is unclear. Also, can the authors elaborate on prediction variance or model-based uncertainties? I feel that uncertainty of estimates is commonly not presented in soil moisture gap-filling efforts despite being helpful for assessing the reliability of soil moisture predictions.***

Response: Thanks for this comment. For the use and role of three passive microwave sensors (AMSR-E, AMSR2 and WindSat) in the presence of the precipitation dataset, we have supplemented more detailed expatiations in our revised manuscript:

“AMSR-E/2 and WindSat global daily soil moisture products are utilized from 2002 to 2022. These three sensors are onboarded at Aqua satellite, GCOM-W1 and Coriolis satellite, respectively. AMSR-E, AMSR2 and WindSat are all passive sensors for soil moisture retrieving. The spatial resolution is all 0.25° grid (about 25km) in these products, as depicted in Fig. 1(a)-(c). The retrieving model adopts the land parameter retrieval model (LPRM) for AMSR-E, WindSat, and AMSR2 products. We select the descending orbit (night-time), and 6.9 GHz band for all these soil moisture products. These three products provide the original information for the using of SGD-SM 2.0. The proposed reconstructing model acquires the gap masks and relies on the valid spatio-temporal soil moisture information from these three products, to fill the missing and gap regions.

The time-series range of AMSR-E sensor starts from 2002.06.19 and ends to 2011.10.04. The time-series range of WindSat sensor starts from 2003.02.01 and ends to 2012.08.02. The time-series range of AMSR2 sensor starts from 2012.07.03 and continues to current date. In consideration of the low-coverage rate in WindSat dataset, we just use WindSat global daily products from 2011.10.5 to 2012.07.02, for acquiring sequential daily products. These recorded AMSR-E and AMSR2 global daily products are all employed for generating SGD-SM 2.0 products.

Precipitation usually has a high correlation with soil moisture in the corresponding regions. Therefore, we fuse the precipitation products into the proposed SGD-SM 2.0 dataset to improve the reconstructing accuracy. The Integrated Multi-satellitE Retrievals for GPM (IMERG) global daily precipitation V6 products are employed for the years 2002∼2022 (Massari et al., 2020). These precipitation products are derived from multiple precipitation-relevant satellite passive microwave sensors. The spatial resolution denotes as 0.1° grid (about 10km) in IMERG level 3 global daily final precipitation products. To keep the uniformity with soil moisture products, the spatial downsampling operation is carried out for the original IMERG precipitation products from 0.1° to 0.25°. Then we normalize these precipitation values via linear transformation for the use of reconstructing model. These precipitation products were all downloaded from GES DIS.”

For the uncertainty of SGD-SM 2.0 and proposed model, we elaborate an uncertainty discussion in current manuscript as follows:

"The uncertainty of SGD-SM 2.0 and proposed model could be classified as three types: 1) The errors of original AMSR-E/WindSat/AMSR2 products; 2) The meteorological factors; 3) The generalization of proposed reconstructing model.

1) The errors of original AMSR-E/WindSat/AMSR2 products: The proposed SGD-SM product is generated based on original AMSR-E/WindSat/AMSR2 products. While these passive soil moisture products also exist errors, due to the satellite sensor imaging and soil moisture retrieval algorithm. As shown in Table 1, the R, RMSE, and MAE evaluation indexes of the original products are 0.679, 0.094, and 0.075, respectively. These errors are also inevitably transmitted into the generated SGD-SM 2.0 products.

2) The meteorological factors: The proposed method relies on the temporal continuity and spatial consistency for daily soil moisture gap-filling. Nevertheless, if the unusual meteorologic occurs in single day such as precipitation and snowfall, it may disturb above assumption and influence the reconstructing effects. This uncertainty can be noticed in time-series validation, especially for the rainy season. Although we fuse the daily precipitation products into the proposed model in SGD-SM 2.0, it still cannot adequately reflect the emergency meteorological factors such as brief precipitation.

3) The generalization of proposed reconstructing model: In this work, we train the proposed LSTM-CNN model through selecting complete soil moisture patches all over the world. 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 and mask size. This uncertainty may disturb the generalization of proposed LSTM-CNN model for SGD-SM 2.0, to some degree."

4.2: ***It is also my opinion that the accuracy limitations or advantages of the new product version are relative to the reader. For example, the authors poorly discuss their accuracy findings against previous research or gap filling efforts of satellite soil moisture estimates across scales.***

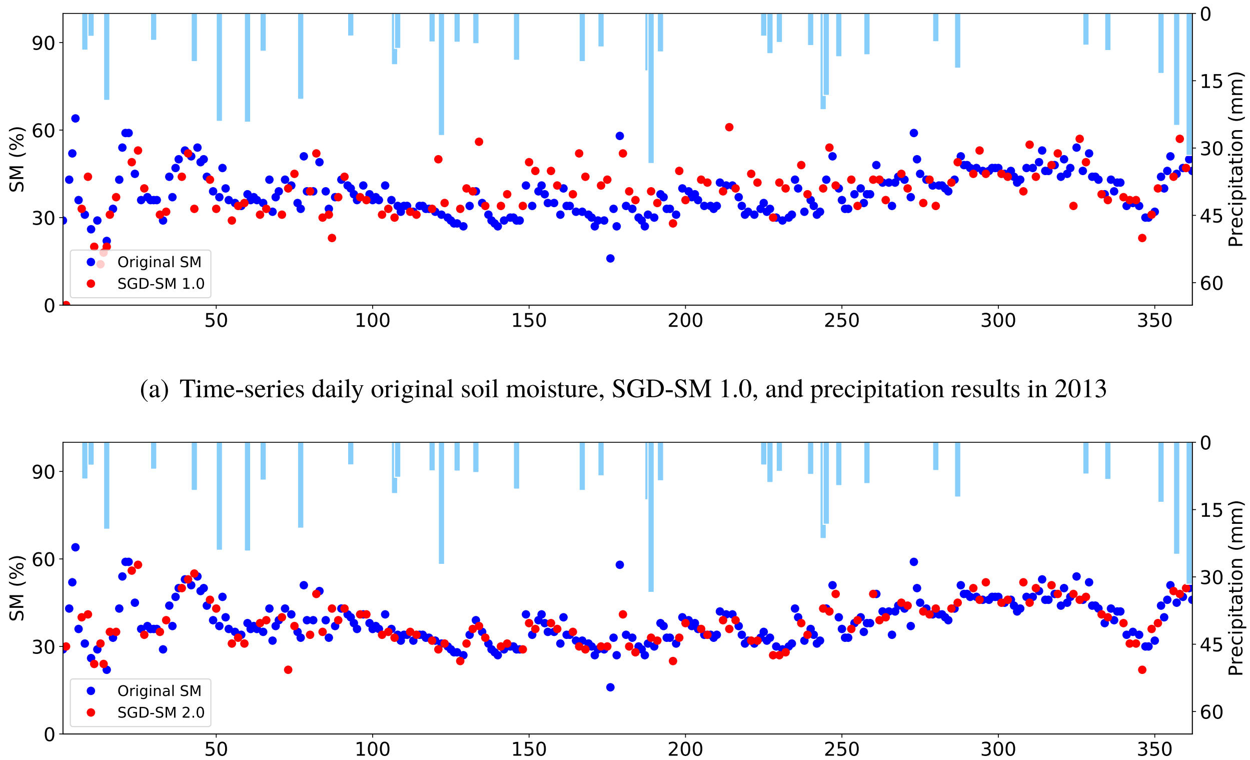
Response: Thanks for this issue. The accuracy findings against previous research have been supplemented in current manuscript. We compare the proposed SGD-SM 2.0 dataset with previous SGD-SM 1.0 dataset, from the perspectives of reconstructing accuracy and time-series consistency. In contrast with SGD-SM 1.0, we fuse the global daily precipitation products into the reconstructing framework. In addition, the LSTM-CNN model is developed to fill the gap and missing regions in SGD-SM 2.0 global daily soil moisture products.

Compared with SGD-SM 1.0 products, SGD-SM 2.0 products outperform on R (0.688), RMSE (0.094), and MAE (0.077). The main reason is that SGD-SM 1.0 ignores the sudden extreme weather condition for one day. If it occurs a sudden precipitation in one day, while there are no abnormalities before and after this day, SGD-SM 1.0 usually behaves with poor performance under this condition. Accordingly, SGD-SM 2.0 introduces the global daily precipitation products into the reconstructing framework. Through fusing auxiliary precipitation information, SGD-SM 2.0 products can consider the sudden extreme weather condition for single day in global daily soil moisture products. The comparisons validate the effectiveness of this point in Table 3.

Table 3. Comparisons between the SGD-SM 1.0 and SGD-SM 2.0 products (from 2013 to 2019) through selected 124 in-situ sites.

Dataset version	Average evaluation indicators			
	R	RMSE	ubRMSE	MAE
Monthly-Averaging	0.612	0.147	0.089	0.115
SGD-SM 1.0	0.659	0.107	0.066	0.083
SGD-SM 2.0	**0.688**	**0.094**	**0.058**	**0.077**

Except the reconstructing accuracy, time-series consistency is also significant for generating seamless daily products (Wang et al., 2021). As portrayed in Fig. 11(a) and (b), we simultaneously depict time-series daily original soil moisture, SGD-SM 1.0/2.0, and precipitation results of the location (48.875°N, 140.375°E) in 2013, respectively. The blue point refers to existing valid values in Fig. 11. Red point stands for the SGD-SM 1.0/2.0 value in Fig. 11, which also represent the invalid gap or missing soil moisture regions. The left vertical coordinate denotes the percent of soil moisture product in original and SGD-SM 1.0/2.0 products. The right vertical coordinate refers to the daily precipitation value (unit: mm) by the IMERG level 3 global daily final precipitation products. The horizontal coordinate denotes the date number in 2013.



(a) Time-series daily original soil moisture, SGD-SM 1.0, and precipitation results in 2013

(b) Time-series daily original soil moisture, SGD-SM 2.0, and precipitation results in 2013

Fig. 11. Time-series daily original soil moisture, SGD-SM 1.0/2.0, and precipitation results at location (48.875°N, 140.375°E) in 2013.

Compared with SGD-SM 1.0, SGD-SM 2.0 outperforms on time-series consistency in Fig. 11(a) and (b). The reconstructed SGD-SM 2.0 points behave more consecutive around their adjacent original soil moistures points than SGD-SM 1.0. While SGD-SM 1.0 exists discrete problem in Fig. 11(a), to some degree. Benefiting from the data fusion of daily precipitation information, the proposed LSTM module can extract time-series features for filling the gaps and missing regions in daily soil moisture products. Therefore, SGD-SM 2.0 can be effectively utilized for global hydrology monitoring analyzing at fine temporal scale, rather than the traditional monthly or yearly averaging operation.

Q4.3: ***The first version of the product has a relatively good number of citations, meaning that the community uses the product and that the methodological approach is being compared with similar research. The authors provide a thorough comparison between product versions, but they do not present the discussion of findings against previous research. I would appreciate more discussion about the potential implications of using the product's old or new version in multiple applications in terms of other available soil moisture estimates.***

Response: Thanks for this meaningful suggestion. We have provided more discussions about the potential implications of using the product's old or new version. Compared with monthly-averaging and SGD-SM 1.0 products, SGD-SM 2.0 products outperform on R (0.688), RMSE (0.094), and MAE (0.077). The main reason is that SGD-SM 1.0 ignores the sudden extreme weather condition for one day. If it occurs a sudden precipitation in one day, while there are no abnormalities before and after this day, SGD-SM 1.0 usually behaves with poor performance under this condition. Accordingly, SGD-SM 2.0 introduces the global daily precipitation products into the reconstructing framework. Through fusing auxiliary precipitation information, SGD-SM 2.0 products can consider the sudden extreme weather condition for single day in global daily soil moisture products. The comparisons validate the effectiveness of this point in Table 3.

Compared with SGD-SM 1.0, SGD-SM 2.0 outperforms on time-series consistency in Fig. 11(a) and (b). The reconstructed SGD-SM 2.0 points behave more consecutive around their adjacent original soil moistures points than SGD-SM 1.0. While SGD-SM 1.0 exists discrete problem in Fig. 11(a), to some degree. Benefiting from the data fusion of daily precipitation information, the proposed LSTM module can extract time-series features for filling the gaps and missing regions in daily soil moisture products. Though this comparison, the advantage of SGD-SM 2.0 could be better reflected via daily precipitation data fusion and LSTM-CNN model. For daily time-series applications, SGD-SM 2.0 is more suitable than SGD-SM 1.0.

Q4.4: ***The paper leaves the value of this product relative to the reader as the comparison is made only between versions one and two, and it does not consider the large availability of other soil moisture estimates for multiple uses and applications. Many (hundreds if not thousands) studies currently report alternatives to downscale or fill gaps in satellite soil moisture data. I invite the authors to provide a more extensive literature review and discussion of previous research to support the value of their product.***

Response: Thanks for this suggestion. We have provided a more extensive literature review and discussion of previous research to support the value of SGD-SM 2.0 below.

Surface soil moisture acts as a significant part on global hydrology and meteorology, especially for forecasting drought and flood disasters (Wigneron et al., 1999; Long et al., 2014; Brocca et al., 2018). In recent years, satellite-based soil moisture retrieving data has been rapidly progressed on both global and daily monitoring (Shi et al., 2006; Dorigo et al., 2012; Al Bitar et al., 2017; Dorigo et al., 2021). For example, AMSR-E, AMSR2, WindSat global daily soil moisture products and so on (Fan et al., 2004). These quantitative products have been widely utilized for global and long-term hydrological analysis and forecast (Chen et al., 2021; Todd-Brown et al., 2021).

However, because of the limitations of soil moisture retrieving models and satellite orbital covering scopes, the obtained daily soil moisture products are fragmentary and incomplete (Shi et al., 2002; Enenkel et al, 2016; Meng et al., 2021). As shown in Fig. 1(a) and (b), these soil moisture products exist plenty of gap regions. Actually, the land coverage rate is only approximately 20% to 80% in daily AMSR-E/2 and WindSat quantitative products (Long et al., 2019).

To settle this adverse effect for global soil moisture applications, most of works adopted the temporal averaging operation such as monthly, quarterly, or yearly averaging (Schaffitel et al., 2020; Guevara et al., 2021; Wang et al., 2021). This strategy could usually acquire full-coverage soil moisture products via averaging abundant daily products. Nevertheless, temporal averaging operation is also a two-edged sword. Firstly, it directly replaces daily temporal resolution with low-frequency temporal resolution (Rebel et al., 2012; Long et al., 2020), which greatly lowers the utilization of daily soil moisture products. Secondly, temporal averaging operation disregards the specific spatial distribution of daily products, and neglects the sequential time-series changing characteristic (Zeng et al., 2015; Wang et al., 2021). In other words, monthly, quarterly, or yearly averaging strategy degrades the original characteristics for daily soil moisture products.

To address this issue, Zhang et al. (2021) generated a seamless, global, daily soil moisture (named SGD-SM 1.0) dataset from 2013 to 2019. The spatial resolution is denoted as 0.25° (about 25km). SGD-SM 1.0 relies on the deep spatio-temporal partial convolutional model to fill the gaps or missing regions in daily soil moisture products. Then three validations are performed to verify the reliability of SGD-SM 1.0 products. Relevant quantitative indexes (R, RMSE and MAE) and results demonstrate that SGD-SM 1.0 products can be extended for global, daily and full-coverage soil moisture measurements (Zhang et al., 2021).

Table 3. Comparisons between the SGD-SM 1.0 and SGD-SM 2.0 products (from 2013 to 2019) through selected 124 in-situ sites.

Dataset version	Average evaluation indicators			
	R	RMSE	ubRMSE	MAE
Monthly-Averaging	0.612	0.147	0.089	0.115
SGD-SM 1.0	0.659	0.107	0.066	0.083
SGD-SM 2.0	**0.688**	**0.094**	**0.058**	**0.077**

In addition, we also discuss the accuracy of the soil moisture modeled values against SGD-SM 1.0 and monthly-averaging strategy in Table 3, to support the value of their product. Compared with the SGD-SM 1.0 and monthly-averaging, SGD-SM 2.0 can be effectively utilized for global hydrology monitoring analyzing at fine (daily) temporal resolution, rather than the traditional coarse (monthly/yearly) temporal resolution.

Q4.5: ***I invite the authors to discuss the main implications of accuracy metrics to assess modeled soil moisture values. Can the authors describe the accuracy of the soil moisture sensors used? I invite the authors to use community accepted standards to report errors on soil moisture products, e.g., ubRMSE https://www.sciencedirect.com/science/article/pii/S0034425720301760, and discuss the accuracy of the soil moisture modeled values against other products or gap-filling efforts. A simple demonstration of the new knowledge that users can obtain from the new product would increase substantially the value of this excellent modeling framework applied to soil moisture satellite estimates.***

Response: Thanks for this comment. The global accuracy metrics could be contrasted between the original soil moisture products and SGD-SM 2.0 in Table 1. We have added the ubRMSE index in Table 1, which is a frequently-used metric to validate soil moisture products. We also discuss the accuracy of the soil moisture modeled values against SGD-SM 1.0 and monthly-averaging strategy in Table 3. Compared with the SGD-SM 1.0 and monthly-averaging, SGD-SM 2.0 can be effectively utilized for global hydrology monitoring analyzing at fine (daily) temporal resolution. In addition, this reference [2] has been cited in our manuscript for the use of ubRMSE index.

Reference:

[1] Gruber, A., Lannoy, G. De, Albergel, C., et al.: Validation practices for satellite soil moisture retrievals: What are (the) errors?, Remote Sens. Environ., 244, 111806, 2020.

Table 1. Comparisons between the original and SGD-SM 2.0 products (from 2002 to 2022) through 124 selected in-situ sites.

Soil moisture products	Average evaluation indicators			
	R	RMSE	ubRMSE	MAE
Original	0.679	0.094	0.058	0.075
SGD-SM 2.0	0.672	0.096	0.061	0.078

Table 3. Comparisons between the SGD-SM 1.0 and SGD-SM 2.0 products (from 2013 to 2019) through selected 124 in-situ sites.

Dataset version	Average evaluation indicators			
	R	RMSE	ubRMSE	MAE
Monthly-Averaging	0.612	0.147	0.089	0.115
SGD-SM 1.0	0.659	0.107	0.066	0.083
SGD-SM 2.0	**0.688**	**0.094**	**0.058**	**0.077**

Q4.6: ***Finally, but more importantly in my opinion (considering that this is a dataset journal), please consider publishing your code in order to fulfill the FAIR principles and contribute to the open-science culture transparently e.g., https://bg.copernicus.org/preprints/bg-2021-323/bg-2021-323.pdf..***

Response: Thanks for this suggestion. To contribute to the open-science culture, we have published our code at https://github.com/qzhang95/SGD-SM. More subsequent information of this code will be maintained at GitHub. In addition, this reference [2] has been cited in our manuscript.

Reference:

[2] Todd-Brown, K. E. O., Abramoff, R. Z., Beem-Miller, et al.: Reviews and syntheses: The promise of big soil data, moving current practices towards future potential, Biogeosciences Discuss. [preprint], https://doi.org/10.5194/bg-2021-323, in review, 2021.

Specific comments:

Q4.7: ***L30 I recommend to avoid the word 'destroy' as aggregated soil moisture values are useful for multiple applications (e.g., to constrain long-term Earth system models). The cited references do not deal with gap-filling daily soil moisture values, please revise.***

Response: Thanks for pointing out this issue. We have changed "destroys" to "degrades" in this sentence.

Q4.8: ***L35 sentence relative to the reader, can the authors be more specific and quantitative and include supporting references, e.g., which quantitative indexes?***

Response: Thanks for this query. We have revised this sentence as "Relevant quantitative indexes (R, RMSE and MAE) and results demonstrate that SGD-SM 1.0 products can be extended for global, daily and full-coverage soil moisture measurements (Zhang et al., 2021)." In current manuscript. [Reference: Zhang, Q., Yuan, Q., Li, J., Wang, Y., Sun, F., and Zhang, L.: Generating seamless global daily AMSR2 soil moisture (SGD-SM) long-term products for the years 2013–2019, Earth Syst. Sci. Data, 13, 1385–1401, https://doi.org/10.5194/essd-13-1385-2021, 2021.]

Q4.9: ***L40-65 Consider combining each weakness or limitation in v1 with their corresponding advantages in v2, instead of two separated lists.***

Response: Thanks for this suggestion. We have combined each weakness or limitation in SGD-SM 1.0 with their corresponding advantages in SGD-SM 2.0 in the revised manuscript:

★ SGD-SM 1.0 only uses single sensor (AMSR2), and the temporal range is insufficient with just seven years. While global soil moisture analysis and applications generally need longer-term and more multi-sensors products. The application range of SGD-SM 1.0 is still limited. Compared with SGD-SM 1.0, SGD-SM 2.0 uses three passive microwave sensors (AMSR-E, WindSat, and AMSR2). Temporal range of SGD-SM 2.0 is extended to twenty years from 2002 to 2022. The application scope of SGD-SM 2.0 could be enlarged through these long-term soil moisture products.

★ SGD-SM 1.0 ignores the daily extreme weather condition. If one day occurs a sudden precipitation, SGD-SM 1.0 usually performs poor under this scenario. The main reason is that SGD-SM 1.0 relies on the internal spatio-temporal correlation, which not considers the external environmental factors. Compared with SGD-SM 1.0, SGD-SM 2.0 introduces the global daily precipitation products into the reconstructing framework. Through fusing auxiliary precipitation data, SGD-SM 2.0 could lead in the daily extreme weather information for gap-filling.

★ Although SGD-SM 1.0 employs 3-D partial convolutional neural network to exploit both spatial and temporal feature, it is still insufficient for utilizing sequential time-series information. For daily soil moisture products, how to effectively reconstruct gaps missing regions through interrelated temporal information is significant. Compared with SGD-SM 1.0, SGD-SM 2.0 develops an integrated long and short-term memory convolutional neural network (LSTM-CNN) to fill the gaps and missing regions in these daily products. The proposed LSTM-CNN model could simultaneously utilize recurrent time-series information and spatial information.

★ Compared with SGD-SM 1.0 products, SGD-SM 2.0 products outperform on R (0.688), RMSE (0.094), and MAE (0.077). In addition, the time-series curves of the improved SGD-SM 2.0 products are more consistency with the original daily time-series soil moisture values. Benefiting from the data fusion of daily precipitation information, the proposed LSTM module can extract time-series features for filling the gaps and missing regions in daily soil moisture products. Therefore, SGD-SM 2.0 can be effectively utilized for global hydrology monitoring analyzing at fine (daily) temporal resolution.

Q4.10: ***L83 how they are employed?***

Response: Thanks for this query. We have rewritten this sentence as “These recorded AMSR-E, WindSat and AMSR2 global daily products are all employed as the initial input of the proposed LSTM-CNN model for generating SGD-SM 2.0 products.” in current manuscript.

Q4.11: ***L98 What is the criteria to select those sites?***

Response: Thanks for this problem. In our in-situ validation, we select 124 sites from ISMN. The selected criteria include three points: 1) The in-situ soil moisture sites are downloadable through the given website. 2) The in-situ soil moisture sites are continuous for the long-term observation, at least one year. 3) The spatial distribution of these in-situ sites covers various continents, land use and soil types. We have supplemented these descriptions in our revised version.

Q4.12: ***L102 It seems to me that the authors solve a regression problem (where soil moisture is a response of precipitation and time) using deep learning, but they use the word assimilation, which is relatively fine for me given how the algorithm they use works. However I recommend to elaborate on the concept of data assimilation applied here for a better and broader understanding of narrative flow.***

Response: Thanks for this suggestion. We also agree that "data assimilation" is generally used optimally combine numerical models with observations. In this work, SGD-SM 2.0 introduces the global daily precipitation products into the reconstructing framework. Through the auxiliary precipitation data, SGD-SM 2.0 could lead in the daily extreme weather information for gap-filling. Therefore, we have replaced "assimilation" as "fusion" in the whole manuscript, to better embody the meaning of multi-source products fusion (precipitation and soil moisture).

Q4.13: ***L108 what soil moisture product? the authors use three products.***

Response: Thanks for this issue. In this sentence, it stands for the arbitrary soil moisture product (AMSR-E, WindSat or AMSR2) for date T. We have added this description in current version.

Q4.14: ***L170 40×40 what?***

Response: Thanks for this query. To optimize the proposed LSTM-CNN model, we need to build the training dataset with huge number. This training dataset is composed of lots of spatial patches, which are cropped from the original soil moisture products. 40×40 represents the spatial dimension of these patches in the training dataset.

Q4.15: ***L219 What was the criteria to select those 124 sites? Can the authors provide a map of points showing in colors the correlation between in-situ and their product for all the stations? I like the presented information but this is a global product and I think it will be useful to interpret the reliability of the product elsewhere. Also for bias indicators (MAE, RMSE), it would be nice to see a map of errors to identify areas with high or low quality of predictions. Please consider***

also the ubRMSE as it has been a widely discussed metric validating local to global soil moisture predictions. Please discuss the values of accuracy metrics in this and other products.

Response: Thanks for this comment. In our in-situ validation, we select 124 sites from ISMN. The selected criteria include three points: 1) The in-situ soil moisture sites are downloadable through the given website. 2) The in-situ soil moisture sites are continuous for the long-term observation, at least one year. 3) The spatial distribution of these in-situ sites covers various continents, land use and soil types. In terms of the map whose points show in colors the correlation between in-situ and their product for all the stations, the scatter is too time-consuming to depict, due to the huge amount points. Therefore, we give six scatters for single in-situ to reveal the accuracy of SGD-SM 2.0. The global indexes and errors could be contrasted between the original soil moisture products and SGD-SM 2.0 in Table 1. We have added the ubRMSE index in Table 1, which is a frequently-used metric to validate soil moisture products. We also discuss the accuracy of the soil moisture modeled values against SGD-SM 1.0 and monthly-averaging strategy in Table 3. Compared with the SGD-SM 1.0 and monthly-averaging, SGD-SM 2.0 can be effectively utilized for global hydrology monitoring analyzing at fine (daily) temporal resolution.

Table 1. Comparisons between the original and SGD-SM 2.0 products (from 2002 to 2022).

Soil moisture products	Average evaluation indicators			
	R	RMSE	ubRMSE	MAE
Original	0.679	0.094	0.058	0.075
SGD-SM 2.0	0.672	0.096	0.061	0.078

Table 3. Comparisons between the SGD-SM 1.0 and SGD-SM 2.0 products (from 2013 to 2019).

Dataset version	Average evaluation indicators			
	R	RMSE	ubRMSE	MAE
Monthly-Averaging	0.612	0.147	0.089	0.115
SGD-SM 1.0	0.659	0.107	0.066	0.083
SGD-SM 2.0	**0.688**	**0.094**	**0.058**	**0.077**

Q4.16: ***L225 can the authors highlight these points in figure 3b?***

Response: Thanks for this suggestion. We have highlighted these six in-situ points in Figure 3b (marked as blue blue circles), for the better reading and understanding.

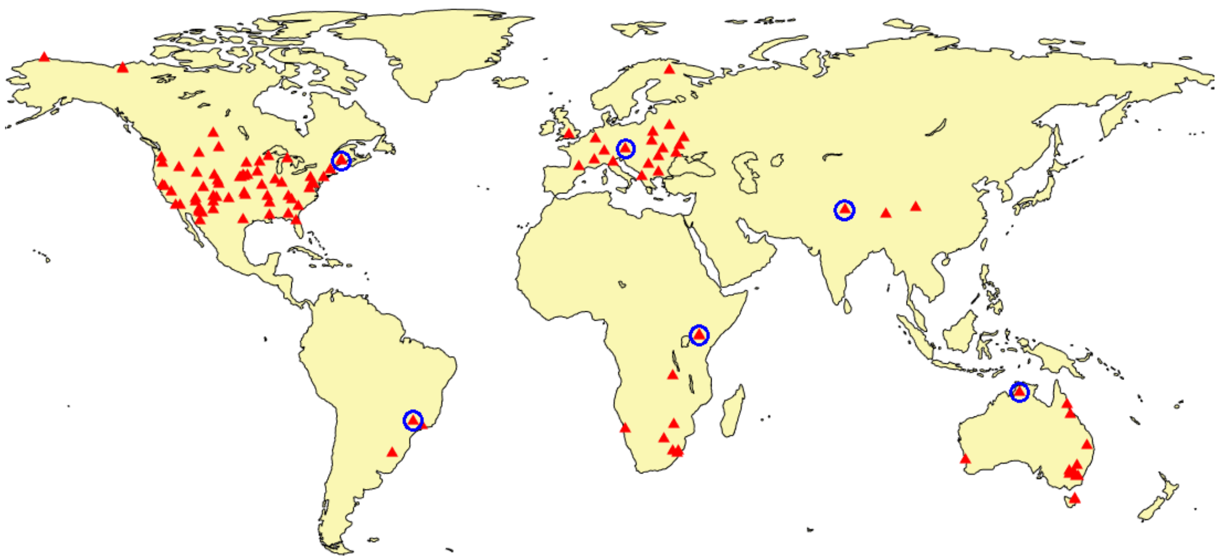


Figure 3b. Spatial distribution of selected in-situ data.

Q4.17: ***L285 the temporal resolution depends on the application.***

Response: Thanks for this comment. We have revised this sentence as "Therefore, SGD-SM 2.0 can be effectively utilized for global hydrology monitoring analyzing at fine (daily) temporal resolution." in current manuscript.

Q4.18: ***Figures 9 and 10, consider using lines instead of points.***

Response: Thanks for this suggestion. In Figures 9 and 10, we also considered use lines to reveal the time-series relation in SGD-SM 2.0. Nevertheless, the main purpose in Figures 9 and 10 is to highlight the reconstructed soil moisture values (red points), especially for the time-series relation with the original soil moisture values (blue points). While the line charts cannot ensure this purpose for SGD-SM 2.0. Therefore, we utilize points rather than lines in the time-series validation.