Interactive comment on '*An improved dataset of satellite observation-based global surface soil moisture covering 2003~2018 (RSSSM)*'

By Yongzhe Chen, Xiaoming Feng, Bojie Fu

To Reviewer #1:

We thank referee #1 for the valuable comments that will help us improve the quality and readability of the manuscript. We have carefully revised the MS following your comments and suggestions. We provide detailed responses to the Referee's comments in the Supplement.

General comment. The authors propose a global dataset of top (0-5cm) soil moisture with 10-day temporal and 0.1 spatial resolution, covering the period 2003-2018. The dataset was produced gradually, backward in time, through machine learning methods (neural networks) for 5 periods that correspond with the availability of 11 different passive and active satellite remote sensing soil moisture products. Besides satellite observations (starting with SMAP in step one), 9 environmental properties were fed to the neural network, and from step two on, previously modeled soil moisture was included to enable the expansion backward in time. The final product is evaluated with observations of the international soil moisture network and, in comparison to other merged products, rated superior, however, the potential for further improvement is also emphasized. Altogether, the work seems sound and the developed method and dataset appear valuable for further scientific studies and applications. Nevertheless, some of the steps in the processing chain need further clarification and the data structure needs to be improved before the manuscript can be considered to suffice for publication.

Response: Thank you for your careful reading and the positive comments on our work. We agree that some steps in the methods were unclearly written, while the data structure is not easy for other researchers to use. We have added the missing important details in the revision to further clarify the processing chain and reuploaded the dataset with filename changes and table additions, according to your valuable suggestions. Please see the details in the responses below.

Specific comment 1. I suggest to remove "new" from the title, since all dataset proposed in this journal are somewhat new. You may consider to name it "combined" or "improved" or "complete" or "optimal". Have you thought about giving the product an acronym? That improves recognizability and makes it easier to reuse it in other studies and publications.

Response: Thank you for the suggestion. We have changed it to 'improved'. We also named the product 'RSSSM' since it is a remote sensing-based surface soil moisture product. In other parts of the article, all the instances of 'SIM' have been changed to 'RSSSM' as well, including those in the figures and tables.

Specific comment 2. L14: more than 10**6 not correctly displayed in the online abstract (here it reads 106)

Response: We have revised it to '*more than one million*'.

Specific comment 3. L15: Please state also the temporal resolution (10 days)

Response: We have added this important information.

Specific comment 4. L32: resolution of ERA INTERIM is rather 0.75°

Response: Thank you for reminding us. We have corrected this accordingly.

Specific comment 5. L34-37: I agree that these products have many shortcomings, but other than the dataset provided by the authors, the models provide also information about the deeper soil layers. This important point should not be omitted here.

Response: We agree that models can simulate soil moisture in deep layers, which is an important advantage. We have added this point to the revised manuscript: '*Apart from surface soil moisture that can be observed by satellites, the modeling method also provides information on the moisture in deep soil layers.*'

Specific comment 6. L75-76: "data averaging" - what type of averaging is meant, spatial or temporal? "can hardly unify the temporal variations." Please specify what the "temporal variations" refer to. Is it the temporal variations of the different soil moisture data products?

Response: We apologize for the unclear expressions. It is neither spatial nor temporal averaging. Instead, the CCI product is achieved by rescaling the soil moisture data retrieved from each microwave sensor first and then averaging the rescaled soil moisture data products during the same period (i.e., the common period for two or more products) based on some criteria (e.g., the estimated error) (Dorigo et al., 2017; Gruber et al., 2017; Gruber et al., 2019; Liu et al., 2012). The 'temporal variations' in this sentence refer to the temporal variations in the different soil moisture data products. Following your question, we have revised the sentence to: '*Rescaling the soil moisture data retrieved from each sensor by using CDF matching followed by averaging the rescaled data during a common period, which is adopted in CCI, will result in problems when unifying the temporal variations in different soil moisture products.*'

Specific comment 7. Instead of Table 1 or in addition, it would be good to have a timeline figure from 2003-2018 that shows a bar for every dataset used in the process of creating the final product, including the 11 soil moisture products, the time-varying quality impact factors and the intermediate modeling products (SIM-1T, SIM-2T,...).

Response: Thank you for this suggestion. Following your comment, we have added a timeline figure showing the temporal coverages (including the used data periods and unused data periods) of all 11 soil moisture products, the time-varying quality impact factor (i.e., three LAI products) and that of the intermediate products. The figure below is attached as Figure 1 in the revised manuscript. Table 1 has thus been removed.

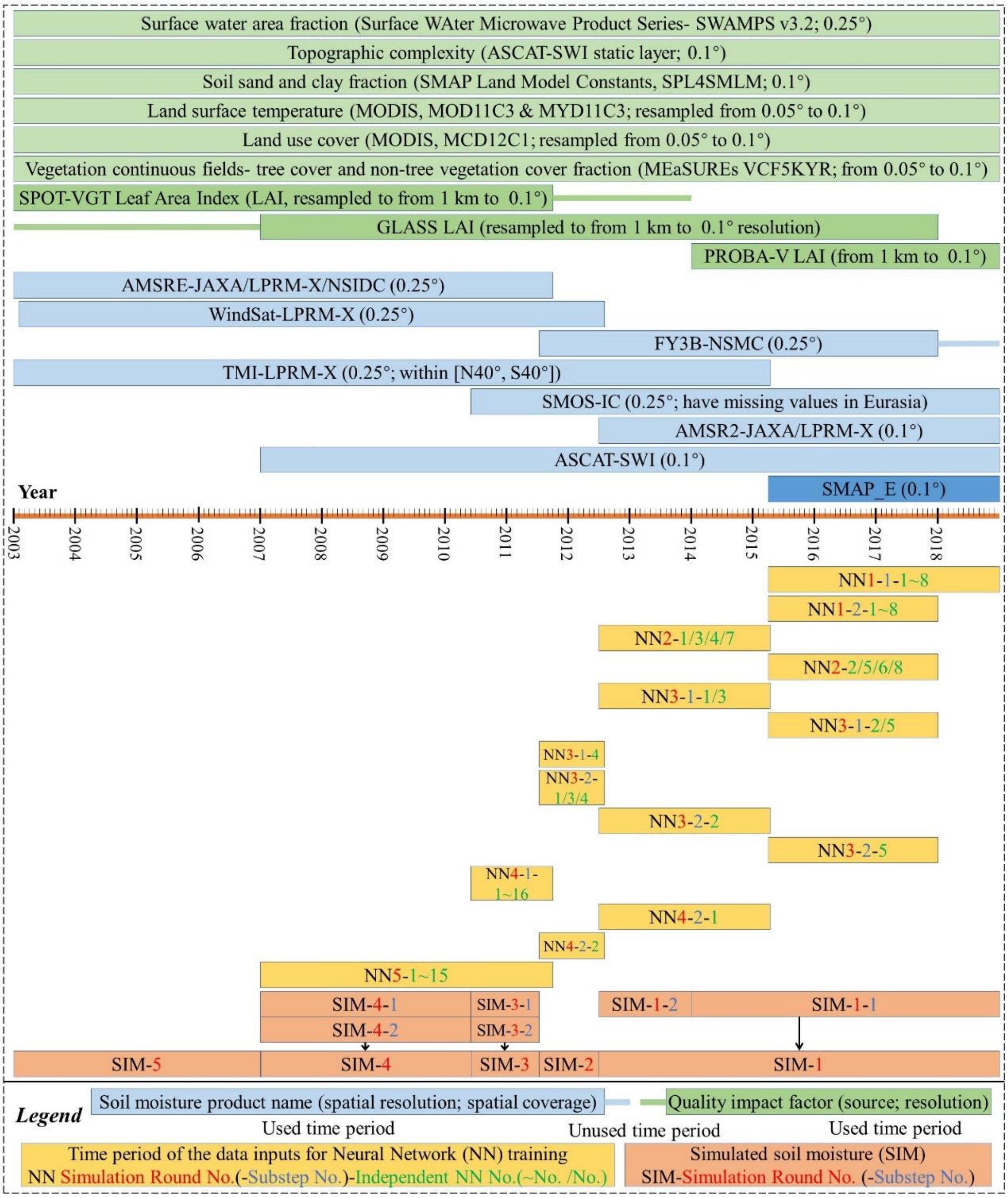

Figure R1: The timeline figure showing the time periods of the soil moisture datasets and the 'quality impact factor' products (e.g., LAI dataset) used in this study (listed above the timeline), as well as the periods of data applied for the training of the 67 independent neural networks and the neural network simulation outputs (i.e., simulated soil moisture) of eight substeps (listed below the timeline).

Specific comment 8. L110: Specify why SMAP is mentioned as the "best product" here. Is it because of the spatial resolution, the algorithms or with respect to the in-situ observations? Can you add a citation to corroborate this statement?

Response: SMAP is the 'highest quality product' with respect to in situ observations. In the Introduction section, this point has been stated: '*Although new sensors such as SMOS (Stillman and Zeng, 2018) and SMAP (Entekhabi et al., 2010) can produce significantly improved estimates because L-band microwaves (1~2 GHz) can penetrate the vegetation canopy better than other bands (Burgin et al., 2017; Chen et al., 2018; Karthikeyan et al., 2017; Kerr et al., 2016; Kim et al., 2018; Leroux et al., 2014; Stillman and Zeng, 2018), the applicability of both products is still limited. SMOS data have too much noise and too many missing values in Eurasia due to high radio frequency interference (RFI) (Oliva et al., 2012). While SMAP has the highest quality (the unbiased RMSE of the passive product can be close to its target of 0.04 m^3/m^3) and has filtered RFI (Chen et al., 2018; Colliander et al., 2017), …*' Following your advice, we revised this sentence and added two new references supporting the best performance of the SMAP product. It reads: '*SMAP currently has the highest quality of all remote sensing-based soil moisture products (Al-Yaari et al., 2019; Liu et al., 2019)…*'.

Specific comment 9. L143: change to "reference coordinate system".

Response: We have changed it accordingly.

Specific comment 10. L182: "based on the correlation between soil dielectric conductivity" - do you mean soil dielectric permittivity or soil electric conductivity?

Response: We apologize for this mistake. It should be 'soil dielectric permittivity' or 'soil dielectric constant'. We have corrected it to '*soil dielectric constant*' in the revision.

Specific comment 11. L186-188: "Because ..." this sentence is unclear.

Response: We apologize for the unclear expression. This sentence explains that the actual LST can determine the bias of every LST estimate, which is used in the corresponding soil moisture retrieval. Hence, the actual LST will influence the biases of different soil moisture products. We have revised the sentence as follows: '*Because different LST estimates are used in the retrievals of different soil moisture products,* *while the bias of each LST estimate compared to the actual LST is influenced by the actual LST, we assume that the actual LST can determine the accuracy of every LST estimate and finally the relative performances of various soil moisture products (Kim et al., 2015).*' We hope this sentence will be easier for readers to understand.

Specific comment 12. L205: Figure 1 is never referenced in the manuscript. This should be done here or later at L225.

Response: Thank you for the reminder. We have added: *'The basic flow of this process is shown in Figure 2'* (note: Figure 2 is Figure 1 in the original manuscript) at the beginning of section 2.2 in the revised manuscript.

Specific comment 13. L219: Do the 140x360 zones include water (ocean) areas?

Response: Yes, the 140×360 zones include water (ocean) areas. However, for zones with no land or very limited land, the number of valid pixels is less than 100, so these ocean zones are not applicable for subnetworks and are excluded.

Specific comment 14. L220: A subnetwork has 100 pixels, but ("for a 0.1pixel in a given 10-day period, if all the subnetwork inputs have valid..."), how can one pixel have more subnetworks? Please improve the formulation.

Response: We apologize for the confusing expression. We have rewritten the paragraph as follows: '*Therefore, we divided the global extent into 140×360 zones in all regions except the polar areas (80°N~60°S). Here, for a 0.1° pixel during a specific 10-day period, if all the input data (soil moisture products and quality impact factors) have valid values, one valid data point is provided. Therefore, the maximal number of valid data points applied to train a subnetwork = 100 × the number of 10-day periods within the training period. The subnetworks with less than 100 valid data points (e.g., those in oceans) were dropped, leaving usually >15,000 zonal subnetworks included in an independent neural network.*'

Specific comment 15. L222: What is an "individual neural network"? Is it the collective of all zonal neural networks for one simulation (SIM-T1, SIM-T2, ...)? Is the maximum possible number of subnetworks 50.400 or less because of ocean cells?

Response: We have changed it to '*independent neural network*' to make it consistent with the expression in the abstract. An independent neural network is the collective of all zonal subnetworks. Several independent neural networks constitute a simulation substep (for example, NN-1-1, NN-1-2, …, NN-1-8 are applied in Round 1- Substep 1), while each substep is responsible for one simulation (there are eight simulations: SIM-1-1, SIM-1-2, SIM-2, SIM-3-1, SIM-3-2, SIM-4-1, SIM-4-2 and SIM-5; for example, SIM-1-1 is the output of Round 1- Substep 1).

The number of subnetworks in each independent neural network is far less than 50400, not only because of ocean zones but also because some soil moisture data are only available in a region (e.g., TMI is available within [-40°S~40°N]). The paragraph has been revised in response to Specific comment 14.

(**Please also note that SIM-1T, SIM-2T, …, SIM-4T are only the postprocessing results that are intended to be used as secondary training targets, while SIM-1, SIM-2, …, SIM-5 are combined to constitute our soil moisture products.)

Specific comment 16. L223: For reproducibility, it is required to state exactly the MATLAB version and the toolbox version and method/function name that was used for training the neural network.

Response: We have added MATLAB version 2016a accordingly.

Specific comment 17. L256: "we classified all pixels" -> "we classified all 0.1 pixels", I suggest to add the resolution information that it is clear which of the different grids is addressed.

Response: We have revised it accordingly.

Specific comment 18. L259: Again, I thought that a pixel is the smallest unit in the process (i.e. subnetwork). So how can a pixel have a subnetwork? Not clear to me.

Response: We apologize for the unclear description. Actually, the subnetwork belongs to a 1° ×1° zone, not a pixel. We have revised it as follows: '*For data simulation in a 0.1° pixel, the most preferable independent neural network is expected to be trained using all the available soil moisture data sources in that pixel. However, in the 1° zone where it is located, the subnetwork belonging to that preferable independent neural network may not exist due to limited valid data points (see section 2.2.1). Then, an alternative subnetwork driven by the combination of fewer soil moisture data inputs should be applied instead.*'

Specific comment 19. L261-262: "Hence, it is a ..." sentence seems incorrect. I think you should better write "neural network collocation" or "neural network constitution" to make it more clear that these are neural network realizations with identical configuration but different ingredients.
Response: We have changed it to 'neural network collocation' accordingly.

Specific comment 20. L272,815 and other occurrences: it is not clear how the 10 day periods are defined and how they relate to the ordinal numbering. A month has between 29 and 31 days, so how are the periods split and how does that affect the last 3rd where the number of days is variable? How does this variable length averaging affect the results and what are the implications for validation?
Response: The first and second 10-day periods in a month both contain exactly 10 days, but the last 10-day period has a variable number of days (9(8)~11). This difference, however, may not have a substantial effect on our results and data quality. This is because it takes at least three days for a microwave sensor to cover the globe. Additionally, for each grid, the days with observations are not the same among different sensors. Therefore, this study only took the average of the available soil moisture retrievals during a 10-day period (we have added a paragraph in section 2.1.1 as: '*To reduce noise and fill the gaps between sensor observation tracks (it takes at least 3 days for a microwave sensor to cover the whole globe), both the daytime and nighttime observations within each 10-day period are combined by data averaging (the relative superiority of daytime and nighttime retrievals is not considered) for every soil moisture*

product. For example, for SMAP, 11% of the global land surface has data for only 5 days or less within a 10-day period.' Moreover, surface soil moisture may vary significantly even in a day due to rainfall events, but the observations are transient. Therefore, either the 10-day averaged microwave soil moisture products or the simulated soil moisture data in this study can only roughly indicate the overall soil moisture condition and is not exactly equal to the mean soil moisture during 10 complete days. Hence, it does not matter whether the 'last 10-day period' in a month has exactly 10 days or not. In fact, this data format is exactly the same as that of the ASCAT-SWI soil moisture and many other products (e.g., LAI) developed by the ESA-Copernicus Land Monitoring Service (https://land.copernicus.eu). For the validation process based on ISMN measurements, the mean in situ soil moisture in the 'last 10-day period' of a month was also calculated by averaging the records over either 10 days or 11 days (or 8~9 days in February), which was consistent with the 'nominal' simulation period. Following this comment, we added this information: '*The temporal resolution is approximately 10 days, or to be specific, there are 3 data records within a month, for days 1~10, 11~20 and from 21 to the last day of that month*' to the abstract in the revision.

Specific comment 21. L270-292: also this section would greatly benefit from a timeline bar plot that shows all the soil moisture products and simulated models, so that the overlaps can be grasped Immediately.

Response: We have added Figure 1, which shows the timelines of the simulated soil moisture corresponding to 8 substeps and the periods of data inputs for the training of 67 independent neural networks. Please find the details in response to Specific comment 7. We also added a sentence: '*The training period for each neural network and the simulation period for each substep are shown in Figure 1.*' in this paragraph.

Specific comment 22. L318: define how R**2 is computed (based on Spearman or Pearson).

Response: The R^2 is computed based on Pearson's correlation, and we have added this information in the revision.

Specific comment 23. L321: lower case r should be used for the correlation coefficient (based on Pearson?). Why are you mixing r and R^2 and do not use R^2 for all analyses?

Response: Following this comment, we have changed R to '*r*' to represent the Pearson correlation coefficient, including those in the figures and tables. In this way, we can better distinguish the correlation coefficient from R^2.

To evaluate the overall performance, we showed the scatter plot between the simulated soil moisture and the measured values. Here, instead of *r*, we used R^2 to better reveal the differences among the performances of the different soil moisture products. However, in the temporal and spatial validation, at some sites or during specific 10-day periods within a climatic region, the simulations and measurements were negatively correlated, as shown in the figures within the manuscript, which are actually of very low quality. However, if we only use R^2, these low-quality data will be overshadowed (for example, if *r* is -0.6, R^2 can be as high as 0.36). Therefore, it is wiser to use temporal correlation and spatial correlation. Previous studies also used '*r*' to evaluate the spatial and temporal accuracy of surface soil moisture products against ISMN measurements, for example (Karthikeyan et al., 2017).

Specific comment 24. L322: please provide formula for A.R computation

Response: 'A.R' in this study represents the correlation coefficient (*r*) between the anomalies of simulated soil moisture and the anomalies of measured soil moisture at a specific ISMN station. Following this comment, we have added the equation below to show how the anomalies of simulated or measured surface soil moisture were calculated in the revised manuscript.

$$\overline{SSM(k)} = \frac{\sum_{y=1}^{ny} SSM(y,k)}{ny} \ (ny \geq 3);\ SSM\ is\ either\ estimated\ or\ measured$$

$$SSM: surface\ soil\ moisture;\ k: the\ ordinal\ of\ a\ 10\ day\ period\ in\ a\ year;$$

$$y: a\ year\ with\ measured\ SSM\ in\ the\ k^{th}\ 10\ day\ period;\ ny: number\ of\ those\ years$$

$$SSM_{anom}(y,k) = SSM(y,k) - \overline{SSM(t)}$$

$SSM_{anom}(y,t)$: $the\ anomalies\ of\ surface\ soil\ moisture\ during\ the\ t^{th}\ 10\ day\ period\ in\ year\ y.$

Specific comment 25. L326: "in all grids", grids or pixels (1 x 1 or 0.1 x 0.1)?

Response: Thank you for your careful reading. We revised it as '*in all 0.1° grids*'.

Specific comment 26. L326: please provide formulas for spatial pattern validation (at least in the supplement)

Response: We have provided more details for spatial pattern validation. Now it reads: '*Finally, we performed spatial pattern validation. In detail, for every 10-day period, we compared all the soil moisture measurements that were upscaled to 0.1° during that period with the corresponding estimated values. The spatial pattern evaluation indexes include the correlation coefficient (r), RMSE, bias and ubRMSE values (Eq. 2).*'

$$\overline{SSM_{est}} = \frac{\sum_{i=1}^{ng} SSM_{est,i}}{ng}\ ;\ \overline{SSM_{act}} = \frac{\sum_{i=1}^{ng} SSM_{act,i}}{ng}\ (ng \geq 20)$$

i: $a\ grid\ with\ upscaled\ surface\ soil\ moisture\ measurements\ during\ a\ specific\ 10\ day\ period;$

ng: $the\ number\ of\ those\ grids\ on\ the\ globe$

$$ubRMSE_{spatial} = \sqrt{\sum_{i=1}^{ng}[(SSM_{est,i} - \overline{SSM_{est}}) - (SSM_{est,i} - \overline{SSM_{act}})]^2/ng} \quad \text{(Eq. 2)}$$

Specific comment 27. Figure 3: Use identical labels for the x-axis, add missing lower frame.

Response: We unified the labels for the x-axis. The figures have been adjusted accordingly. The revised Figure 3 (Figure 5 in the revised manuscript) is shown below:

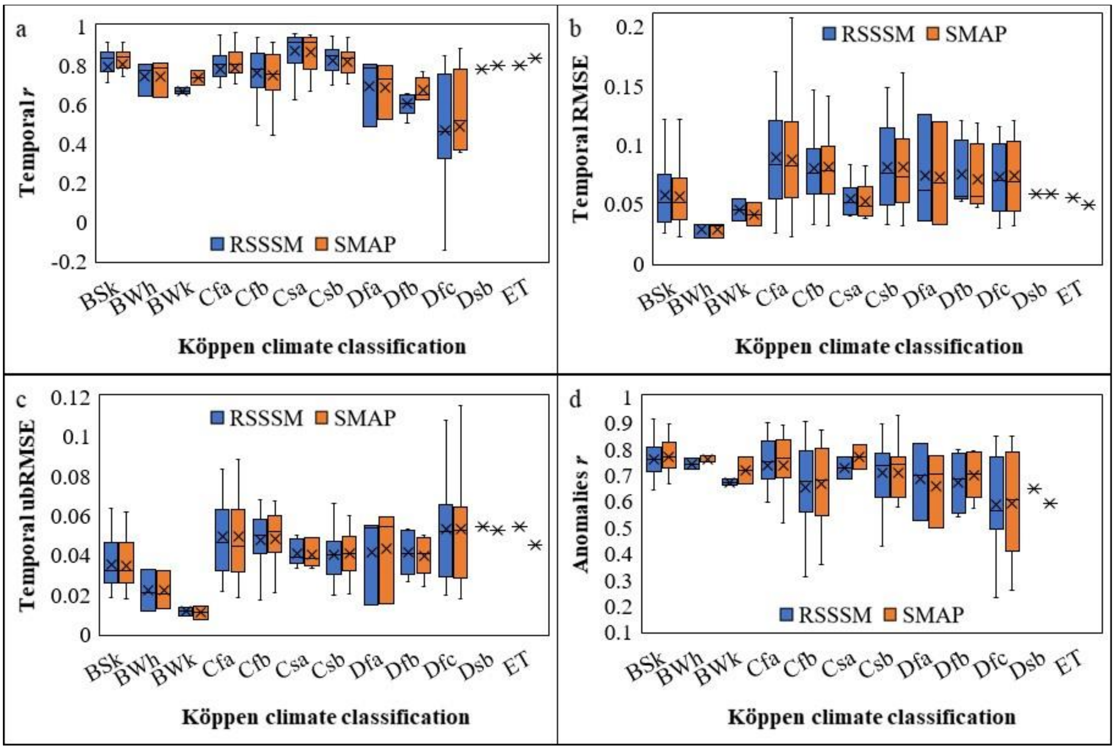

Figure R2: Comparison between the temporal accuracy of RSSSM and SMAP in regions with different Köppen-Geiger climate types. The four indexes are (a) r, (b) RMSE, (c) ubRMSE and (d) Anomalies r (A.R). The lengths of the error bars are 1.5 times that of the interquartile range, while the upper and lower boundaries and the central lines of the boxes indicate the 75th, 50th and 25th percentile values, with mean values marked by '×' (the forms of all the following boxplots are the same).

Specific comment 28. Figure 4: If the color key is put below the figure, the figure can be increased in the horizontal direction which leads to wider bars. You could even remove the x-axis labels and names and leave only the lowermost. By this you can increase the size of the bars and hence the readability (reduce redundancy).

Response: We moved the color key below the figure and removed the x-axis names to increase the size of the bars (shown in Figure R3, Figure 6 in the revised manuscript). Other figures were also revised and made larger and clearer.

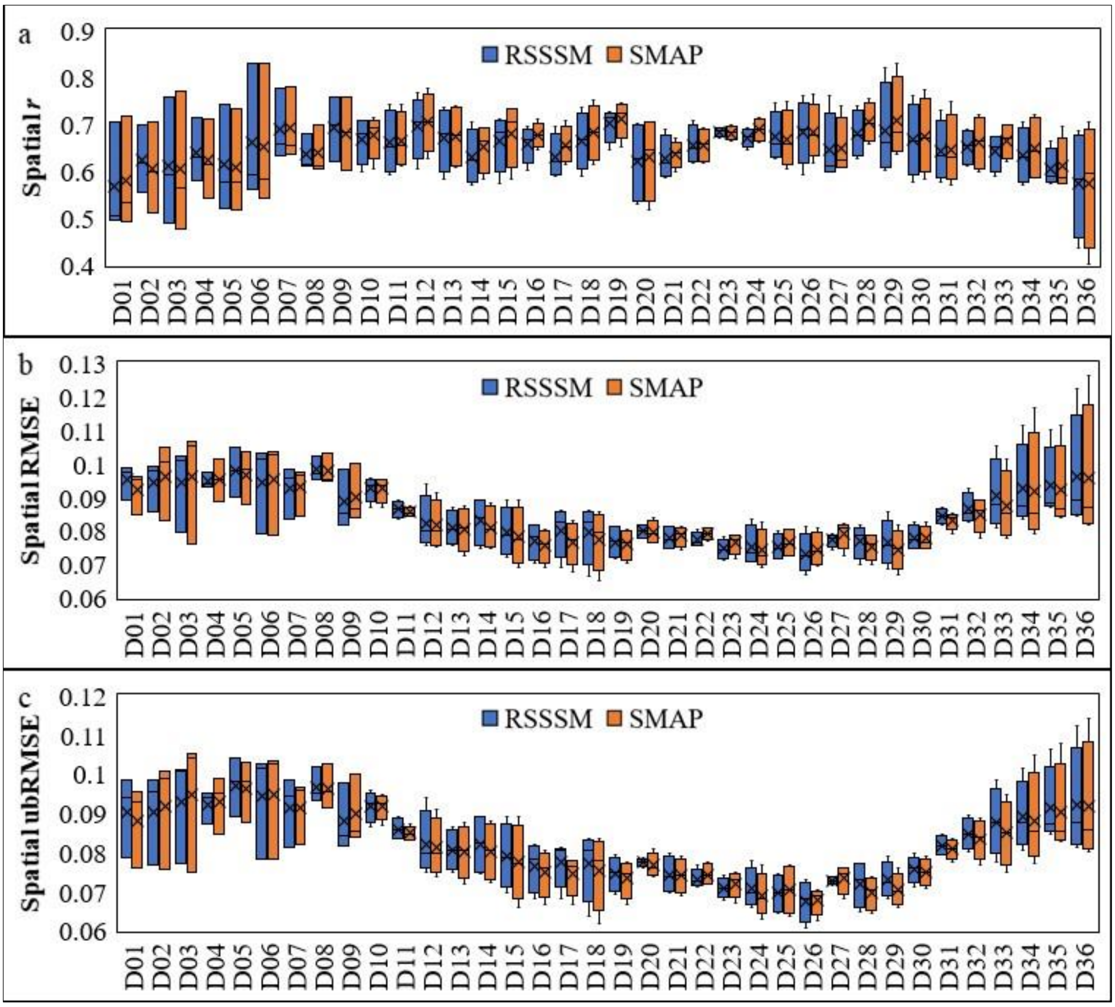

Figure R3: Comparison between the spatial pattern accuracy of RSSSM and SMAP in different 10-day periods during April 2015~2018. The three evaluation indexes are (a) r, (b) RMSE and (c) ubRMSE. The length of each box/error bar is determined from the evaluation index values in three (January to March) or four (April to December) years.

Specific comment 29. L381: How is the performance of SIM if the SMAP training period is omitted, i.e. from 2003 until 2015D01, as compared to ASCAT-SWI?

Response: We have added this information to the manuscript accordingly. It reads as: '*If the data period of SMAP (2015D10~2018) is excluded, the overall R^2 and RMSE for RSSSM are 0.43 and 0.087, respectively, which are still better than those for ASCAT-SWI (R^2=0.33, RMSE=0.1).*'

Specific comment 30. Figure 7,10: As for fig. 4 place color key below the plots and increase the bars horizontally.

Response: We have revised all the figures accordingly.

Specific comment 31. Do you see any chance to improve the temporal resolution of the product in the future? If not, what are the constraints?

Response: Currently, it is probably not a good choice to further increase the temporal resolution of the long-term microwave surface soil moisture product. As illustrated in the response to Specific comment 20, for each grid, both the days and the hours of the observations by different microwave sensors differ from each other. Because surface soil moisture has high variability in a short time period (even in a day) due to rainfall events, the actual soil moisture at the passing time of various sensors is not the same. However, this study used multiple sources of microwave surface soil moisture products as predictors in the neural networks and SMAP soil moisture data as the training target, meaning that the neural network training should be based on the assumption that the products retrieved by different sensors contain exactly the same actual soil moisture information. As we can see, a conflict exists. To solve this conflict, for each sensor, we took the average of its available retrievals during a certain time period, and the larger the amount of data applied for averaging is, the better the result represents the mean soil moisture during that period. Because 11% of global land has only 5 or fewer days with observations during a 10-day period, if the temporal resolution is improved, for example, to 5 days, there may be only 2~3 observations available. Considering the high temporal variability of surface moisture, the average of those limited data can hardly indicate the average soil moisture condition. This phenomenon will lead to large uncertainties in the neural network training and, finally, our soil moisture simulation results.

This problem is an inherent constraint of microwave remote sensing data integration. Therefore, to improve the temporal resolution, other data sources need to be incorporated. Soil moisture retrieved from other remote sensing techniques (e.g., optical) exhibits low quality over vegetated areas and is heavily affected by clouds. Therefore, model simulation may be the only solution to this problem. For example, assimilating the observational-based surface soil moisture into models such as GLEAM can achieve surface/root-zone soil moisture mapping at a daily scale. Therefore, we have revised the last paragraph as follows: '*Another way to improve global surface soil moisture data accuracy as well as the temporal resolution is to combine satellite-based products with land surface models such as GLEAM. Remote sensing inversion can delineate more detailed spatial information on soil moisture, whereas reanalysis-based models have advantages in characterizing temporal variations and even on a daily scale, except for…*'.

Specific comment 32. L499-500: Is SIM also superior to the other products if only the prior to SMAP period is considered (2003 until 2015D01)?

Response: Thank you for this advice. We have added the following comparisons to the manuscript.

1) If the data period of SMAP (2015D10~2018) is excluded, the overall R^2 and RMSE for RSSSM are 0.43 and 0.087, respectively, which are still better than those for ASCAT-SWI (R^2=0.33, RMSE=0.1).

2) When excluding the SMAP (training target) data period, the R^2 and RMSE for RSSSM are 0.41 and 0.089, respectively, which are also superior to those for GLDAS (R^2: 0.37; RMSE: 0.099).

3) Without considering the SMAP period, the conditions are the same (the R^2 values for RSSSM and ERA5-Land are 0.41 and 0.38; the RMSE values for these two products are 0.089 and 0.125, respectively).

4) when the SMAP data period is excluded, the R^2 and RMSE for CCI are 0.28 and 0.098, compared to 0.41 and 0.089 for RSSSM.

5) if the SMAP data period is excluded, RSSSM's R^2 and RMSE values are 0.41 and 0.089, respectively, which are still better than both GLEAM v3.3a (R^2: 0.35; RMSE: 0.141) and GLEAM v3.3a (R^2: 0.34; RMSE: 0.128).

Therefore, the comparisons above can prove that our product (RSSSM) is superior to the other products even if the SMAP period is excluded.

Specific comment 33. Are there plans to update the data-set on a regular basis?

Response: Yes. We plan to update the whole dataset when more advanced microwave sensors (e.g., P-band sensors) are launched and global-scale higher-quality surface soil moisture data are available in the future. We have added this information to the discussion. Now it reads: '*Therefore, if microwave sensors with higher SNR or better penetration of vegetation canopy than SMAP are launched in the future (for example, the upcoming P-band microwave sensors (Etminan et al., 2020; Ye et al., 2020)), we can develop a temporally continuous soil moisture dataset beginning in 2003 by using the soil moisture or Tb retrieved from the new sensors as the reference. This newly developed product is expected to have even higher accuracy than the SMAP product (we will update the complete RSSSM product then). In that sense, the data fusion algorithm proposed here will be very meaningful in the future.*'

Specific comment 34. The dataset is organized as an archive of geotiff files. The problem with this structure is that the time identifier is only contained in the file name, but without practical formatting. If one wants to import a time series for a region or a single pixel, the data structure is quite unhandy. Also from the readme file and the metadata it is not quite clear what the 10 days ordinal numbering means exactly. Is it always the [1-9],[10-19],[20-29] or [1-10],[11-20],[21-30] periods? How are the months with variable length considered (28,29,30,31 days)? That's not clear also not from the manuscript.

Further, I would suggest to add a table (csv) that links the different file names to their specific period using ISO 8601 https://en.wikipedia.org/wiki/ISO_8601 notation:

e.g., a file named inventory.dat with a list like the following one:

Period, Filename 2003-01-01/2003-01-10, SMY2003DECA01.tif 2003-01-11/2003-01-20, SMY2003DECA02.tif ...

Response: Thank you for the suggestion on the naming and structure of our data. Actually, it is [1-10], [11-20], [21, the end of each month]. We have added a csv table named 'filename' linking the different file names to their specific period, following your instructions.

Specific comment 35. Also the numbering should be formatted as %02d so that, e.g., SMY2003DECA1.tif becomes SMY2003DECA01.tif. This is important if one wants create a chronological file list for looping over time. With the current scheme, the order would become SMY2003DECA1.tif SMY2003DECA10.tif, SMY2003DECA11.tif, ... This should be also applied to all tables in the manuscript (e.g., 2005D01 instead of 2005D1).

Response: We have changed the naming of the product as well as the abbreviations for each 10-day period, both in the manuscript and in the Supplement.

Specific comment 36. Figure S1: The figure and description is not completely clear. I assume that every number (yellow and blue frames) is one pixel (0.1x 0.1)? I think it would become more clear if you superimposed a light gray mesh for the pixels over the 1x1zones. But then, why are there 4 steps required to smooth the borders? It means that every boarder gets smoothed twice, and every corner point even four times.

Response: We apologize for the unclear description. The figure has been revised (see Figure R4), with light gray mesh superimposed for all the pixels over one 1°×1° zone. The four steps were used to process the four borders of each 1°×1° zone (please note that in each step, only the border colored in blue is smoothed). We have added more details to clarify this information, which now reads as: '*A sketch of the four substeps in boundary fuzzification. The 1°×1° zones are separated by solid black lines (the 0.1°×0.1° pixels in one zone are superimposed by light gray mesh). For each substep (subfigures a~d), the soil moisture value within each pixel that is colored in blue is recalculated as the average of its original surface soil moisture and the original soil moisture value in its most adjacent yellow color pixel, weighted by the corresponding numbers labeled (i.e., 2 and 1). In this way, every border of a 1°×1° zone gets smoothed once (substeps 'a~d' are for four borders, respectively, where a~b are for the horizontal borders while c~d are for the vertical borders), but the four corners get smoothed twice (both horizontally and vertically).*'

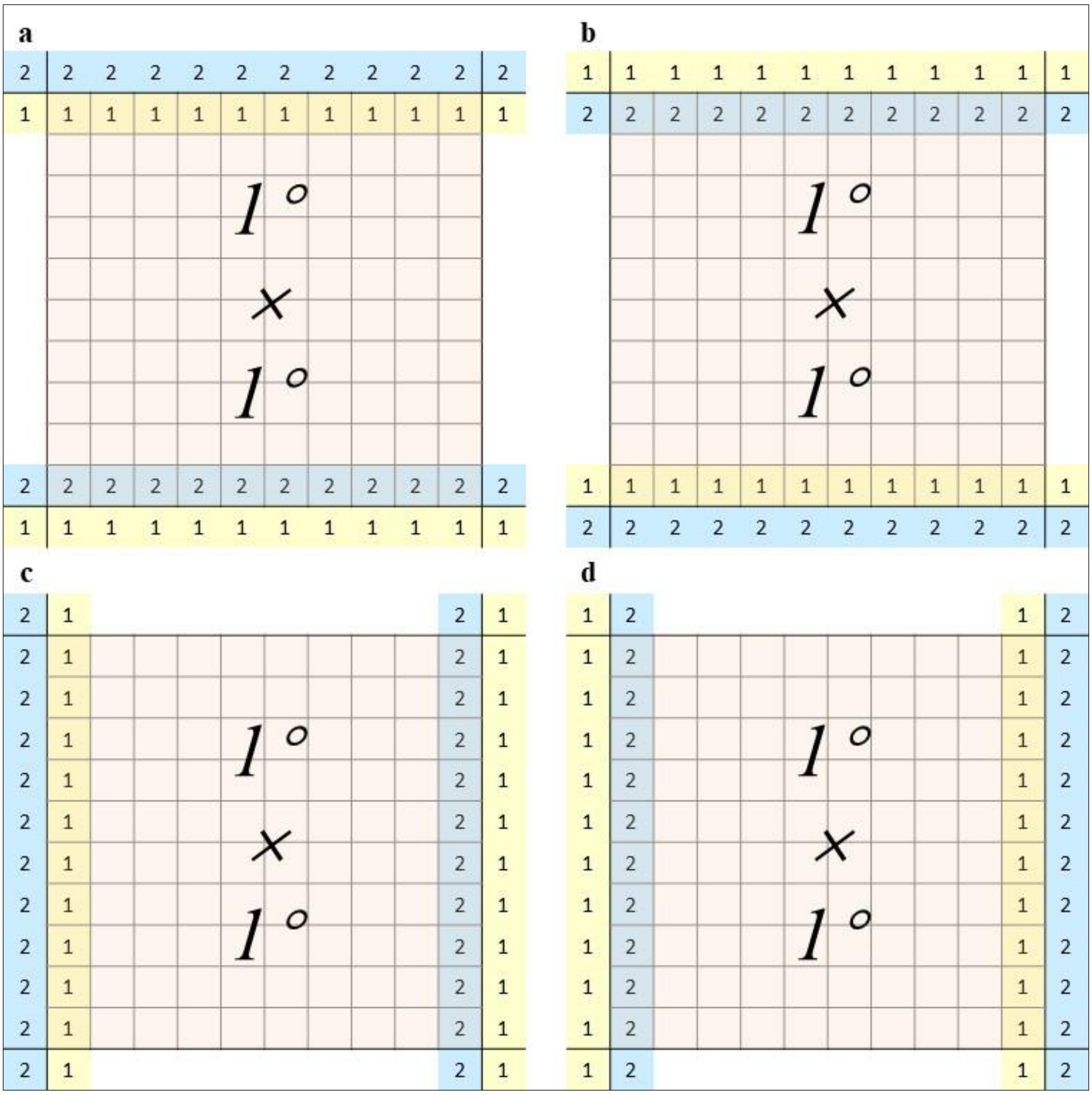

Figure R4. A sketch of the four substeps in boundary fuzzification. The 1°×1° zones are separated by solid black lines (the 0.1°×0.1° pixels in one zone are superimposed by light gray mesh). For each substep (subfigures a~d), the soil moisture value within each pixel that is colored in blue is recalculated as the average of its original surface soil moisture and the original soil moisture value in its most adjacent yellow color pixel, weighted by the corresponding numbers labeled (i.e., 2 and 1). In this way, every border of a 1°×1° zone gets smoothed once (substeps 'a~d' are for four borders, respectively, where a~b are for the horizontal borders while c~d are for the vertical borders), but the four corners get smoothed twice (both horizontally and vertically).

Specific comment 37. Figures S5, S8, S11: put the color-key to the bottom of the figure (a single key would be sufficient for all sub-figures), you could even remove the x-axis labels and names and leave only the lowermost. By this you can increase the size of the bars and hence the readability (reduce redundancy).

Response: We have revised these figures, making the size of the bars much larger now by adjusting the locations of the color keys and removing the x-axis names.

Specific comment 38. There are often blanks missing between words. DOIs are completely missing in the reference list.

Response: We apologize for these mistakes. We have added the missing blanks and rewritten the reference list (added DOIs, abbreviated the journal names, corrected the incorrect references) to ensure that it meets the format requirement of ESSD. Thank you again for your careful reading and valuable suggestions.

References

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