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 #3:

We thank referee #3 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 a detailed response to the Referee's comments in the Supplement.

****

General comment: The authors used an iterative neural network approach to produce a new satellite-based soil moisture dataset using 11 microwave soil moisture products, using SMAP data for training and ISMN database for validation. The approach is quite original and efficient resulting is a improvement in the accuracy of the spatio-temporal patterns at the global scale, and at a 0.1 degree resolution. However, the manuscript will need to be improved before acceptance, in its structure, clarity and tone.

Response: Thank you for your positive comments on our work. We have adjusted the article structure, revised the Methods section to make it clearer, and modified the tone of the expressions of the comparison of our product against other products. In addition, we have revised the figures and tables following each of the comments. Please find the details in the responses to the following comments.

Major comment 1: The introduction would need to be improved. Several statements need to be supported by existing literature, others would need to be clarified. Finally the introduction would need to end with a brief description of the approach used in the study and how this approach will address the three major concerns raised from existing soil moisture products. See detailed comments below for details.

Response: We have carefully addressed all the identified problems, including adding additional references, clarifying the confusing phrases, and briefly introducing how the approach addressed the three major concerns. Please see our responses to Specific comments 3~11 for details. Thank you for these suggestions.

Major comment 2: The tone of the manuscript when referring to the new product and to past studies is not always appropriate. For instance, stating that the present product is "superior to the existing products" is useless, not informative and condescending. I would encourage the authors to rather explain how their product is an improvement to the global estimation of soil moisture, without necessarily condemn other products. In the result section, while nonlinearities between estimate and in-situ soil moisture measurements are identified for other products, it is not reported for the author's product which I find quite biased.

Response: We apologize for the inappropriate descriptions. We have corrected the descriptions in the abstract as follows: '*This new dataset, named RSSSM, is comparable to the in situ surface soil moisture measurements at the International Soil Moisture Network sites (overall* R^2 *and RMSE values of 0.42 and 0.087* m^3/m^3*), while the overall* R^2 *and RMSE values for the existing products (ASCAT-SWI, GLDAS Noah, ERA5-Land, CCI/ECV and GLEAM) are within the range of 0.31~0.41 and 0.095~0.142* m^3/m^3*, respectively. The advantage of RSSSM is especially obvious in arid or relatively cold areas and during growing seasons. Moreover, the persistent high data quality as well as complete spatial coverage ensure the applicability of RSSSM to studies on both spatial and temporal patterns.*' We have also reported the nonlinearity of the relationship between our data and in situ measurements, following: '*However, RSSSM overestimates soil moisture when it is low, which is a problem inherited from the SMAP product (Figure 4) and is slightly nonlinearly correlated with the measured values (Figure 7a).*'

Major comment 3. The validation approach is based on site specific comparison. However, soil moisture being so spatially variable within a 0.1 degree pixel, validation based on single site observations within 0.1 degree pixels can be quite meaningless. This might be particularly true when one considers that site selection for in-situ measurement is rarely motivated by representativity of the surrounding landscape, but by specific ecological reasons.

Response: We agree that although only the 'good' quality data records were used, due to high spatial variability in surface soil moisture, it is not very reasonable to compare the 0.1° resolution soil moisture product against the ISMN site-scale measurements. However, the currently available global-scale soil moisture products are all coarse resolution, usually approximately 0.25°. To evaluate these coarse resolution products, previous studies also had to rely on the site-measured soil moisture, especially the ISMN dataset, while the validation process and the evaluation indicators are almost the same as those used in this study (Al-Yaari et al., 2019; Albergel et al., 2012; Dorigo et al., 2015; Fernandez-Moran et al., 2017; Gao et al., 2020; Karthikeyan et al., 2017; Kerr et al., 2016; Kim et al., 2015b; Kolassa et al., 2018; Lievens et al., 2017; Zhang et al., 2019). For 29 ISMN networks used for validation in this study, 19 are dense networks (usually with multiple stations within one 0.1° pixel (Dorigo et al., 2015)), including AMMA-CATCH (Cappelaere et al., 2009; De Rosnay et al., 2009; Lebel et al., 2009; Mougin et al., 2009; Pellarin et al., 2009), BIEBRZA_S-1 (http://www.igik.edu.pl/en), BNZ-LTER (Van Cleve et al., 2015) (http://www.lter.uaf.edu/), CTP_SMTMN (Yang et al., 2013), FLUXNET-AMERIFLUX (http://ameriflux.lbl.gov/), FR_Aqui (Al-Yaari et al., 2018), HiWATER_EHWSN (Jin et al., 2014; Kang et al., 2014), HOBE (Bircher et al., 2012), HYDROL-NET_PERUGIA (Morbidelli et al., 2014), iRON (Osenga et al., 2019), MAQU (Su et al., 2011), OZNET (Smith et al., 2012; Young et al., 2008), REMEDHUS (http://campus.usal.es/~hidrus/), SASMAS (Rüdiger et al., 2007), SKKU (Hyunglok et al., 2016), SOILSCAPE (Moghaddam et al., 2010; Moghaddam et al., 2016), SWEX_POLAND (Marczewski et al., 2010), VAS (http://nimbus.uv.es/) and WSMN (http://www.aber.ac.uk/wsmn). This information has been added to Text S2. Therefore, the average of the data obtained from two or more stations within a 0.1° pixel, which was calculated in this study, can best represent the grid-scale soil moisture conditions (Gruber et al., 2020).

In addition, to avoid the errors induced by the high spatial variability of soil moisture as much as possible, we excluded pixels with nonnegligible open water, wetland or inundated fields. In Supplementary Text- Text S2, the related details now read: '*It has been acknowledged that the scale difference between the records at ISMN sites and the 0.1° pixel-scale soil moisture data may lead to incomparability, especially for pixels with open water and inundated land (Loew, 2008). If the measurement site is located* *on land, away from water, yet the corresponding pixel contains much water, the pixel-scale soil moisture can be significantly higher than the site-measured values. Conversely, if the site is in or close to the open water or inundated areas but land also exists in the pixel, the soil moisture measured at the station will be much higher than the average pixel value. The absolute values are unmatchable, and the temporal variations cannot be directly compared as well, because the moisture conditions of riverside (or wetland) soil and the land soil may change with precipitation differently. Therefore, the sites located in the pixels with an average annual maximal water area fraction greater than 5% according to SWAMPS data are excluded (for example, some sites in wetlands in Canada).*' We also added more explanations in the manuscript as follows: 1) '*After data screening and processing (for example, in the case of high spatial variability in soil moisture, we excluded the pixels with average annual maximal water area fractions greater than 5%, see Text S2), …*'; 2) *More than 90% of the stations are located in relatively flat areas with topographic complexity less than 10%;* and 3) '*Hence, to make full use of all the high-quality records and to reduce the problem caused by the scale difference between simulation and measurement, the site-scale 10-day averaged soil moisture data are further aggregated to a 0.1° pixel-scale by averaging all the data (different stations or different sensors) within the pixel (Gruber et al., 2020).*'

Specific comment 1: "This new dataset, once validated against the International Soil Moisture Network (ISMN) records, is supposed to be superior to the existing products" . Do you mean this validation hasn't been done yet? Superior in what way?

Response: We apologize for the confusion. Following this comment, we show the situation that our product is preferred, according to the validation against site measurements, instead of the general description that our product is superior to other products. We have made the clarification as follows: '*This new dataset, named RSSSM, is comparable to the in situ surface soil moisture measurements at the International Soil Moisture Network sites (overall R^2 and RMSE values of 0.42 and 0.087 m^3/m^3), while the overall R^2 and RMSE values for the existing products (ASCAT-SWI, GLDAS Noah, ERA5-Land, CCI/ECV and GLEAM) are within the range of 0.31~0.41 and 0.095~0.142 m^3/m^3, respectively. The advantage of RSSSM is especially obvious in arid* *or relatively cold areas and during growing seasons. Moreover, the persistent high data quality as well as complete spatial coverage ensure the applicability of RSSSM to studies on both spatial and temporal patterns.*'

Specific comment 2: "reveals that the surface moisture decline on rainless days is highest in summers over the low-latitudes but highest in winters over most mid-latitude areas." Soil moisture being so spatially variable, I find the impact of this statement quite limited – e.g. low latitude regions range from tropical/equatorial rain forests to deserts and one would expect as much differences in the sensitivity of soil moisture to precipitation between a desert and a tropical forest than between a tropical forest and a temperate prairie.

Response: We apologize for the unclear sentences. In the calculation of soil moisture decline on consecutive rainless days, because '*In desert areas, the random noise of the surface soil moisture product can hide the signal of moisture changes, while in wet areas (e.g., rainforests), 20 days without effective precipitation seldom occurs, leading to no results over most areas.*', the acquired results can represent the conditions in only regions excluding deserts and rainforests. Following this comment, we have revised the sentence as follows: '*These data also reveal that without considering the deserts and rainforests, the surface moisture decline on consecutive rainless days is highest in summers over the low latitudes (30°S~30°N) but highest in winters over most midlatitude areas (30°N~60°N; 30°S~60°S).*'

Specific comment 3: "L47: "due to various disturbances": what type of disturbances?

Response: Following your comment, we have revised this phrase as '*due to various disturbances, such as high vegetation cover, high open water fractions and complex topography (Draper et al., 2012; Fan et al., 2020; Ye et al., 2015)*' to improve the clarity.

Specific comment 4: "L49: " Although new sensors, SMOS : : :." -> "Although new sensors such as SMOS: : :"

Response: We have revised this phrase accordingly.

Specific comment 5: L 50: "better penetrability" -> please be more specific: what depth?

Response: We apologize for the unclear expression. It does not indicate the nominal soil depth of the microwave soil moisture. We have revised it to '... *because L-band microwaves (1~2 GHz) can penetrate the vegetation canopy better than other bands,'* by referring to (Piles et al., 2018).

Specific comment 6: L66: "Because the temporal variation in soil moisture is often better captured by model simulations than remote sensing inversions": please include a reference that support this statement. L67: "CCI may undesirably combine the disadvantages of both." Be more specific here (low accuracy of temporal variations from remote sensing products and low spatial accuracy from model simulations – am I right?). And please include another reference here for this second statement.

Response: We apologize for the arbitrary statements. We agree that there is no strong evidence supporting the claim that the temporal variation in soil moisture is better captured by model simulations than remote sensing inversions. Following this comment, we have deleted these two sentences in the Introduction of the manuscript. Thank you for the reminder!

Specific comment 7: L70: "are assimilated instead": instead of what? this sentence is not clear.

Response: Following this comment, we have revised the sentence as follows: '*Currently, anomalies of CCI soil moisture (the deviations to the seasonal climatology that indicate whether the soil moisture at a time point is more humid or drier than the multi-year average) are assimilated instead of the original CCI time series (Martens et al., 2017).*'

Specific comment 8: L85: "Among these three approaches, machine learning proves to be probably the best choice" based on what criteria – again, please be more specific

Response: Following this comment, we revised the sentence as follows: '*Among these* *three approaches, machine learning has been proven to be the best choice according to the connection between precipitation and the changes in soil moisture, as evaluated through a data assimilation technique and triple collocation analysis results (Van der Schalie et al., 2018).*'

Specific comment 9: "L102: "substantial success has not been achieved yet." This is a rather strong and yet vague statement that denies the merits of a large body of research. Please remove this statement.

Response: We apologize for the confusion. We have revised the sentence as follows: '*In conclusion, while previous studies have focused on developing long-term satellite-based surface moisture products using machine learning, some major concerns remain that need to be solved. 1)…*'

Specific comment 10: "L102/103:" the high-quality microwave observations are not fully utilized": this is not clear from the literature review – please develop this point in earlier sections of the introduction (i.e. in what way high-quality microwave observations haven't been fully utilized, and how the authors are proposing to utilize them more efficiently).

Response: To avoid potential misunderstanding, we have revised the sentence as follows: '*1) The microwave observations from only three sensors at most are utilized, leading to large temporal and spatial gaps and limited the training efficiency*.' This point has been illustrated in the earlier sections of the introduction: '*A global long-term observational-based soil moisture product was recently developed by building a neural network between the SMOS product and the Tb data from AMSRE (2003~September 2011) and AMSR2 (July 2012~2015) (Yao et al., 2017)…. The gap between the temporal spans of AMSRE and AMSR2 and the lack of SMOS data in Asia resulted in large quantities of missing data.*'

Specific comment 11: "L106-107: This statement should be removed from the introduction section. - this is rather a concluding statement. Instead please describe your approach in a couple sentences and how this approach addresses the three major concerns identified.

Response: Thank you for your advice. We have rewritten the paragraph as: '*... some major concerns remain that need to be solved. 1) The microwave observations from only three sensors at most are utilized, leading to large temporal and spatial gaps and limited the training efficiency; 2) it remains unclear which environmental factors should be incorporated as ancillary inputs and why; and 3) the training designed for soil moisture estimation at the global scale should be more complex than that for only a specific region to ensure satisfactory training efficiency. In this study, 11 high-quality microwave soil moisture products since 2003 are incorporated into 5 rounds of neural networks to achieve a spatially and temporally continuous simulation for 2003~2018, using as many sources of microwave observational data as possible as predictors in each neural network. The factors impacting the quality of microwave soil moisture retrievals are also determined and then utilized as ancillary inputs to improve the training efficiency. Moreover, we designed localized subnetworks instead of only one global-scale neural network to account for the regional differences in training rules.*'

Specific comment 12: "Section 2.1 L110: please add citation to literature supporting this statement.

Response: In the Introduction section, the best overall quality of SMAP soil moisture has been stated as follows: '*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 have revised this sentence and added two new references supporting the best performance of SMAP product. It reads: '*SMAP currently has the best quality of all remote sensing-based soil moisture products (Al-Yaari et al., 2019; Liu et al., 2019)…*'

Specific comment 13: L115-118: This sentence is too long and too complex. Please split into shorter and clearer sentences.

Response: We apologize for the complex sentence. We have revised it to: '*However, in this study, the well-acknowledged surface soil moisture products retrieved through mature algorithms (see Figure 1) are directly applied instead of Tb. These products are chosen because 1) the primary goal of this study is to calibrate and then fuse the existing popular microwave soil moisture products, and 2) the Tb signals at multiple bands contain too much information that is not related to soil moisture, which may weaken the training efficiency and lead to overfitting.*'

Specific comment 14: Section 2.2 L147/160: the purpose of this argumentation is quite unclear as the environmental predictors that are selected are also important drivers of soil moisture dynamic.

Response: We apologize for the arbitrary sentence. Here, we would like to express the idea that without the incorporation of any microwave remote sensing product, these factors (LAI, topographic complexity, LST, etc.) alone may not predict surface soil moisture very well. This phenomenon occurs because although we agree that they are somewhat related to soil moisture (e.g., soil moisture is usually limited in areas with low vegetation cover), they can hardly be considered direct indexes of surface soil moisture content (since the relationships are rather uncertain; for example, as found in this study, in Europe, the soil moisture is low in summers when vegetation peaks). On the other hand, however, we admit that the water area fraction is a direct indicator of surface soil moisture and have corrected it by adding the sentence '*Environmental factors, including DEM, LST and vegetation cover (indicated by NDVI, MVI, etc.), were used as ancillary neural network inputs to improve the soil moisture simulation (Lu et al., 2015; Qu et al., 2019; Yao et al., 2017). According to these studies, these factors* *alone may not predict surface soil moisture well without the incorporation of any microwave remote sensing data, which can also be justified by the contribution analysis results (Figure S1a). This phenomenon occurs because although these data are somewhat related to soil moisture (e.g., soil moisture is generally limited in areas with low vegetation cover but high in forests (McColl et al., 2017)), the relationships are rather uncertain (e.g., at small scales, leaf area index (LAI) may have a negative influence on soil moisture due to the variation in evapotranspiration (Naithani et al., 2013) or may not have clear impacts (Zhao et al., 2010); also, soil moisture can be either high or low in summers when vegetation peaks (Baldocchi et al., 2006; Méndez-Barroso et al., 2009)). However, these factors are essential due to their direct impacts on soil moisture retrieval through the radiative transfer model using microwave remote sensing data (Fan et al., 2020) and are factors that impact the retrieval quality. The detailed explanations are as follows: 1) …*'

Specific comment 15: L201: since precipitation is such an important driver of soil moisture, the reasons why this variable hasn't been included as a quality impact factor should be included in the main document.

Response: We have revised the sentence as follows: '*The contribution analysis results (Figure S1) show that because various microwave soil moisture data have already been included, precipitation data are not an essential indicator of soil moisture and are not utilized as a physically based 'quality impact factor' either (see Text S1 for detailed explanations).*'

The Text S1 is a bit long, so we did not move all the information to the manuscript, but we summarized the key reasons in the revised manuscript, following your advice. Text S1 has been revised as follows:

'*Because it takes at least 3 days for a microwave sensor to cover the globe, for 11% of global land, there will be only 5 or fewer observations for random days within a 10-day period. By taking the average of these available data, this study focuses on only the mean soil moisture condition during that 10-day period. Then, to see how much the incorporation of precipitation data can improve the neural network training efficiency,* *we calculated the 10-day averaged GPM Final-Run precipitation, which can indicate the overall precipitation water availability (the antecedent precipitation index is not used because it must be calculated on a daily scale, and the attenuation coefficient is difficult to determine at a global scale (Kohler and Linsley, 1951)). Taking the first primary independent neural network, NN1-1-1, as an example, we performed contribution tests on all the input features at the global scale (not for each separate zone), including 9 'quality impact factors', 4 soil moisture predictor products and precipitation - a potential ancillary soil moisture indicator. For each predictor, we added a random error that is controlled within the standard deviation of the predictor, and then an increase in MSE during neural network training can indicate the relative contribution of that variable. The results (Figure S1a) show that precipitation will contribute to only 1.7% of the training efficiency, which is much lower than the contribution of any soil moisture product (the total contribution fraction of the four soil moisture products is 61.2%) and is also lower than that of most 'quality impact factor'. This result suggests that various microwave soil moisture datasets together with several 'quality impact factors' of microwave soil moisture retrieval are enough to predict the training target, SMAP soil moisture, and there is no need to add precipitation as another ancillary indicator of soil moisture.*

'Quality impact factors' are defined in this study as the variables that will have a significant impact on the retrieval errors of soil moisture by microwave remote sensing (section 2.1.2). Although the relative performances of different soil moisture products are related to surface moisture conditions (Kim et al., 2015a), it is found mainly due to the less vegetation in arid areas. After all, no explicit mechanism can support the idea that the retrieval errors of soil moisture are significantly influenced by water availability. Even if this is true, the soil water availability can already be indicated by the microwave soil moisture products. Therefore, it is unreasonable to incorporate the precipitation variable as a 'quality impact factor'. On the other hand, LAI, water area fraction, LST, land use cover, tree cover fraction, non-tree vegetation area fraction, topographic complexity, and soil sand/clay fractions all have direct impacts on the microwave soil moisture retrieval errors, with solid physical mechanisms (see section 2.1.2). Therefore, theoretically, these variables should be added to the neural network, even though the land use cover type and soil sand fraction data have been proven to have limited contributions to NN training efficiency.

One may argue that if NARX (nonlinear autoregressive with external input) is applied instead, in which the soil moisture in the previous 10-day period is also incorporated as a predictor, precipitation data can be very beneficial to neural network training. This is true because precipitation directly contributes to increases in soil moisture. However, NARX is not suitable for global-scale long-term continuous soil moisture mapping because the base map (i.e., soil moisture at the beginning of the simulation period) is difficult to determine. Moreover, in mid to high latitudes, the lack of soil moisture retrievals over frozen ground in winters will lead to missing data there in summers when soil moisture data are otherwise available. Therefore, if NARX is adopted, we can only estimate long-term surface soil moisture in the tropics and subtropics with air temperatures consistently higher than 0 ℃. Finally, if the soil moisture in the previous phase and the current precipitation amount are both incorporated, they will largely conceal the role of satellite-observed signals. As shown in Figure S1b, the total contribution fraction of all four microwave soil moisture products is reduced to only 10.6%, while the roles of ASCAT, AMSR2-JAXA and AMSR2-LPRM are all negligible. Without taking full advantage of remote sensing, simulations based on previous soil moisture and current precipitation products will lead to errors in regions where soil moisture gains are mostly driven by glacier melting or in places with high levels of radiation-driven soil evaporation. The reliability of the derived soil moisture will be reduced in irrigated croplands and afforestation/deforestation areas as well.

On account of all of the above, precipitation data are neither included as an ancillary soil moisture indicator nor added as a 'quality impact factor' in this study.'

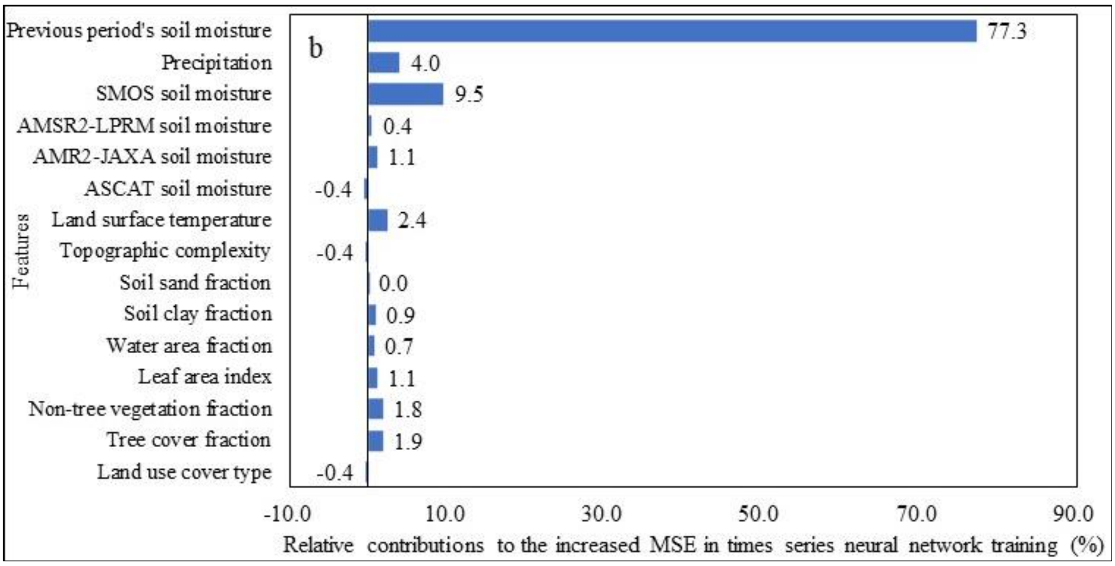

Figure R1 (Figure S1 in the revised Supplement): The roles of different input features *in the soil moisture simulations based on BP neural networks and nonlinear autoregressive with external input (NARX) with microwave soil moisture products incorporated: (a) the contributions of different input features of a primary neural network: NN1-1-1, including 4 predictor soil moisture products, 9 quality impact factors of microwave soil moisture retrieval, plus 1 probable ancillary soil water indicator: 10-day averaged precipitation, to the neural network training efficiency indicated by the increased MSE; (b) the contributions of all the input features to the training efficiency if NN1-1-1 is changed into a NARX, in which the SMAP soil moisture for the previous period is also applied as a predictor.*

Specific comment 16: L202/203: This sentence should start this section, not end it. A table similar to table 1 but for the quality impact factors would be useful. The table would indicate the source of the data, the resolution and the temporal span for the dynamic factors.

Response: Following your suggestion, we have revised this section, moving this concluding sentence to the beginning. It now reads as:

‘*In this study, 9 quality impact factors, LAI, water fraction, LST, land use cover, tree cover fraction, non-tree vegetation fraction, topographic complexity, and sand and clay fractions, are selected and incorporated (see Figure 1). The reasons for the selection of these factors are as follows.*

Based on the two criteria above, the first environmental factor to be included is the ‘vegetation factor’ (i.e., vegetation water content, VWC) … Because the LAI stands for the total leaf area per unit land, which is closely related to VWC assuming a relatively stable leaf equivalent water thickness (Yilmaz et al., 2008), LAI is a suitable surrogate….’

We also added a timeline figure (Figure 1 in the revised manuscript) to show the temporal spans, sources and spatial resolution of all microwave soil moisture products and the data for 9 quality impact factors. This figure presents the information more clearly than a table.

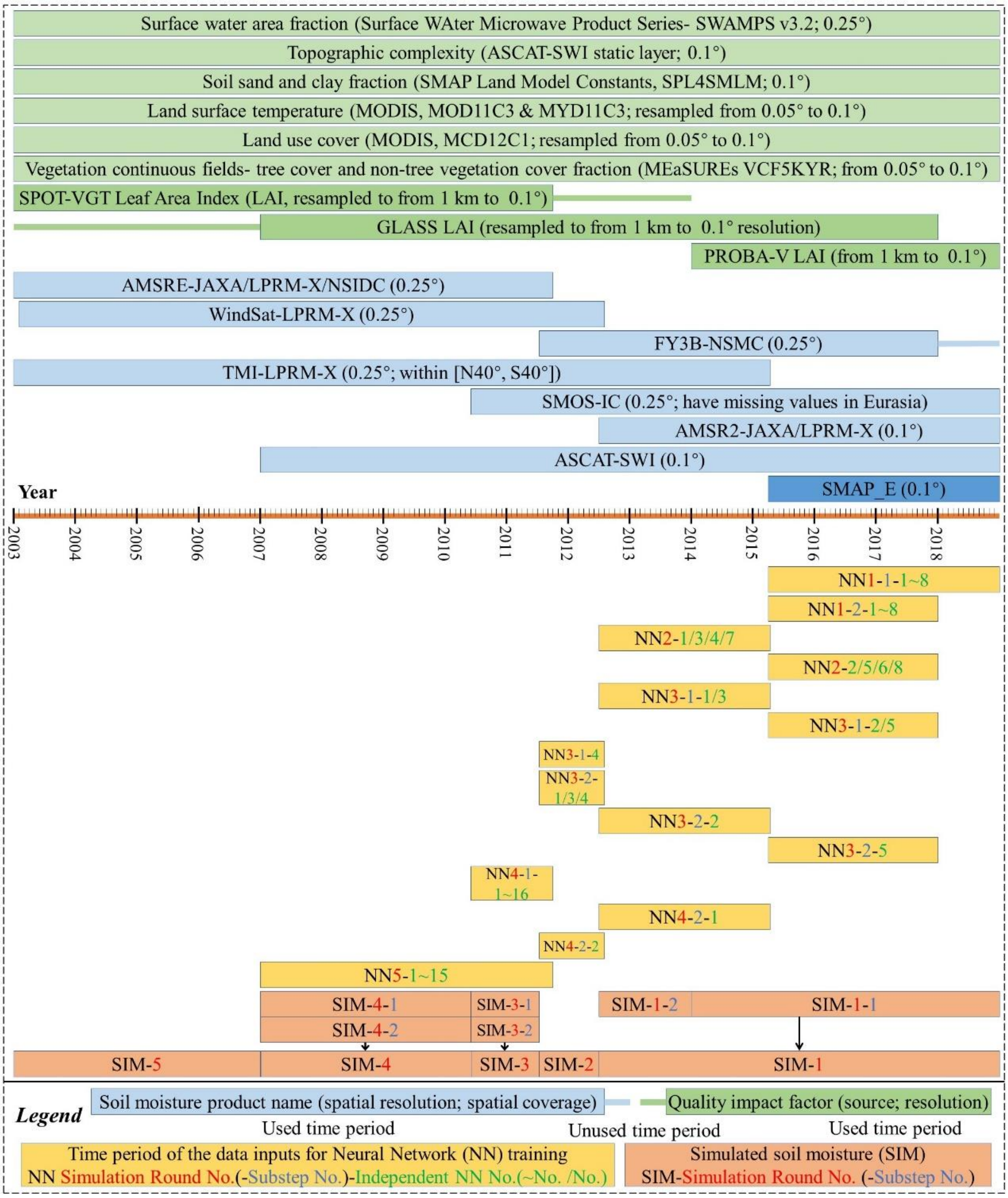

Figure R2 (Figure 1 in the revised manuscript): The timeline figure showing the time periods of the soil moisture datasets and the 'quality impact factor' products (e.g., LAI dataset) used in this study (listed above the timeline), as well as the periods of data applied for the trainings of the 67 independent neural networks and the neural network simulation outputs (i.e., simulated soil moisture) of eight substeps (listed below the timeline).

Specific comment 17: Section 2.3 Sections 2.4, 2.5 and 2.6 should be included in section 2.3 as it details the different steps of the calculation flow. A clear justification on why a neural network approach was adopted should be included in this section.

Response: We have made the revision accordingly. The structure for the Data and Method Section is now as follows:

'2 Data and methods

2.1 Data for the production of global long-term surface soil moisture data

2.1.1 Satellite-based surface soil moisture data products

2.1.2 The quality impact factors of soil moisture retrievals

2.2 Methods for the production of global long-term surface soil moisture data

The steps taken to produce global long-term surface soil moisture data include three basic parts, which are as follows. 1) Preprocessing: the production of high-quality neural network inputs; 2) neural network operation: the network training and soil moisture simulation; and 3) postprocessing: the correction of potential errors or deficiencies in the soil moisture simulation outputs…

2.2.1 Neural network design (1): localized neural networks

2.2.2 Preprocessing and postprocessing steps

2.2.3 Neural network design (2)- five rounds of simulations

2.3 Methods for the validation of surface soil moisture products

2.4 Methods for the intra-annual variation analysis of surface soil moisture'.

The justification of the neural network approach is now in the Introduction: '*Among these three approaches, machine learning has been proven to be the best choice according to the connection between precipitation and the changes in soil moisture, as evaluated through a data assimilation technique and triple collocation analysis results (Van der Schalie et al., 2018).*' In section 2.1.2, we have already mentioned the use of neural network approach in this study, '*…were used as ancillary neural network inputs to improve the soil moisture simulation (Lu et al., 2015; Qu et al., 2019; Yao et al., 2017)*'.

Specific comment 18: L223: what is a hidden layer?

Response: In neural networks, the hidden layer is located between the input and output layers. This layer is the result of nonlinear transformations of the input data through the activation function and can also be transformed into the output data. We have revised the sentence as '*…, and the number of nodes in the hidden layer (between the input and output layers (Stinchcombe and White, 1989)) of each subnetwork was set to 7.*'

Specific comment 19: L242: reference required for the "suspicious value removal".

Response: We apologize for the confusing phrase. Actually, it is a detailed method invented by this study to ensure that only the most reliable estimates are applied as the training target of the next round of neural networks to avoid significant error propagation along the subsequence of neural network rounds. Because multiple rounds of the neural network is a characteristic of this study, this processing step was not found in previous studies (i.e., no reference). We have revised the sentence, removing the phrase '*suspicious value removal*'. It now reads: '*On the other hand, to avoid error propagation with training times by ensuring a high-quality training target for the next round's simulation, we remove all suspicious values for every simulated result. This preprocessing step is performed by first obtaining the maximal and minimum values of SMAP_E soil moisture in each pixel. If the simulated value is out of the range of the SMAP data during 2015~2018, the value is considered suspicious and is not used as a training target.*'

Specific comment 20: L259: Here you are referring to a 1 degree pixel a presume? Please specify.

Response: We apologize for the confusing sentences. We have revised the sentences to: '*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..*' In the revised manuscript, the word 'pixel' only stands for 0.1-degree resolution, while the word 'zone' indicates 1° scale.

Specific comment 21: Please specify. L268: why 74 networks? Please explain.

Response: We have corrected it to '67 independent neural networks' because the remaining 7 networks are optional and not independent. There are multiple independent networks included in each round. That is because '*... While increasing the sources of soil moisture data inputs can be beneficial to the training efficiency, the spatial coverage of the simulation output is sacrificed because the overlapping area decreases with the increase in the number of soil moisture products. After all, most products have missing data in specific regions ... To solve that dilemma, we classified all 0.1° pixels according to the available predictor soil moisture products over a 10-day period (for example, if there are at most four soil moisture data inputs in one round, there should be 4+3+2+1=10 combinations). However, to avoid soil moisture simulation under snow or ice cover (Section 2.2.2), not all combinations are considered. Then, corresponding to each selected combination, an independent neural network is trained*' (Lines 269~277 in the revised manuscript). The revised explanations are clearer than the original version.

In addition, the training periods of the 67 independent neural networks are now shown in Figure R2 (Figure 1 in the revised manuscript). Therefore, this sentence is now revised to: '*Based on these principles, five rounds of neural networks are designed as follows, with 8 substeps containing a total of 67 independent neural networks. The training period for each neural network and the simulation period for each substep are shown in Figure 1 (below the timeline), and the details are as follows: ...*'

Specific comment 22: Section 2.7 Figure S2 should be included in the main manuscript as the spatial distribution of validation data is critically important to evaluate the overall strength of this validation. It is surprising that none of the Canadian sites of the Russian sites made it to the final set of sites for validation.

Response: Thank you for this advice. We have moved the figure showing the spatial distribution of the validation sites to the main manuscript (shown in Figure 3).

The soil moisture measurement depths for the Russian sites are 0~10 cm (RUSWET-

GRASS) or 0~20 cm (RUSWET-AGRO and RUSWET-VALDAI) (Robock et al., 2000), which do not match the nominal simulation depth (0~5 cm) of our soil moisture product (constrained by SMAP).

On the other hand, the Canadian sites are actually very limited (Dorigo et al., 2011; Dorigo et al., 2013) (https://www.geo.tuwien.ac.at/insitu/data_viewer/) and are often wetland sites with nonnegligible water fractions, which should be removed. Previous studies also utilized very few sites in Canada and Russia (Kolassa et al., 2018; Lievens et al., 2017; Zhang et al., 2019).

In the revised manuscript, we added the information '*Accordingly, the measurements used for validation are limited to ≤ 5 cm in depth (e.g., the Russian networks were not applicable for this reason).*'

Specific comment 23: L304/306: This is an important point. Soil moisture being so spatially variable, validation based on single site observations within 0.1 degree pixels can be quite meaningless. Especially when one considers that site selection for in situ measurement is rarely motivated by representativity of the surrounding landscape, but by specific ecological reasons.

Response: Thank you for your careful consideration. Because grid-scale soil moisture measurements are unavailable, almost all recent studies rely on in situ soil moisture records for the validation of remote sensing soil moisture products. Moreover, we have taken the average of the data at multiple stations in a 0.1° grid and excluded grids with potentially high spatial heterogeneity of surface soil moisture. Please see the response to Major comment 3 for details.

Specific comment 24: Section 2.8 L335: "probably the best choice for periodic function fitting" : please support this statement by adequate reference to literature.

Response: We have revised it to '*Fourier functions can characterize intra-annual variation well (Brooks et al., 2012; Hermance et al., 2007). Therefore, for the remaining areas …, we fit the intra-annual cycle of soil moisture using the Fourier function…*'

Specific comment 25: L344/345: I don't understand this argument. Why restricting this analysis to 10 consecutive rainless days and not the whole range of 10-days sum of precipitation?

Response: This study explored the impact of dry periods (20 consecutive days without effective rainfall) on the surface soil moisture in different areas. Moreover, without effective precipitation, the surface soil moisture changes are mainly driven by evaporation and deep percolation and thus should be negative. This process is simpler and can help us exclude unreliable soil moisture values from the analysis. However, if we consider the sum of precipitation over 10 days, the surface soil moisture changes will be rather complex, and there would be much more erroneous data included, leading to unreliable analysis results.

We have revised the sentence to: '*Because RSSSM indicates the average soil moisture condition during every 10-day period, we evaluate the surface soil moisture decline after 20 consecutive days (i.e., two adjacent 10-day periods) without effective precipitation to explore the impact of dry periods on surface soil moisture.*'

Specific comment 26: Tables 3 to 8 could be synthesized into only two tables: one for temporal accuracy assessment and one for spatial accuracy assessment for the three products comparisons with SIM. Similarly, it would be nice to have figures 3, 4, 6, 7, 9 and 10 summarized in 2 figures where all four products appear (SIM, SMAP, GLDAS and ASCAT). This would facilitate comparison between products.

Response: Thank you for this advice. The periods corresponding to these comparisons differ from each other. SMAP has data since March 2015, ASCAT is available from 2007, while SIM (named 'RSSSM' in the revised manuscript), GLDAS, ERA5 Land and GLEAM v3.3a all cover the whole study period (2003~2018), but with missing values in different areas. Although CCI (ECV) also covers the entire period, it lacks data in many places, especially before 2007 (Figure 13d). Therefore, the in situ surface soil moisture measurements entering the comparison between RSSSM and SMAP are limited to March 2015~2018, whereas only the ISMN site data during 2007~2018 were applied for the accuracy comparison between RSSSM and ASCAT. Additionally, when comparing RSSSM against CCI (ECV), we included the soil moisture records in only the grids with both RSSSM and CCI data during the specific period. As we can see, the overall accuracy of RSSSM in Figure 4c (for the comparison with SMAP, during April 2015~2018) is R^2=0.46, RMSE=0.083, but in Figure 10 (for comparison against GLDAS, during 2003~2018), the overall R^2 of RSSSM is 0.42, and the RMSE is 0.087. In addition, the temporal accuracy of RSSSM in all climatic regions (Figure 5, Figure 8, Figure 11 in the revised paper) and its spatial accuracy during all seasons (Figure 6, Figure 9, Figure 12) are different among the comparisons against different soil moisture products. For that reason, if the 6 figures are combined into 2 figures, they will be too crowded, and the comparison will be not clear enough.

Following your comment, we have combined the tables as follows:

Table R1 (Table 2 in the revised manuscript): The mean and median values of the five evaluation indexes (correlation coefficient: r, RMSE, bias, unbiased RMSE (ubRMSE), and the anomalies r (A.R)) on the temporal accuracy of the surface soil moisture simulated in this study (RSSSM) and the other surface soil moisture products when validated using ISMN in situ measurements. Note: 1) for the comparison of RSSSM against the SMAP_E (SMAP) product, the validation period is from April 2015 to 2018; 2) for the comparison between RSSSM and ASCAT-SWI (ASCAT), the period is 2007~2018; 3) the comparison period for RSSSM and GLDAS Noah v2.1 (GLDAS), ERA5-Land (ERA5-L), CCI or GLEAM v3.3a (GLE-a) surface soil moisture product is 2003~2018; 4) the common period for RSSSM and GLEAM v3.3b (GLE-b) is from 2003 to September 2018.

Index	*r*		RMSE		bias		ubRMSE		A.R	
Product	RSSSM	SMAP	RSSSM	SMAP	RSSSM	SMAP	RSSSM	SMAP	RSSSM	SMAP
Mean	0.756	0.762	0.075	0.074	0.015	0.016	0.043	0.043	0.700	0.707
Median	0.795	0.798	0.067	0.066	0.009	0.013	0.043	0.043	0.720	0.744
Product	RSSSM	ASCAT	RSSSM	ASCAT	RSSSM	ASCAT	RSSSM	ASCAT	RSSSM	ASCAT
Mean	0.687	0.561	0.079	0.095	0.002	-0.007	0.047	0.062	0.627	0.554
Median	0.735	0.627	0.074	0.088	-0.001	-0.010	0.048	0.062	0.654	0.595
Product	RSSSM	GLDAS	RSSSM	GLDAS	RSSSM	GLDAS	RSSSM	GLDAS	RSSSM	GLDAS
Mean	0.689	0.613	0.080	0.091	0.001	0.028	0.047	0.051	0.620	0.519
Median	0.737	0.661	0.075	0.082	-0.002	0.029	0.048	0.049	0.661	0.567

Product	RSSSM	ERA5-L	RSSSM	ERA5-L	RSSSM	ERA5-L	RSSSM	ERA5-L	RSSSM	ERA5-L
Mean	0.689	0.734	0.080	0.112	0.001	0.082	0.047	0.050	0.620	0.648
Median	0.737	0.758	0.075	0.094	-0.002	0.073	0.048	0.049	0.661	0.672
Product	RSSSM	CCI	RSSSM	CCI	RSSSM	CCI	RSSSM	CCI	RSSSM	CCI
Mean	0.690	0.642	0.080	0.091	0.002	-0.002	0.047	0.049	0.620	0.530
Median	0.735	0.666	0.074	0.080	-0.002	0.006	0.049	0.047	0.658	0.552
Product	RSSSM	GLE-a	RSSSM	GLE-a	RSSSM	GLE-a	RSSSM	GLE-a	RSSSM	GLE-a
Mean	0.689	0.735	0.080	0.126	0.001	0.093	0.047	0.047	0.620	0.681
Median	0.737	0.771	0.075	0.119	-0.002	0.104	0.048	0.046	0.661	0.715
Product	RSSSM	GLE-b	RSSSM	GLE-b	RSSSM	GLE-b	RSSSM	GLE-b	RSSSM	GLE-b
Mean	0.688	0.729	0.080	0.117	0.001	0.077	0.047	0.046	0.618	0.670
Median	0.730	0.762	0.075	0.112	-0.002	0.091	0.048	0.045	0.659	0.705

Table R2 (Table 3 in the revised manuscript): The mean and median values of the four evaluation indexes (r, RMSE, bias and ubRMSE) on the spatial pattern accuracy of RSSSM and the other global long-term surface soil moisture products (SMAP_E, ASCAT-SWI, GLDAS Noah v2.1, ERA5-Land, CCI, GLEAM v3.3a and GLEAM v3.3b) in every 10-day period. For each pair of comparisons, the evaluation indexes are for the common period of the two products, which is the same as Table 2. The abbreviations for the products are also the same as those in Table 2.

Index	*r*		RMSE		bias		ubRMSE	
Product	RSSSM	SMAP	RSSSM	SMAP	RSSSM	SMAP	RSSSM	SMAP
Mean	0.652	0.659	0.084	0.084	0.016	0.016	0.082	0.081
Median	0.655	0.664	0.082	0.081	0.019	0.019	0.080	0.078
Product	RSSSM	ASCAT	RSSSM	ASCAT	RSSSM	ASCAT	RSSSM	ASCAT
Mean	0.636	0.561	0.087	0.102	0.005	-0.010	0.085	0.097
Median	0.650	0.572	0.086	0.100	0.007	-0.009	0.085	0.095
Product	RSSSM	GLDAS	RSSSM	GLDAS	RSSSM	GLDAS	RSSSM	GLDAS
Mean	0.617	0.593	0.090	0.097	-0.005	0.035	0.086	0.087
Median	0.643	0.630	0.089	0.096	0.001	0.041	0.086	0.086
Product	RSSSM	ERA5-L	RSSSM	ERA5-L	RSSSM	ERA5-L	RSSSM	ERA5-L
Mean	0.616	0.575	0.090	0.125	-0.005	0.077	0.086	0.095
Median	0.641	0.633	0.089	0.125	0.001	0.082	0.086	0.092
Product	RSSSM	CCI	RSSSM	CCI	RSSSM	CCI	RSSSM	CCI
Mean	0.618	0.497	0.090	0.099	-0.004	0.003	0.086	0.093
Median	0.647	0.554	0.089	0.098	0.002	0.006	0.086	0.093
Product	RSSSM	GLE-a	RSSSM	GLE-a	RSSSM	GLE-a	RSSSM	GLE-a
Mean	0.617	0.576	0.090	0.139	-0.005	0.105	0.086	0.089
Median	0.643	0.616	0.089	0.142	0.001	0.112	0.086	0.088

Product	RSSSM	GLE-b	RSSSM	GLE-b	RSSSM	GLE-b	RSSSM	GLE-b
Mean	0.616	0.560	0.090	0.128	-0.005	0.088	0.086	0.090
Median	0.643	0.613	0.089	0.130	0.001	0.094	0.086	0.089

Specific comment 27: L380-383: However, it looks like the relationship between SIM estimates and in situ observations is nonlinear (Figure 5a). Furthermore, SIM seems to overestimate soil moisture in the lowest range (winter?) when a density of pixels is quite high. Please include these remarks in the results.

Response: Thank you for the reminder. We have added a sentence accordingly. It reads: '*However, RSSSM overestimates soil moisture when it is low, which is a problem inherited from SMAP product (Figure 4), and is a bit nonlinearly correlated with the measured values (Figure 7a).*'

Specific comment 28: L393: the relationship between SIM and in situ measurements is also obviously nonlinear. Please include this remark in the text for fairness.

Response: We have revised the description accordingly. It now reads: '*While RSSSM is nonlinearly correlated with measured soil moisture, the relationship between GLDAS soil moisture and the measurements appears to be slightly more nonlinear, resulting in a smaller R^2 of 0.39 and higher RMSE of 0.097 for the GLDAS product than those for RSSSM (R^2: 0.42; RMSE: 0.087, see Figure 10).*'

Specific comment 29: Why table S19 and Figure S7 do not appear in the main document like the other product comparison? Please move them to the main manuscript

Response: We have combined Table S17, Table S19, Table S21, and Table S22 in the original Supplement to Table 2 in the revised manuscript (see Table R1). Table S18, Table S20, Table S23 and Table S24 are integrated into Table 3 as well (see Table R2). For the reasons described in the response to Specific comment 26 (the time periods and spatial extents for the comparisons of RSSSM in this study against the different existing surface soil moisture products), the figures were not combined to avoid over-crowding the figures and unnecessary confusion. Thus, we retained Figure S7, Figure S8, etc. in the Supplement to prevent the main manuscript from being too long and too complex to read.

Specific comment 30: L422-434: This belongs to the discussion section.

Response: We have moved the sentences belonging to the discussion section to the Discussion section. The revised sentences in the Results section now read: '*Next, we focus on the interannual change in data quality. According to Figure 13a~c, while the correlation coefficient for RSSSM does not vary significantly among different years, the RMSE and ubRMSE values in earlier periods are somewhat higher than those after 2012. Although the data quality of RSSSM is difficult to maintain, the degree of degradation is much lower than that of CCI. The comparison of the spatial coverages of the 10-day scale RSSSM and CCI data (rainforests are excluded) shows that RSSSM covers all land surfaces except for permafrost, while the interannual variation in coverage is also negligible throughout the period (the intra-annual cycles of data coverages result from the changes in frozen areas), which are preferable to CCI, whose data coverage before 2007 is limited (Figure 13d).*'

After the removal, the Discussion section has been revised as follows: '*In this study, an improved global long-term satellite-based surface soil moisture dataset, …. Our product is temporally continuous during 2003~2018 and covers the whole globe except for frozen grounds (CCI has limited spatial coverage before 2007, when ASCAT data are unavailable), ensuring its applicability to global long-term studies or ecosystem modeling…. The RMSE and ubRMSE values in earlier periods are somewhat higher than those after 2012 because 1) five rounds of simulations were performed, with the output converted into the training target of the next round's neural networks, leading to little error propagation as the simulation period extended to the past; and 2) the quality of microwave soil moisture data is generally low in early periods due to the relatively unadvanced microwave sensors with low signal-to-noise ratio (SNR). However, due to the elaborate design of the neural network set (localized networks, full use of 11 microwave soil moisture products, the determination of quality impact factors and the organization of 67 independent neural networks), high training efficiency is achieved,* *resulting in limited amplification of noise and high maintenance of valid information during 16 years of simulation. This method turns out to be better than the simple CDF matching algorithm, which may not efficiently calibrate the low-quality soil moisture data retrieved from early sensor measurements.*’

References

Al-Yaari, A., Dayau, S., Chipeaux, C., Aluome, C., Kruszewski, A., Loustau, D., and Wigneron, J. P.: The AQUI Soil Moisture Network for Satellite Microwave Remote Sensing Validation in South-Western France, Remote Sens., 10, http://doi.org/10.3390/rs10111839, 2018

Al-Yaari, A., Wigneron, J. P., Dorigo, W., Colliander, A., Pellarin, T., Hahn, S., Mialon, A., Richaume, P., Fernandez-Moran, R., Fan, L., Kerr, Y. H., and De Lannoy, G.: Assessment and inter-comparison of recently developed/reprocessed microwave satellite soil moisture products using ISMN ground-based measurements, Remote Sens. Environ., 224, 289-303, https://doi.org/10.1016/j.rse.2019.02.008, 2019

Albergel, C., de Rosnay, P., Gruhier, C., Muñoz-Sabater, J., Hasenauer, S., Isaksen, L., Kerr, Y., and Wagner, W.: Evaluation of remotely sensed and modelled soil moisture products using global ground-based in situ observations, Remote Sens. Environ., 118, 215-226, https://doi.org/10.1016/j.rse.2011.11.017, 2012

Baldocchi, D., Tang, J., and Xu, L.: How switches and lags in biophysical regulators affect spatial-temporal variation of soil respiration in an oak-grass savanna, Journal of Geophysical Research: Biogeosciences, 111, https://doi.org/10.1029/2005JG000063, 2006

Bircher, S., Skou, N., Jensen, K. H., Walker, J. P., and Rasmussen, L.: A soil moisture and temperature network for SMOS validation in Western Denmark, Hydrol. Earth Syst. Sci., 16, 1445-1463, http://doi.org/10.5194/hess-16-1445-2012, 2012

Brooks, E. B., Thomas, V. A., Wynne, R. H., and Coulston, J. W.: Fitting the Multitemporal Curve: A Fourier Series Approach to the Missing Data Problem in Remote Sensing Analysis, IEEE Trans. Geosci. Remote Sensing, 50, 3340-3353, http://doi.org/10.1109/TGRS.2012.2183137, 2012

Burgin, M., Colliander, A., Njoku, E., Chan, S., Cabot, F., Kerr, H. Y., Bindlish, R., Jackson, T., Entekhabi, D., and Yueh, S.: A Comparative Study of the SMAP Passive Soil Moisture Product With Existing Satellite-Based Soil Moisture Products, IEEE Trans. Geosci. Remote Sensing, 55, 2959-2971, http://doi.org/10.1109/TGRS.2017.2656859, 2017

Cappelaere, B., Descroix, L., Lebel, T., Boulain, N., Ramier, D., Laurent, J. P., Favreau, G., Boubkraoui, S., Boucher, M., Bouzou Moussa, I., Chaffard, V., Hiernaux, P., Issoufou, H. B. A., Le Breton, E., Mamadou, I., Nazoumou, Y., Oi, M., Ottlé, C., and Quantin, G.: The AMMA-CATCH experiment in the cultivated Sahelian area of south-west Niger – Investigating water cycle response to a fluctuating climate and changing environment, J. Hydrol., 375, 34-51, https://doi.org/10.1016/j.jhydrol.2009.06.021, 2009

Chen, F., Crow, W. T., Bindlish, R., Colliander, A., Burgin, M. S., Asanuma, J., and Aida, K.: Global-scale evaluation of SMAP, SMOS and ASCAT soil moisture products using triple collocation, Remote Sens. Environ., 214, 1-13, https://doi.org/10.1016/j.rse.2018.05.008, 2018

Colliander, A., Jackson, T. J., Bindlish, R., Chan, S., Das, N., Kim, S. B., Cosh, M. H., Dunbar, R. S., Dang, L., Pashaian, L., Asanuma, J., Aida, K., Berg, A., Rowlandson, T., Bosch, D., Caldwell, T., Caylor, K., Goodrich, D., al Jassar, H., Lopez-Baeza, E., Martínez-Fernández, J., González-Zamora, A., Livingston, S., McNairn, H., Pacheco, A., Moghaddam, M., Montzka, C., Notarnicola, C., Niedrist, G., Pellarin, T., Prueger, J., Pulliainen, J., Rautiainen, K., Ramos, J., Seyfried, M., Starks, P., Su, Z., Zeng, Y., van der Velde, R., Thibeault, M., Dorigo, W., Vreugdenhil, M., Walker, J. P., Wu, X., Monerris, A., O'Neill, P. E., Entekhabi, D., Njoku, E. G., and Yueh, S.: Validation of SMAP surface soil moisture products with core validation sites, Remote Sens. Environ., 191, 215-231, https://doi.org/10.1016/j.rse.2017.01.021, 2017

De Rosnay, P., Gruhier, C., Timouk, F., Baup, F., Mougin, E., Hiernaux, P., Kergoat, L., and LeDantec, V.: Multi-scale soil moisture measurements at the Gourma meso-scale site in Mali, J. Hydrol., 375, 241-252, https://doi.org/10.1016/j.jhydrol.2009.01.015, 2009

Dorigo, W. A., Gruber, A., De Jeu, R. A. M., Wagner, W., Stacke, T., Loew, A., Albergel, C., Brocca, L., Chung, D., Parinussa, R. M., and Kidd, R.: Evaluation of the ESA CCI soil moisture product using ground-based observations, Remote Sens. Environ., 162, 380-395, https://doi.org/10.1016/j.rse.2014.07.023, 2015

Dorigo, W. A., Wagner, W., Hohensinn, R., Hahn, S., Paulik, C., Xaver, A., Gruber, A., Drusch, M., Mecklenburg, S., van Oevelen, P., Robock, A., and Jackson, T.: The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements, Hydrol. Earth Syst. Sci., 15, 1675-1698, https://doi.org/10.5194/hess-15-1675-2011, 2011

Dorigo, W. A., Xaver, A., Vreugdenhil, M., Gruber, A., Hegyiová, A., Sanchis-Dufau, A. D., Zamojski, D., Cordes, C., Wagner, W., and Drusch, M.: Global Automated Quality Control of In Situ Soil Moisture Data from the International Soil Moisture Network, Vadose Zone J., 12, https://doi.org/10.2136/vzj2012.0097, 2013

Draper, C. S., Reichle, R. H., De Lannoy, G. J. M., and Liu, Q.: Assimilation of passive and active microwave soil moisture retrievals, Geophys. Res. Lett., 39, http://doi.org/10.1029/2011GL050655, 2012

Entekhabi, D., Njoku, E., O'neill, P., Kellogg, K. H., Crow, W., Edelstein, W. N., Entin, J. K., Goodman, S. D., Jackson, T., Johnson, F. M., Kimball, J., Piepmeier, J., Koster, R. D., Martin, E., McDonald, C. K., Moghaddam, M., Moran, M. S., Reichle, R., Shi, J. C., Spencer, D., Thurman, S. W., Tsang, L., and Zyl, J. V.: The Soil Moisture Active Passive (SMAP) Mission, Proc. IEEE, 98, 704-716, https://doi.org/10.1109/JPROC.2010.2043918, 2010

Fan, X., Liu, Y., Gan, G., and Wu, G.: SMAP underestimates soil moisture in vegetation-disturbed areas primarily as a result of biased surface temperature data, Remote Sens. Environ., 247, 111914, https://doi.org/10.1016/j.rse.2020.111914, 2020

Fernandez-Moran, R., Wigneron, J. P., De Lannoy, G., Lopez-Baeza, E., Parrens, M., Mialon, A., Mahmoodi, A., Al-Yaari, A., Bircher, S., Al Bitar, A., Richaume, P., and Kerr, Y.: A new calibration of the effective scattering albedo and soil roughness parameters in the SMOS SM retrieval algorithm, Int. J. Appl. Earth Obs. Geoinf., 62, 27-38, https://doi.org/10.1016/j.jag.2017.05.013, 2017

Gao, L., Sadeghi, M., and Ebtehaj, A.: Microwave retrievals of soil moisture and vegetation optical depth with improved resolution using a combined constrained inversion algorithm: Application for SMAP satellite, Remote Sens. Environ., 239,

111662, https://doi.org/10.1016/j.rse.2020.111662, 2020
Gruber, A., De Lannoy, G., Albergel, C., Al-Yaari, A., Brocca, L., Calvet, J. C., Colliander, A., Cosh, M., Crow, W., Dorigo, W., Draper, C., Hirschi, M., Kerr, Y., Konings, A., Lahoz, W., McColl, K., Montzka, C., Muñoz-Sabater, J., Peng, J., Reichle, R., Richaume, P., Rüdiger, C., Scanlon, T., van der Schalie, R., Wigneron, J. P., and Wagner, W.: Validation practices for satellite soil moisture retrievals: What are (the) errors?, Remote Sens. Environ., 244, 111806, https://doi.org/10.1016/j.rse.2020.111806, 2020
Hermance, J. F., Jacob, R. W., Bradley, B. A., and Mustard, J. F.: Extracting Phenological Signals From Multiyear AVHRR NDVI Time Series: Framework for Applying High-Order Annual Splines With Roughness Damping, IEEE Trans. Geosci. Remote Sensing, 45, 3264-3276, http://doi.org/10.1109/TGRS.2007.903044, 2007
Hyunglok, K., Wooyeon, S., Seongkyun, K., and Minha, C.: Construction and estimation of soil moisture site with FDR and COSMIC-ray (SM-FC) sensors for calibration/validation of satellite-based and COSMIC-ray soil moisture products in Sungkyunkwan university, South Korea, Journal of Korea Water Resources Association, 49, 133-144, http://doi.org/10.3741/JKWRA.2016.49.2.133, 2016
Jin, R., Li, X., Yan, B., Li, X., Luo, W., Ma, M., Guo, J., Kang, J., Zhu, Z., and Zhao, S.: A Nested Ecohydrological Wireless Sensor Network for Capturing the Surface Heterogeneity in the Midstream Areas of the Heihe River Basin, China, IEEE Geosci. Remote Sens. Lett., 11, 2015-2019, https://doi.org/10.1109/LGRS.2014.2319085, 2014
Kang, J., Li, X., Jin, R., Ge, Y., Wang, J., and Wang, J.: Hybrid Optimal Design of the Eco-Hydrological Wireless Sensor Network in the Middle Reach of the Heihe River Basin, China, Sensors, 14, https://doi.org/10.3390/s141019095, 2014
Karthikeyan, L., Pan, M., Wanders, N., Kumar, D. N., and Wood, E. F.: Four decades of microwave satellite soil moisture observations: Part 2. Product validation and inter-satellite comparisons, Adv. Water Resour., 109, 236-252, https://doi.org/10.1016/j.advwatres.2017.09.010, 2017
Kerr, Y. H., Al-Yaari, A., Rodriguez-Fernandez, N., Parrens, M., Molero, B., Leroux, D., Bircher, S., Mahmoodi, A., Mialon, A., Richaume, P., Delwart, S., Al Bitar, A., Pellarin, T., Bindlish, R., Jackson, T. J., Rüdiger, C., Waldteufel, P., Mecklenburg, S., and Wigneron, J. P.: Overview of SMOS performance in terms of global soil moisture monitoring after six years in operation, Remote Sens. Environ., 180, 40-63, https://doi.org/10.1016/j.rse.2016.02.042, 2016
Kim, H., Parinussa, R., Konings, A. G., Wagner, W., Cosh, M. H., Lakshmi, V., Zohaib, M., and Choi, M.: Global-scale assessment and combination of SMAP with ASCAT (active) and AMSR2 (passive) soil moisture products, Remote Sens. Environ., 204, 260-275, https://doi.org/10.1016/j.rse.2017.10.026, 2018
Kim, S., Liu, Y. Y., Johnson, F. M., Parinussa, R. M., and Sharma, A.: A global comparison of alternate AMSR2 soil moisture products: Why do they differ?, Remote Sens. Environ., 161, 43-62, https://doi.org/10.1016/j.rse.2015.02.002, 2015a
Kim, S., Parinussa, R. M., Liu, Y. Y., Johnson, F. M., and Sharma, A.: A framework for combining multiple soil moisture retrievals based on maximizing temporal correlation, Geophys. Res. Lett., 42, 6662-6670, http://doi.org/10.1002/2015GL064981, 2015b

Kohler, M. A. and Linsley, R. K.: Predicting the runoff from storm rainfall, US Department of Commerce, Weather Bureau, 1951.
Kolassa, J., Reichle, R. H., Liu, Q., Alemohammad, S. H., Gentine, P., Aida, K., Asanuma, J., Bircher, S., Caldwell, T., Colliander, A., Cosh, M., Holifield Collins, C., Jackson, T. J., Martínez-Fernández, J., McNairn, H., Pacheco, A., Thibeault, M., and Walker, J. P.: Estimating surface soil moisture from SMAP observations using a Neural Network technique, Remote Sens. Environ., 204, 43-59, https://doi.org/10.1016/j.rse.2017.10.045, 2018
Lebel, T., Cappelaere, B., Galle, S., Hanan, N., Kergoat, L., Levis, S., Vieux, B., Descroix, L., Gosset, M., Mougin, E., Peugeot, C., and Seguis, L.: AMMA-CATCH studies in the Sahelian region of West-Africa: An overview, J. Hydrol., 375, 3-13, https://doi.org/10.1016/j.jhydrol.2009.03.020, 2009
Leroux, D. J., Kerr, Y. H., Bitar, A. A., Bindlish, R., Jackson, T. J., Berthelot, B., and Portet, G.: Comparison Between SMOS, VUA, ASCAT, and ECMWF Soil Moisture Products Over Four Watersheds in U.S, IEEE Trans. Geosci. Remote Sensing, 52, 1562-1571, https://doi.org/10.1109/TGRS.2013.2252468, 2014
Lievens, H., Martens, B., Verhoest, N. E. C., Hahn, S., Reichle, R. H., and Miralles, D. G.: Assimilation of global radar backscatter and radiometer brightness temperature observations to improve soil moisture and land evaporation estimates, Remote Sens. Environ., 189, 194-210, https://doi.org/10.1016/j.rse.2016.11.022, 2017
Liu, J., Chai, L., Lu, Z., Liu, S., Qu, Y., Geng, D., Song, Y., Guan, Y., Guo, Z., Wang, J., and Zhu, Z.: Evaluation of SMAP, SMOS-IC, FY3B, JAXA, and LPRM Soil Moisture Products over the Qinghai-Tibet Plateau and Its Surrounding Areas, Remote Sens., 11, http://doi.org/10.3390/rs11070792, 2019
Loew, A.: Impact of surface heterogeneity on surface soil moisture retrievals from passive microwave data at the regional scale: The Upper Danube case, Remote Sens. Environ., 112, 231-248, https://doi.org/10.1016/j.rse.2007.04.009, 2008
Lu, Z., Chai, L., Ye, Q., and Zhang, T.: Reconstruction of time-series soil moisture from AMSR2 and SMOS data by using recurrent nonlinear autoregressive neural networks, 26-31 July 2015 2015, 980-983, https://doi.org/10.1109/IGARSS.2015.7325932.
Marczewski, W., Slominski, J., Slominska, E., Usowicz, B., Usowicz, J., Romanov, S., Maryskevych, O., Nastula, J., and Zawadzki, J.: Strategies for validating and directions for employing SMOS data, in the Cal-Val project SWEX (3275) for wetlands, Hydrol. Earth Syst. Sci., 2010, 7007-7057, http://doi.org/10.5194/hessd-7-7007-2010, 2010
Martens, B., Miralles, D. G., Lievens, H., van der Schalie, R., de Jeu, R. A. M., Fernández-Prieto, D., Beck, H. E., Dorigo, W. A., and Verhoest, N. E. C.: GLEAM v3: satellite-based land evaporation and root-zone soil moisture, Geosci. Model Dev., 10, 1903-1925, https://doi.org/10.5194/gmd-10-1903-2017, 2017
McColl, K. A., Alemohammad, S. H., Akbar, R., Konings, A. G., Yueh, S., and Entekhabi, D.: The global distribution and dynamics of surface soil moisture, Nat. Geosci., 10, 100, https://doi.org/10.1038/ngeo2868, 2017
Méndez-Barroso, L. A., Vivoni, E. R., Watts, C. J., and Rodríguez, J. C.: Seasonal and interannual relations between precipitation, surface soil moisture and vegetation dynamics in the North American monsoon region, J. Hydrol., 377, 59-70,

https://doi.org/10.1016/j.jhydrol.2009.08.009, 2009
Moghaddam, M., Entekhabi, D., Goykhman, Y., Li, K., Liu, M., Mahajan, A., Nayyar, A., Shuman, D., and Teneketzis, D.: A Wireless Soil Moisture Smart Sensor Web Using Physics-Based Optimal Control: Concept and Initial Demonstrations, IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens., 3, 522-535, https://doi.org/10.1109/JSTARS.2010.2052918, 2010
Moghaddam, M., Silva, A. R., Clewley, D., Akbar, R., Hussaini, S. A., Whitcomb, J., Devarakonda, R., Shrestha, R., Cook, R. B., Prakash, G., Santhana Vannan, S. K., and Boyer, A. G.: Soil Moisture Profiles and Temperature Data from SoilSCAPE Sites, USA., ORNL DAAC, Oak Ridge, Tennessee, USA., https://doi.org/10.3334/ORNLDAAC/1339, 2016
Morbidelli, R., Saltalippi, C., Flammini, A., Rossi, E., and Corradini, C.: Soil water content vertical profiles under natural conditions: matching of experiments and simulations by a conceptual model, Hydrol. Process., 28, 4732-4742, https://doi.org/10.1002/hyp.9973, 2014
Mougin, E., Hiernaux, P., Kergoat, L., Grippa, M., de Rosnay, P., Timouk, F., Le Dantec, V., Demarez, V., Lavenu, F., Arjounin, M., Lebel, T., Soumaguel, N., Ceschia, E., Mougenot, B., Baup, F., Frappart, F., Frison, P. L., Gardelle, J., Gruhier, C., Jarlan, L., Mangiarotti, S., Sanou, B., Tracol, Y., Guichard, F., Trichon, V., Diarra, L., Soumaré, A., Koité, M., Dembélé, F., Lloyd, C., Hanan, N. P., Damesin, C., Delon, C., Serça, D., Galy-Lacaux, C., Seghieri, J., Becerra, S., Dia, H., Gangneron, F., and Mazzega, P.: The AMMA-CATCH Gourma observatory site in Mali: Relating climatic variations to changes in vegetation, surface hydrology, fluxes and natural resources, J. Hydrol., 375, 14-33, https://doi.org/10.1016/j.jhydrol.2009.06.045, 2009
Naithani, K. J., Baldwin, D. C., Gaines, K. P., Lin, H., and Eissenstat, D. M.: Spatial Distribution of Tree Species Governs the Spatio-Temporal Interaction of Leaf Area Index and Soil Moisture across a Forested Landscape, PLOS ONE, 8, e58704, https://doi.org/10.1371/journal.pone.0058704, 2013
Oliva, R., Daganzo, E., Kerr, Y. H., Mecklenburg, S., Nieto, S., Richaume, P., and Gruhier, C.: SMOS Radio Frequency Interference Scenario: Status and Actions Taken to Improve the RFI Environment in the 1400–1427-MHz Passive Band, IEEE Trans. Geosci. Remote Sensing, 50, 1427-1439, https://doi.org/10.1109/TGRS.2012.2182775, 2012
Osenga, E. C., Arnott, J. C., Endsley, K. A., and Katzenberger, J. W.: Bioclimatic and Soil Moisture Monitoring Across Elevation in a Mountain Watershed: Opportunities for Research and Resource Management, Water Resour. Res., 55, 2493-2503, https://doi.org/10.1029/2018WR023653, 2019
Pellarin, T., Laurent, J. P., Cappelaere, B., Decharme, B., Descroix, L., and Ramier, D.: Hydrological modelling and associated microwave emission of a semi-arid region in South-western Niger, J. Hydrol., 375, 262-272, https://doi.org/10.1016/j.jhydrol.2008.12.003, 2009
Piles, M., Schalie, R. v. d., Gruber, A., Muñoz-Marí, J., Camps-Valls, G., Mateo-Sanchis, A., Dorigo, W., and Jeu, R. d.: Global Estimation of Soil Moisture Persistence with L and C-Band Microwave Sensors, 22-27 July 2018 2018, 8259-8262,

https://doi.org/10.1109/IGARSS.2018.8518161.
Qu, Y., Zhu, Z., Chai, L., Liu, S., Montzka, C., Liu, J., Yang, X., Lu, Z., Jin, R., Li, X., Guo, Z., and Zheng, J.: Rebuilding a Microwave Soil Moisture Product Using Random Forest Adopting AMSR-E/AMSR2 Brightness Temperature and SMAP over the Qinghai–Tibet Plateau, China, Remote Sens., 11, https://doi.org/10.3390/rs11060683, 2019
Robock, A., Vinnikov, K. Y., Srinivasan, G., Entin, J. K., Hollinger, S. E., Speranskaya, N. A., Liu, S., and Namkhai, A.: The Global Soil Moisture Data Bank, Bull. Amer. Meteorol. Soc., 81, 1281-1300, http://doi.org/10.1175/1520-0477(2000)081<1281:TGSMDB>2.3.CO;2, 2000
Rüdiger, C., Hancock, G., Hemakumara, H. M., Jacobs, B., Kalma, J. D., Martinez, C., Thyer, M., Walker, J. P., Wells, T., and Willgoose, G. R.: Goulburn River experimental catchment data set, Water Resour. Res., 43, https://doi.org/10.1029/2006WR005837, 2007
Smith, A. B., Walker, J. P., Western, A. W., Young, R. I., Ellett, K. M., Pipunic, R. C., Grayson, R. B., Siriwardena, L., Chiew, F. H. S., and Richter, H.: The Murrumbidgee soil moisture monitoring network data set, Water Resour. Res., 48, https://doi.org/10.1029/2012WR011976, 2012
Stillman, S. and Zeng, X.: Evaluation of SMAP Soil Moisture Relative to Five Other Satellite Products Using the Climate Reference Network Measurements Over USA, IEEE Trans. Geosci. Remote Sensing, 56, 6296-6305, https://doi.org/10.1109/TGRS.2018.2835316, 2018
Stinchcombe and White: Universal approximation using feedforward networks with non-sigmoid hidden layer activation functions, 1989 1989, 613-617 vol.611, http://doi.org/10.1109/IJCNN.1989.118640.
Su, Z., Wen, J., Dente, L., van der Velde, R., Wang, L., Ma, Y., Yang, K., and Hu, Z.: The Tibetan Plateau observatory of plateau scale soil moisture and soil temperature (Tibet-Obs) for quantifying uncertainties in coarse resolution satellite and model products, Hydrol. Earth Syst. Sci., 15, 2303-2316, https://doi.org/10.5194/hess-15-2303-2011, 2011
Van Cleve, K., Chapin, F. S. S., and Ruess, R. W.: Bonanza Creek Long Term Ecological Research Project Climate Database - University of Alaska Fairbanks., 2015
Van der Schalie, R., De Jeu, R., Parinussa, R., Rodríguez-Fernández, N., Kerr, Y., Al-Yaari, A., Wigneron, J.-P., and Drusch, M.: The Effect of Three Different Data Fusion Approaches on the Quality of Soil Moisture Retrievals from Multiple Passive Microwave Sensors, Remote Sens., 10, https://doi.org/10.3390/rs10010107, 2018
Yang, K., Qin, J., Zhao, L., Chen, Y., Tang, W., Han, M., Lazhu, Chen, Z., Lv, N., Ding, B., Wu, H., and Lin, C.: A Multiscale Soil Moisture and Freeze–Thaw Monitoring Network on the Third Pole, Bull. Amer. Meteorol. Soc., 94, 1907-1916, https://doi.org/10.1175/BAMS-D-12-00203.1, 2013
Yao, P., Shi, J., Zhao, T., Lu, H., and Al-Yaari, A.: Rebuilding Long Time Series Global Soil Moisture Products Using the Neural Network Adopting the Microwave Vegetation Index, Remote Sens., 9, https://doi.org/10.3390/rs9010035, 2017
Ye, N., Walker, J. P., Guerschman, J., Ryu, D., and Gurney, R. J.: Standing water effect

on soil moisture retrieval from L-band passive microwave observations, Remote Sens. Environ., 169, 232-242, https://doi.org/10.1016/j.rse.2015.08.013, 2015
Yilmaz, M. T., Hunt, E. R., and Jackson, T. J.: Remote sensing of vegetation water content from equivalent water thickness using satellite imagery, Remote Sens. Environ., 112, 2514-2522, https://doi.org/10.1016/j.rse.2007.11.014, 2008
Young, R., Walker, J., Yeoh, N., Smith, A., Ellett, K., Merlin, O., and Western, A.: Soil Moisture and Meteorological Observations From the Murrumbidgee Catchment, 2008.
Zhang, R., Kim, S., and Sharma, A.: A comprehensive validation of the SMAP Enhanced Level-3 Soil Moisture product using ground measurements over varied climates and landscapes, Remote Sens. Environ., 223, 82-94, https://doi.org/10.1016/j.rse.2019.01.015, 2019
Zhao, Y., Peth, S., Wang, X. Y., Lin, H., and Horn, R.: Controls of surface soil moisture spatial patterns and their temporal stability in a semi-arid steppe, Hydrol. Process., 24, 2507-2519, https://doi.org/10.1002/hyp.7665, 2010