Response to #1

The study presents a method for gap-filling ESA CCI soil moisture data. For filling the gaps, the approach utilizes information from the spatiotemporal domain around the missing value as well as from other explanatory variables. This is a timely contribution to the ever-growing field of gap-filling and data fusion in Earth system science. The study benchmarks the method over China, which covers a large variety of different climate zones and topography, making it a suitable test bed. Particularly with the severity of missing values in microwave remote sensing soil moisture retrievals, it is vital to use as much information as possible, both from the spatial and temporal domain as well as from other available observations. Therefore, the proposed method seems promising to be able to do the task. Furthermore, comparing the gap filled values to in-situ observations gives an independent insight into gap filling performance.

However, the poor use of language and grammar hinder understanding of the methods and results in many cases. Additionally, the structure of the results and methods sections are a bit unclear and seem arbitrary, such that following the storyline of the paper is difficult. Finally, the purpose, aim and implementation of some of the methodological choices and evaluations in the result section are unclear and should either be replaced or clarified.

I therefore think the paper requires major revisions. Please see below my general and specific comments.

Response: Thanks for your valuable time and constructive comments. We tried our best to incorporate them in the new version. Especially, the English language usage in this version has been improved deeply by one fluent English researcher that is suggested by the commercial corporation. The detailed modifications can be found in the highlighted text throughout the manuscript.

GENERAL COMMENTS

1. The study needs restructuring especially in the methods and results section. It is hard to follow the methods and results section, since they are structured very differently. Please align Figure 2 with the structure of Section 3, such that it is easy for the reader to follow which part of the model is described. For example, the subsections could have the same header names as the boxes in Figure 2. Also, it is not clear why only parts of Figure 2 are described in the subsections. Furthermore within the results, sometimes two different results are explained in one subsection (e.g. Section 4.2. compares to in-situ measurements and to the “cross-validation”, Section 4.3 compares to literature and to other employed methods). I suggest making individual sections for individual results, or clarify why the results are thrown together in one Section like this.

Response: Thanks for pointing out this issue. In the revised version, the Figure 2 and the related context have been rewritten to make it align with the structure of section 3. Meanwhile, the Section 3 and 4 is reorganized, in particular, the subsection in these two sections are rearranged to make it clear and readable.

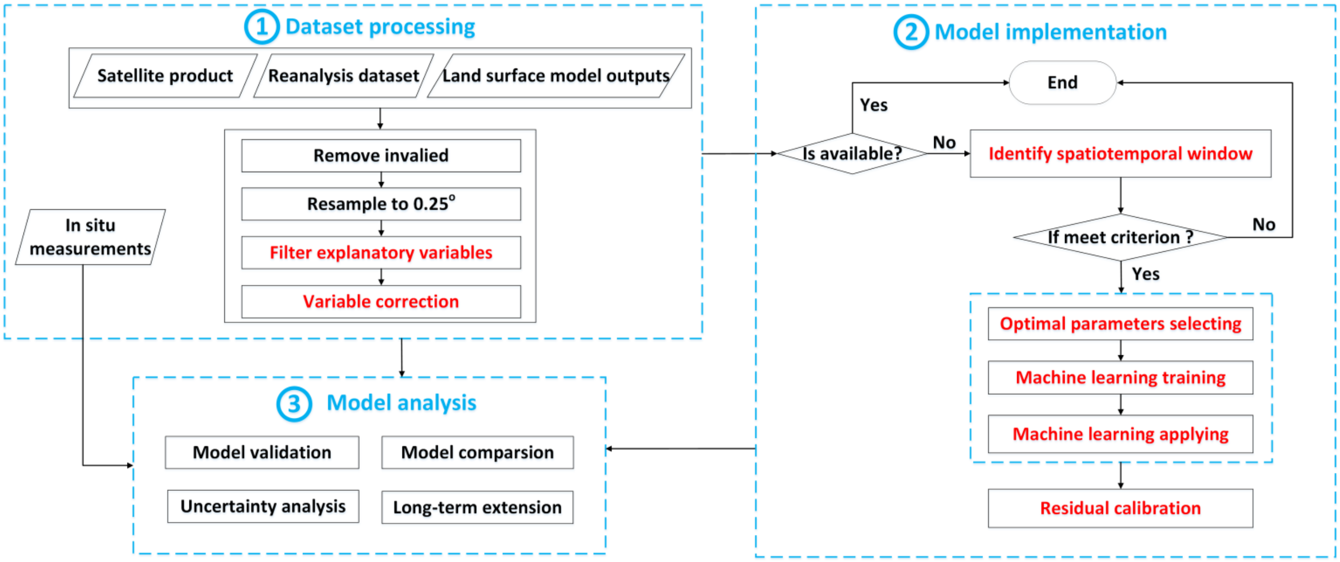


Figure 2: The schematic of overall procedure. The red text denotes the core procedures conducted in the proposed model, which will be described in the following sections.

2. In general within the result section, the results are described with generic terms like "good coindicence", "capacity for reconstruction", "high accuracies", "strong variation delineating capacity". Whilst those all are incorrect English terms, they also do not go into detail or describe the results well. While it is important to give statistical evidence of the algorithm performance, it is of equal importance to discuss the difference between the statistical measures and possible reasons for it, as well as evaluating the physical plausibility and coherency of the gap filled values. It would highly benefit the study if the results were described more concisely, more descriptive words would be used, and the results would be discussed, taken into context and described better. A good example of a good explanation of results is for example found in L433-436. Please more of those. Furthermore, it would be beneficial to add at least one plot that evaluates the physical plausibility of the gap-filled values for a possible application of the gap filled dataset. As an example, since soil moisture values are often important when analysing droughts, it would be interesting to see whether the gap-filling method is able to not only work in the mean of the values, which all the statistical metrics aim at, but also see whether the extreme values are gap-filled well. This could be done by showing some maps of a known drought event over China, possibly compare with the in-situ measurements and the original, gappy CCI SM data.

Response: Thanks for the reviewer's suggestion. In the new version, the result section has been revised and more descriptive words are added to make it more convinced and concise, e.g., regarding the applicability of the selected explanatory factors and the merits of RF model in gap-filling. The detailed modifications can be found in the highlighted text throughout the manuscript.

According to the reviewer's suggestions, we pay particular attention to the gap-filling SMs under extremely dry conditions to reveal the physical plausibility of gap-filled soil moisture. The extreme drought is defined based on meteorological condition, i.e., the Palmer Drought Severity Index (PDSI) is less than −2 over 8 consecutive months or longer (Fig. S2). Specifically, 1) we add the accuracy evaluation in Fig. 7 and 8 focusing on the drought regions, and find the accuracy of the gap-filling products tend to be diminished by drought conditions, but the impact is limited; 2) we label the drought regions in Fig. 9 to make it more readable, and we observe the accuracies are lower over the regions experienced drought due to perturbations of the soil water content, but without noticeably poor performances; and 3) we analyze two typical drought regions by comparing the difference source SM (Fig. S4). The focused analyses illustrate the consistency of the gap-filling SM with the in-situ measurements and the original SM under extremely dry conditions, illustrating the physical plausibility of the gap-filled values for specific application. The detailed modifications can be found in the highlighted text in the revised version.

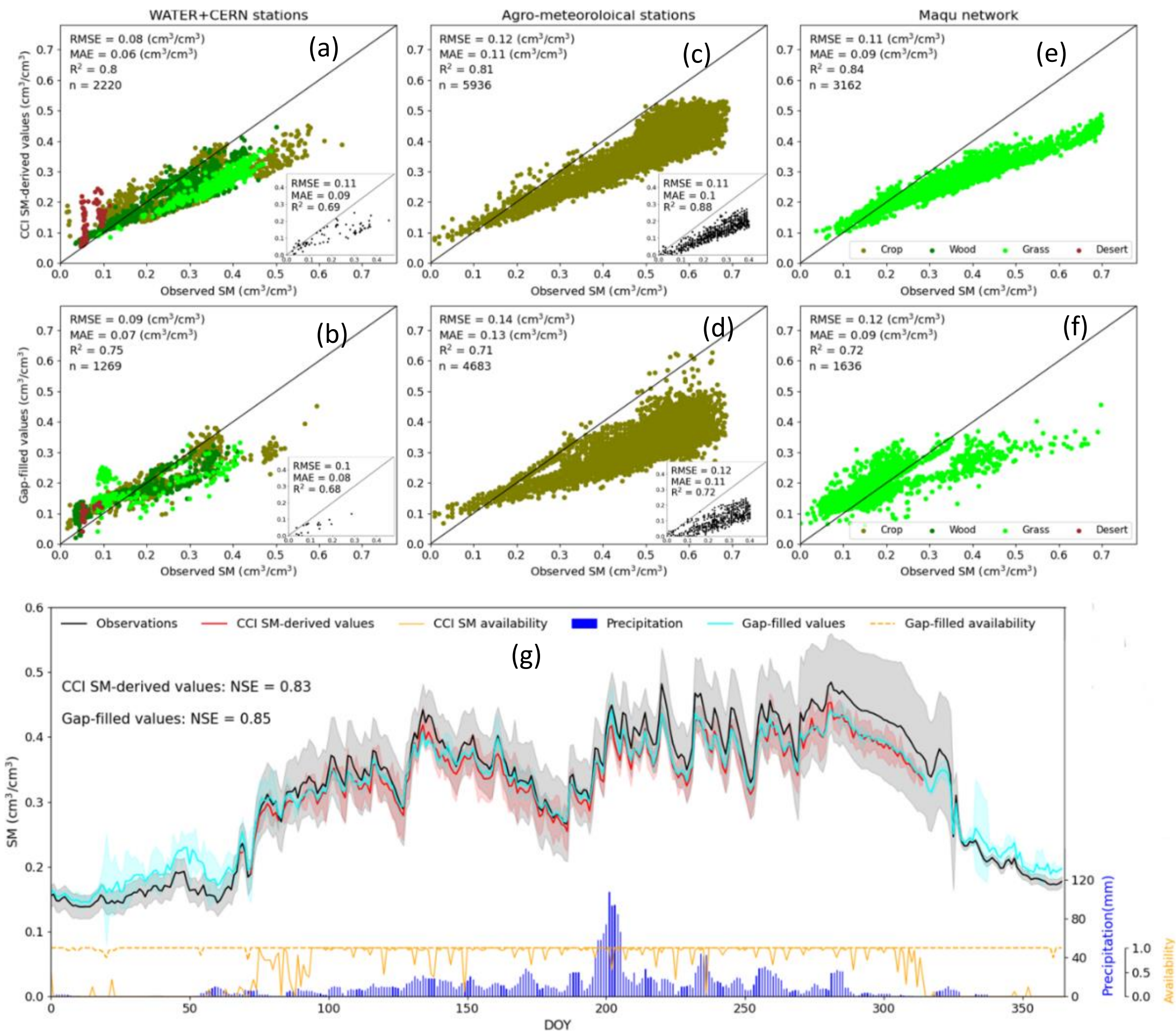


Figure 7: The evaluations of model results. (a), (c) and (e) are the scatter plots of 1-km CCI SM-derived values against field measures regarding WATER/CEERN, agro-meteorological stations, and Mauqu network, respectively, and (b), (d) and (f) are the scatter plots of 1-km gap-filled SM-derived values against field measures. The sub-figures in the lower corner of (a)-(d) are the scatter plots under extremely dry conditions. (g) are the time series of average CCI SM-derived values against site measures in the Maqu region. The shaded area in (g) denotes ±1 standard error.

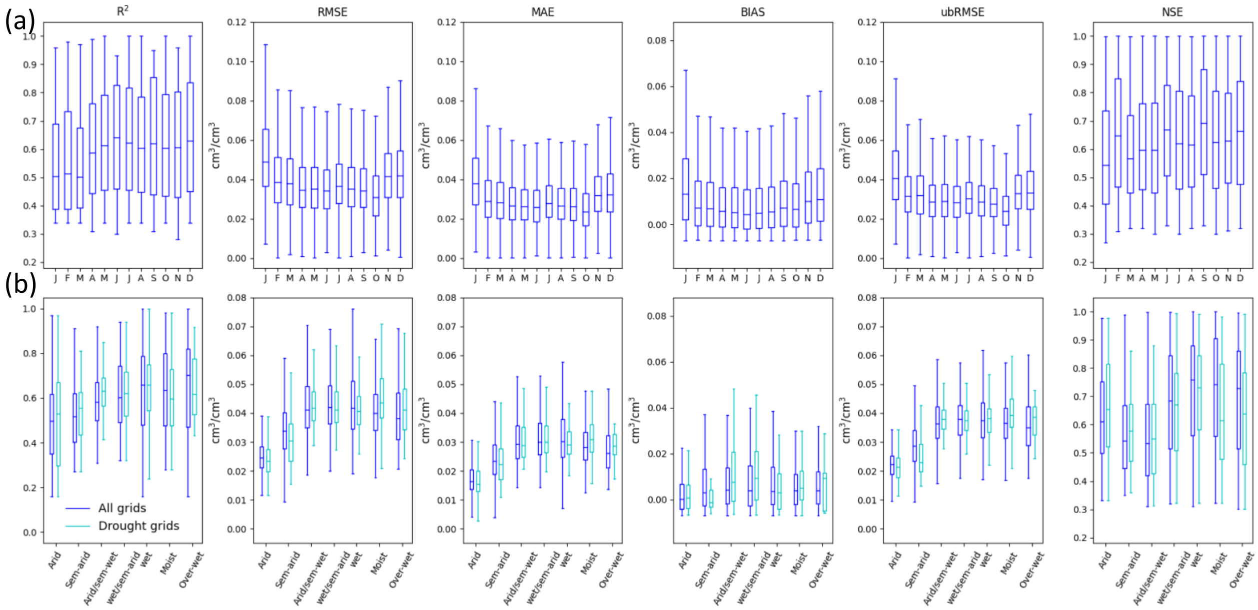


Figure 8: The accuracy metrics of 10-cross validation for R2, RMSE, MAE, BIAS, ubRMSE and NSE: (a) is averagely obtained on a month basis, and (b) is averagely obtained for each climate region and for drought grids.

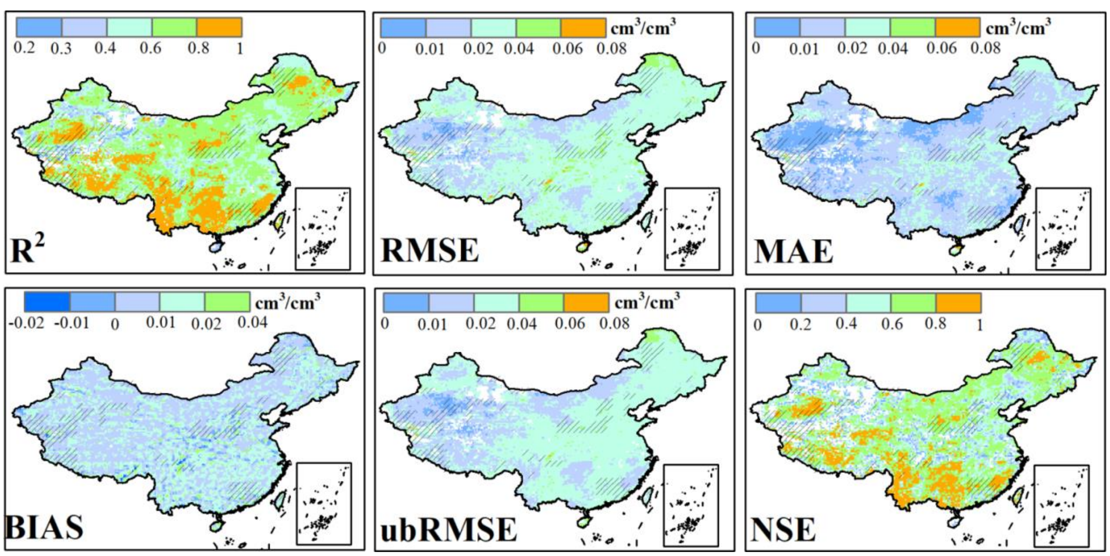


Figure 9: The spatial distributions of accuracy metrics of 10-cross validation in 2009 for R2, RMSE, MAE, BIAS, ubRMSE and NSE. The slash represents the regions impacted by drought.

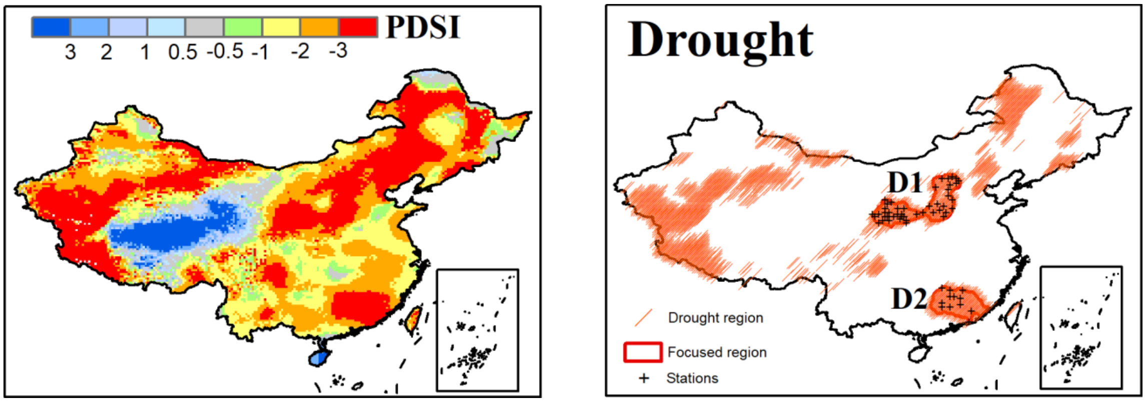


Figure S2. (a) The annual PDSI in 2009. (b) The spatial distribution of drought events, and two severe drought events (D1 and D2) selected for further analysis.

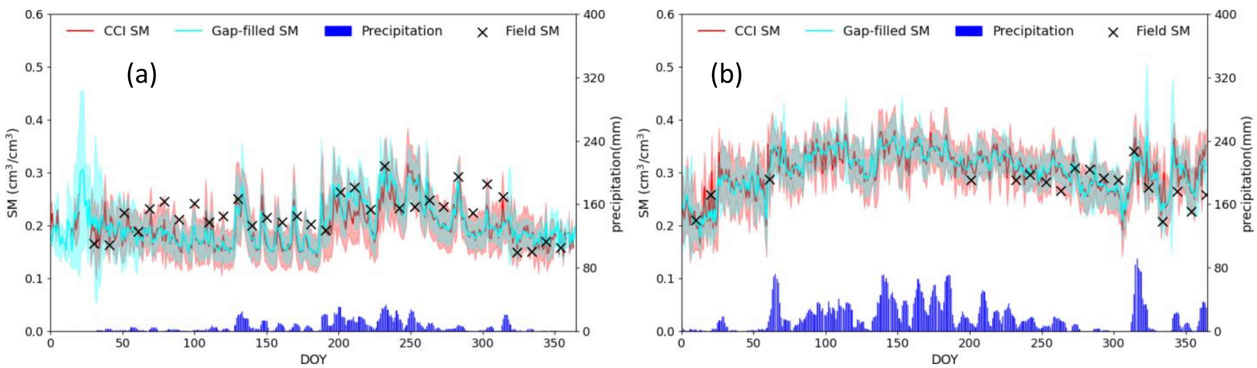


Figure S4. The time series in the (a) region D1 and (b) D2. D1 and D2 are identified in Figure S2.

3. Throughout the script, there are many spelling and grammar mistakes, some of which significantly hamper understanding of particular methodological decisions or results. It is vital that these mistakes, some but not all of which are listed below, should be removed from the script. A thorough cleanup of the language and individual sentences is necessary. Many statements could also be reduced, whilst keeping the meaning, to a minimum of words, effectively improving the structure and readability of the script and at the same time reducing its size.

Response: Thanks for pointing out this issue. In the new version, the English language usage has been improved deeply by one fluent English researcher that is suggested by the commercial corporation. We also reduce some statements to improve the structure and readability of the script. The detailed modifications can be found in the highlighted text throughout the manuscript.

4. It is a reasonable and thoughtful decision to investigate the importance of the different selected variables for the gap-filling process. However, I am not yet fully sure whether the selected method is the best in this context and whether it is applied correctly. Firstly, the mentioned model produces a significance score that I cannot assess, since the equation is not provided. It would be vital to add this, since only then the meaning of the significance (e.g. in Fig 3a) can be understood. Furthermore, the cited literature uses this method only for exploratory variable importance in hydrological case studies and not to limit variables that feed a gap-filling model. In the latter case I suggest another method that is well-known and often used in the machine learning context for feature selection prior to model employment could be used. These methods include the feature importance assessment of the Random Forest model, a permutation feature importance assessment, introducing a regularised regression that puts weights on the input features, or evaluating using the SHAP value. Please provide in your answer to this review a discussion on which method you settled and why you chose this one. Furthermore, the used method is a linear regression, which screens for important variables only in linear relationships to soil moisture. However, the relationship between soil moisture and the provided explanatory variables is in many cases non-linear, therefore there is a chance that important dependencies are missed if only for a linear relationship is screened. Additionally, the missing regularisation in the linear regression makes it prone to overfitting. Finally, it is unclear to me why a variable selection / importance assessment is conducted twice, in Section 3.1 and in Section 4.4. I suggest only making one of those assessments, e.g. by removing Section 4.4. and potentially replacing the assessment in Section 3.1 with a more robust method, see my suggestions above.

Response: Thanks for the reviewer's valuable suggestion. Currently, there is no consensus on the optimal model to select explanatory variables considering the complexity of hydrological scenarios. For example, RF analysis can indicate plausible governing processes from emergent relationships, but by construction it does not suggest causality. One of our study aims is to provide one general framework for gap-fill soil moisture that can be extended to other machine learning approaches. Accordingly, one general method, Pearson correlation, is used to select the explanatory variables. It should be mentioned that the Parson correlation have been extensively used in delineating soil moisture especially considering it can depict some specific non-linear properties, e.g., lag time when combing with step strategies [1, 2].

- In this version, according to the reviewer's suggestion, details descriptions about the factors selection approach are provided in the supplementary Text S1, as following.

  Text S1: The regression subset selection approach

  The main assumption beneath this regression subset selection approach is that the suppressor variables are associated significantly with each other in regression models, although they may be less correlated with the dependent variables. To be specific, this approach can be conducted with the following steps: (1) using least-squares linear regression to check the potential relationships between SM and explanatory variables; (2) applying a backward stepwise (remove) regression to explore the potential explanatory variables based on the Akaike Information Criterion (AIC); (3) exploiting the best models from all variable combination to identify the important variables impacting SM; and (4) quantifying the relative contributions of each explanatory variable to SM based on the determination coefficient.

- To validate results of Pearson correlation, according to the reviewer's suggestion, we also employ permutation feature importance which measures the relative importance of each predictor variable from the difference of errors before and after a temporal permutation applied to the particular variable. Consistent patterns (Figure 3(a)) between the significance percentage and permutation importance further indicate the feasibility of the selected variables in modelling SM.

- According to the reviewer's suggestion, the importance score produced by RF has been removed to supplementary.

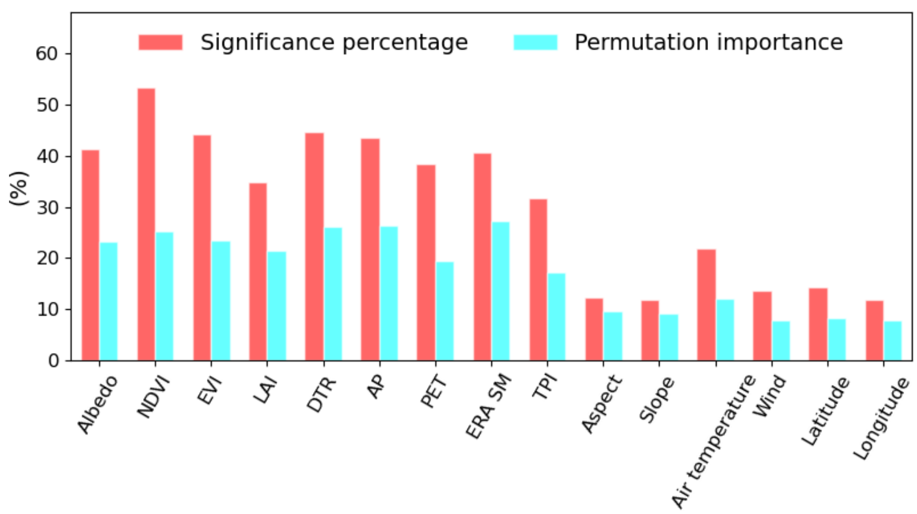


Figure 3: The significance percentage and permutation importance of the selected variables in correlation to CCI SM.

[1] Almendra-Martín, Laura, et al. "Comparison of gap-filling techniques applied to the CCI soil moisture database in Southern Europe." Remote Sensing of Environment 258 (2021): 112377.

[2] Yu J, Zhang X, Xu L, et al. A hybrid CNN-GRU model for predicting soil moisture in maize root zone. Agricultural Water Management, 2021, 245: 106649.

5. Why do you use a combination of scaling algorithms in Section 3.1.2? Since you never compare ESA and ERA soil moisture values in the results, you could just compute standardised anomalies of the ESA values, run the gap filling model and then add mean and standard deviation again, to convert back to physical values? Please explain, in case I have missed why this step is necessary, or just use standardised anomalies for simplification.

Response: Although the reanalyses dataset could reproduce observed characteristics, its performance might be limited when there are some systematic errors in reanalysis products [1]. Systematic biases are unavoidable in global reanalyses dataset, and these biases can be propagated through the simulation process (e.g., gap-filling and downscaling) with far reaching implications on the simulation products and any subsequent applications [2]. Accordingly, bias correction of reanalyses prior to dynamical simulation is required to ensure that errors are corrected, leading to better skill and consistent simulated products that are independent of the choice of the domain.

Our study is hoped to verify the ability of bias correction of reanalysis or model simulations prior to gap-filling procedure, especially considering our study is focused on the reanalysis and model outputs. On the other hand, running the model using the standardized anomalies might be unfit for some variables that own complex characteristics such as the land surface temperature [3], consequently one improved non-linear model is demand and encouraged.

In the new version, we revise the related context to make it clearer. Meanwhile, the histograms are provided in supplementary Fig. S1 to illustrate the differences in soil moisture between ESA and ERA.

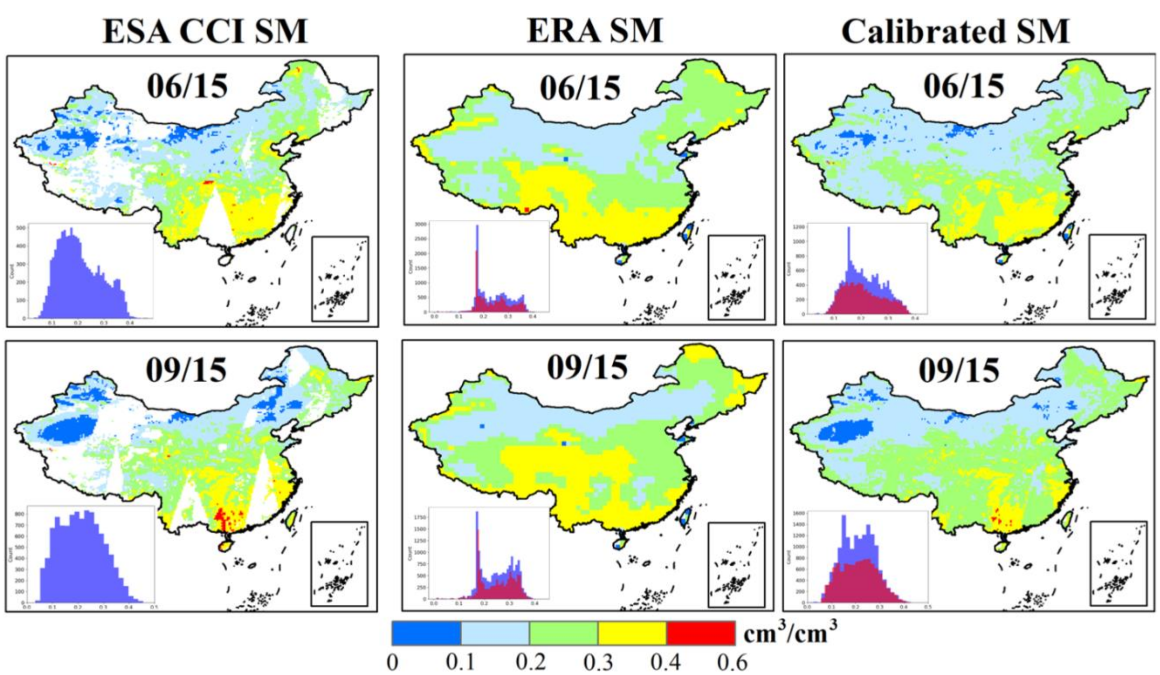


Figure S1. The spatial distributions of ESA CCI SM, ERA5 SM and calibrated ERA SM on the selected days of 2009. The lower-left panel in each sub-figure shows the histogram, and the blue color represents the pixels in which the ESA dataset are available while the red color represents the pixels in which the ERA dataset are available.

[1] Moalafhi D B, Sharma A, Evans J P, et al. Impact of bias-corrected reanalysis-derived lateral boundary conditions on WRF simulations. Journal of Advances in Modeling Earth Systems, 2017, 9(4): 1828-1846.

[2] Mehrotra R, Sharma A. Correcting for systematic biases in multiple raw GCM variables across a range of timescales. Journal of Hydrology, 2015, 520: 214-223.

[3] Song P, Zhang Y. An improved non-linear inter-calibration method on different radiometers for enhancing coverage of daily LST estimates in low latitudes. Remote Sensing of Environment, 2021, 264: 112626.

6. In result Section 4.1 you compare the original daily CCI SM and the corresponding gap-filled dataset for the year 2009. You argue that the model performance has merit based on the fact that the two datasets show similar characteristics in Figure 6. This however is not an argument that is relevant in gap-filling. Since the missing values in the original CCI SM data are missing not (completely) at random, but are missing systematically where vegetation cover is high or the soil is frozen, this dataset is biased towards the underlying, unobservable gap-free "truth". Comparing the original, gappy data with the gap-filled that is supposed to produce biases, i.e. change the statistical moments of the data because it is missing not at random (see e.g. Rubin et al, 1976, Little et al 2014, Van Buuren et al 2018, Bessenbacher et al 2022). If these two datasets are compared, it should be aimed towards physical plausibility and coherency, and not about whether they are statistically similar.

Response: Thanks for pointing out this issue. For our work, snow- and water- covered pixels are removed considering their low accuracy in satellite SM retrievals [1].

- In the new version, we add the related context to describe the bias issue. Meanwhile, the histograms of two dataset are compared to explore the value distribution properties of different products (Fig. 6), as following,

  "Because missing earth data are to a large extent not at random, statistical measures of comparative analysis among them tends to produce bias (Bessenbacher et al., 2022b). To account for this, paired histograms of two datasets are compared to explore the value distribution properties. The histograms show the gap-filled dataset does not impact the SM distribution in warm seasons, that is, in agreement with the CCI dataset. There is also noticeable bias in cold seasons, especially in the very low range of SM."

- In addition, the Nash-Sutcliffe Efficiency (NSE) is also added to measure the overall performance of the proposed model, as illustrated in Fig. 8 and 9.

[1] Cui Y, Yang X, Chen X, et al. A two-step fusion framework for quality improvement of a remotely sensed soil moisture product: A case study for the ECV product over the Tibetan Plateau. Journal of Hydrology, 2020, 587: 124993.

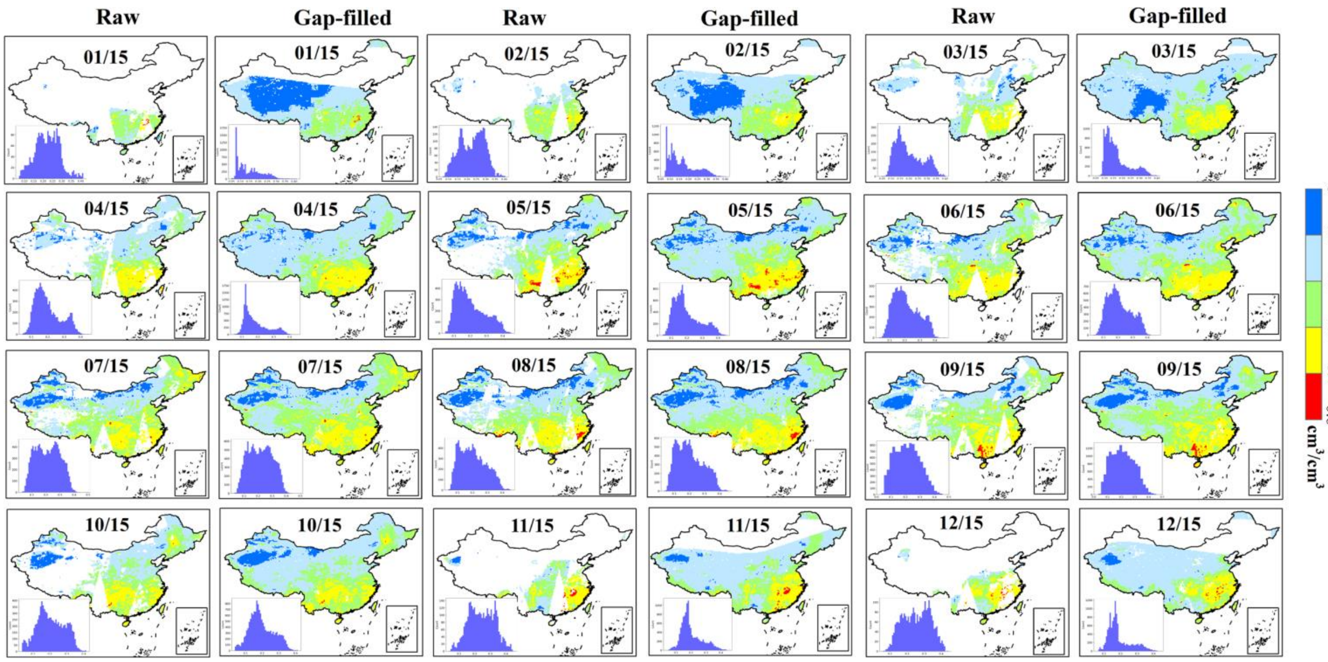


Figure 6: The spatial distributions and histogram of the raw and gap-filled CCI SM on the 15th of each month in 2009.

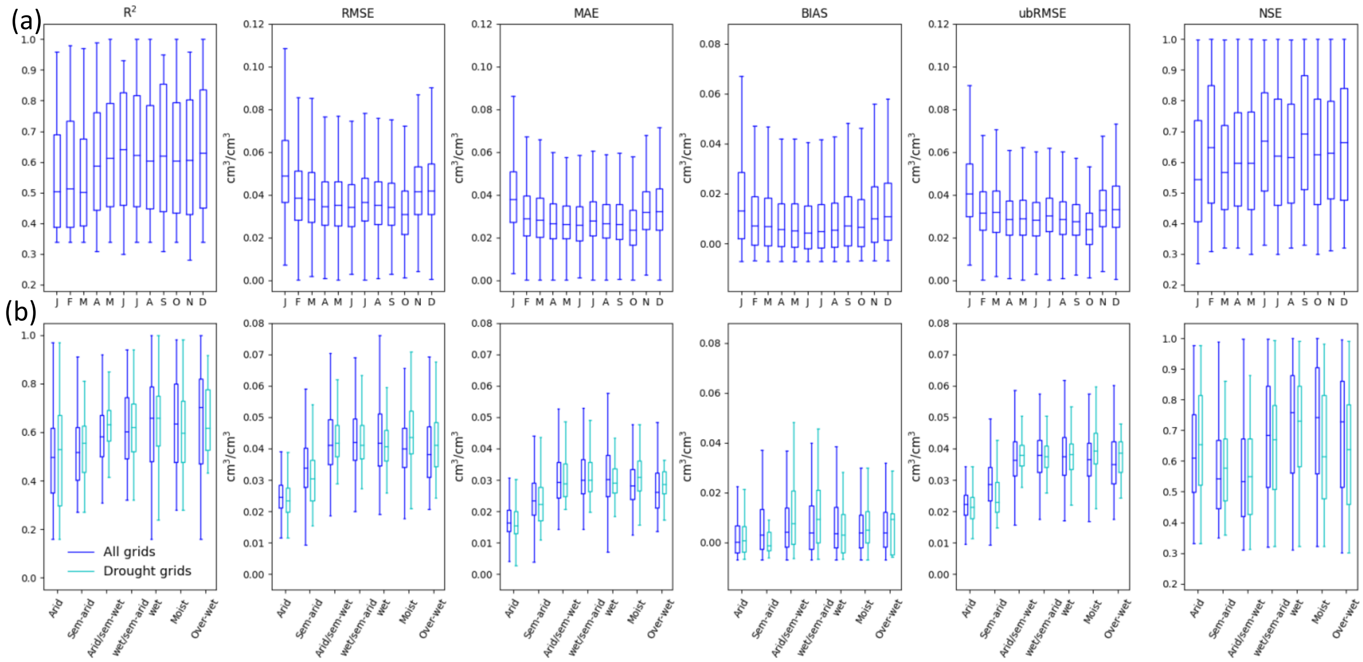


Figure 8: The accuracy metrics of 10-cross validation for R2, RMSE, MAE, BIAS, ubRMSE and NSE: (a) is averagely obtained on a month basis, and (b) is averagely obtained for each climate region.

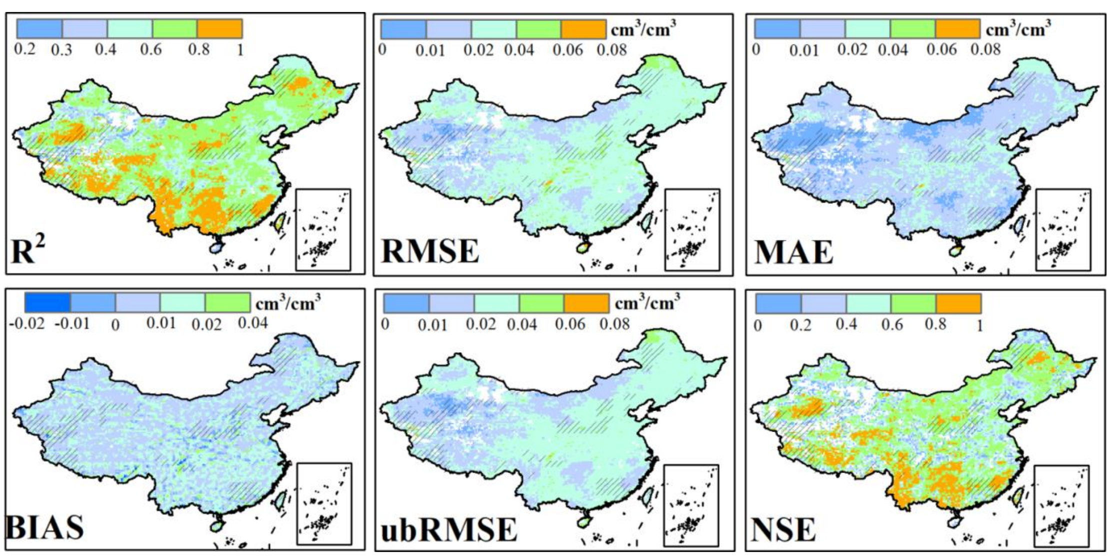


Figure 9: The spatial distributions of accuracy metrics of 10-cross validation in 2009 for R2, RMSE, MAE, BIAS, ubRMSE and NSE. The slash represents the regions impacted by drought.

7. It is unclear why a cross-validation is performed on presumably the year 2009. L335 only cites generically "model performance" as a reason. A cross-validation is usually performed to find the corresponding parameter values of the model (here the Random Forest), but this procedure is already described in Section 3.2 and refers to the years 2003-2008 which are never shown in the result section.

Which parameters are defined with the cross-validation as described in L334-335? Which values are Figures 10 and 11 comparing to? The purpose and aim of this part of the results section is unclear to me.

Response: Evaluating the gap-filled SM with in situ stations is supposed to produce biases that can be caused by scale mismatching and disaggregation model performance. To account for this, the artificial gaps were created to mitigate potential bias in model performance for any particular gap sequence. Specifically, one holdout cross validation with ten replicates is performed in 2009 to comprehensively evaluate the model performance.

Specifically, for each replicate, we randomly hold out 10% of pixels, i.e., introducing the manual gaps for these pixels, and train the model with the remaining 90% of the dataset. After the gap-filled SM series of held-out pixels are reconstructed from the training set, they will be validated with the original SM. Based on this, the reconstructed values in Figures 10 and 11 are compared against the references values for the 10% manual gaps.

This strategy regarding cross validation has been extensively used for evaluating the accuracy of the gap-filled data, considering its merits in overcoming the systematic errors and scale mismatches between the reconstructed values and field measures [1-3]. In the new version, we have revised the related context to make it clearer.

[1] Almendra-Martín L, Martínez-Fernández J, Piles M, et al. Comparison of gap-filling techniques applied to the CCI soil moisture database in Southern Europe. Remote Sensing of Environment, 2021, 258: 112377.

[2] Zhang T, Zhou Y, Zhu Z, et al. A global seamless 1 km resolution daily land surface temperature dataset (2003–2020). Earth System Science Data, 2022, 14(2): 651-664.

[3] Meng X, Liu C, Zhang L, et al. Estimating PM2. 5 concentrations in Northeastern China with full spatiotemporal coverage, 2005–2016. Remote sensing of environment, 2021, 253: 112203.

8. Section 4.5: It is unclear why suddenly focus regions are introduced and used, and why this analysis cannot be conducted on the whole area (all China). Also, it is unclear why the focus regions are so different in size. This makes them harder to compare, as the wet region has less datapoints to compare and covers a much less diverse climate zone (compare Figure 1). Please clarify why these decisions are necessary or make the analysis on the whole of China. Furthermore within this section, please verify that none of the SM data from ESA, GLEAM and Noah is used for ERA. If that would be the case, the datasets are not independent, and this could for example explain that they are more similar. Similarly, check that neither MODIS or GLDAS are used for Noah or ERA runs.

Response: One uncertainty analysis regarding LST and reanalysis SM is conducted in our study. On the one hand, although satellite LST is closely related to surface soil moisture, it is also impacted by contamination problems. On the other hand, the reanalysis dataset and outputs from land surface model can provide the full coverage data, but its accuracy is generally impacted by the numerical model used. Accordingly, the uncertainty analysis should be focused by investigating the substitution performance of other dataset sources in reconstructing SM.

Specifically, Noah soil moisture and LST is introduced for conduct uncertainty analysis. In our study, this Noah model is run with regional forcing variables rather than the global parameterizations, and thus could provide more accurate soil moisture and LST. Moreover, the utilization of regional model simulations can provide references for dataset gap-filling with other regional reanalysis dataset. The two focused regions (i.e., NC and SC) are selected because sufficient soil moisture and surface temperature can be provided by Noah model from our previous studies [1, 2]. Mention that we merely used these regions for uncertainty analysis rather than the comprehensive comparison. What's more, it is not cost-effective to run the Noah model for the whole China.

As far as I known, ERA is a reanalysis dataset that is forced by reanalysis meteorological dataset. The soil moisture of ERA doesn't depend on the products from ESA, GLEAM and Noah [3]. The noticeable differences among them have been illustrated in previous studies [4, 5]. Meanwhile, the surface temperature of all the available dataset is not depended.

According to the reviewer's suggestion, in the new version, we add the related context to make it clearer.

1] Liu K, Su H, Li X, et al. Development of a 250-m Downscaled Land Surface Temperature Data Set and Its Application to Improving Remotely Sensed Evapotranspiration Over Large Landscapes in Northern China. IEEE Transactions on Geoscience and Remote Sensing, 2020, 60: 1-12.

[2] Liu K, Li X, Wang S. Characterizing the spatiotemporal response of runoff to impervious surface dynamics across three highly urbanized cities in southern China from 2000 to 2017. International Journal of Applied Earth Observation and Geoinformation, 2021, 100: 102331.

[3] Muñoz-Sabater J, Dutra E, Agustí-Panareda A, et al. ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. Earth System Science Data, 2021, 13(9): 4349-4383.

[4] Ling X, Huang Y, Guo W, et al. Comprehensive evaluation of satellite-based and reanalysis soil moisture products using in situ observations over China. Hydrology and Earth System Sciences, 2021, 25(7): 4209-4229.

[5] Wu Z, Feng H, He H, et al. Evaluation of soil moisture climatology and anomaly components derived from ERA5-land and GLDAS-2.1 in China. Water Resources Management, 2021, 35(2): 629-643.

9. Since this gap-filling method could be an important contribution to the problem of missing values in soil moisture remote sensing observation and Earth observations in general, it would be beneficial if the code of the method could be published, preferably on a platform that enables easy use for interested users and a versioning system (e.g. Github). Also for the purpose of this review, if possible, it would be interesting to have a look at the code to understand better what is going on and how exactly this is implemented.

Response: Thanks for pointing out this issue. Our work is primarily conducted in the Python with core packages including gdal, NumPy, scikit-learn and scipy, as well as in the RStudio with the package of spgwr. After this public is accepted, we will reorganize the python code in a friend manner and put it on the Github platform following the HEES's requirement.

Regarding our work, two core codes mainly includes that i) for finding the searched windows (nw) and searched days (nd), and ii) for using the random forest to gap-fill object soil moisture. The core part is provided in the following text.

```
##### Code #1 for finding the searched windows (nw) and searched days (nd)
        nw = 4
        nd = 1
        n_sample = 0
        while (nw <= 10) & (n_sample < 8*num_variable) :
          sm_local = np.ravel(sm[iband, i-nw:i+nw, j-nw:j+nw])
          index = (sm_local > 0)
          n_sample = len(sm_local[index])
          nw = nw + 1
        nw = nw - 1

        if (n_sample < 8*num_variable):
          nd = nd+1
          while (nd <= 4) & (n_sample < 8*num_variable) :
            sm_local = np.ravel(sm[iband-nd:iband+nd, i-nw:i+nw, j-nw:j+nw])
            index = (sm_local > 0)
            n_sample = len(sm_local[index])
            nd = nd + 1
          nd = nd – 1

###Code #2 for using the rf to gap-fill object sm
            sm_rg = sm_local[index]
            albedo_rg = albedo_local[index]
            ndvi_rg = ndvi_local[index]
            pet_rg = pet_local[index]
            ap_rg = qp_local[index]
            era_sm_rg = era_sm_local[index]
            tpi_rg = tpo_local[index]
            dtr_rg = dtr_local[index]

            explain_value = np.vstack([albedo_rg,ndvi_rg,pet_rg,ap_rg,era_sm_rg,tpi_rg,dtr_rg])
            rfr = RandomForestRegressor(n_estimators=estimators[itype], max_depth=depth[itype],
min_samples_split=split[itype],max_features=feature[itype])
            rfr.fit(explain_value.T, sm_rg)
            pred_value=
np.vstack([albedo[iband,i,j],ndvi[iband,i,j],pet[iband,i,j],ap[iband,i,j],era_sm[iband,i,j],tpi[iband,i,j],dtr[ib
and,i,j]])
            value_temp = rfr.predict(pred_value.T)
            if (value_temp > 0) and (value_temp < 1):
              sm_fill[iband,i,j] = value_temp
```

SPECIFIC COMMENTS + TECHNICAL CORRECTIONS

Response: Thanks again for the reviewer's valuable suggestions. The English language usage in this version has been improved deeply by one fluent English researcher that is suggested by the commercial corporation. The detailed modifications can be found in the highlighted text throughout the manuscript.

1. L20 "Compared to that…" I don't understand this sentence. Please clarify

Response: Thanks for pointing out this. We have revised this in the new version, as following,

"In comparison with gap-filled SM data based on a satellite-derived diurnal temperature range (DTR), the gap-filled SM data from bias-corrected model-derived DTRs exhibited relatively lower accuracy but higher spatial coverage."

2. l31: "SM has been declared" please add citation

Response: This has been revised in the new version.

3. L44 there is some literature on the shortcomings of soil moisture assimilation into reanalysis, see e.g. Dorigo et al 2017

Response: Thanks for pointing out this issue. The related references have been added in this version.

4. L62: "some studies" but only one study is cited.

Response: Some other related references have been added in this version.

5. L74 and all other occurrences throughout the text: the word "delineating" is used in an unusual way. I suggest replacing it with depict/represent/show/ or similar in all occurrences

Response: Thanks for pointing out this issue. We solve this issue in the new version.

6. L89 and all other occurrences throughout the text: using "the" in front of an previously unmentioned fact is confusing. Replace with "a" if not referring to a specific one.

Response: Thanks for pointing out this issue. We revise this in the new version.

7. L95 consider citing Bessenbacher et al 2022

Response: The related references have been added in this version.

8. Fig 1: please increase resolution. Explain acronym DEM at first occurrence.

Response: Thanks for pointing out this issue. The quality of Fig 1 has been improved in the new version.

9. L119 “mainly”. What is not included in this list?

Response: We have revised this in the new version.

10. Table 1: remove lines below “model analysis” in first column. Left-aligning columns could improve readability

Response: Thanks for pointing out this issue. We solve this in the new version.

11. L 121: mention already here what the difference between “model establishment” and “model analysis” is. Is one the features used to run the model, and the other the evaluation? Not clear.

Response: Thanks for pointing out this issue. We have revised this in the new version.

12. L130: data is a plural word. Always “data are”

Response: We double check this throughout the manuscript.

13. L142: to better understand the negative correlation of TPI and CCI SM in Figure 3 please add a short sentence explaining what a high / low TPI mean.

Response: Thanks for pointing out this issue. We have revised this sentence to make it cleaner, as following，

“Positive (negative) TPI values mean that the target grid is higher (lower) than the average of its surroundings”.

14. L159: this is a good example of how the text can easily be shortened without losing understanding. “Precipitation, air temperature, … are obtained from the Chinese …”. Please look for those sentences elsewhere as well to clear up text.

Response: Thanks for pointing out this issue. We double check this throughout the manuscript.

15. L160: since this is dataset from ground stations, but you state it is gridded, how was the gridding procedure performed? Is there literature that you could cite?

Response: The dataset is generated through fusion of in-situ station data, remote sensing products and reanalysis datasets, and it has a temporal resolution of 3-hourly and a spatial resolution of 0.1° (He et al., 2020). We will revise this sentence in the new version.

16. Table 2: Since you never discuss results at the individual stations of the WATER and CERN stations, I don't think it is necessary to add a table here naming them all. Consider moving to Supplementary Material or adjust such that table only includes networks and not individual stations.

Response: Thanks for pointing out this issue. In the new version, the Table 2 is moved to Supplementary Material.

17. L184 please add citation for this claim.

Response: The related citations have been added for this claim regarding the station measurements.

18. L194 "a vector the sample number of which is decided by" no correct English sentence.

Response: Thanks for pointing out this issue. We have revised this sentence in the new version, as following,

"V_i can be a vector, and the sample number is determined the spatial domain (N) and temporal domain (T)"

19. L197ff: I don't understand how steps (i) through (iii) are related to the four boxes in Figure 2. Adjust Figure 2 such that it has the same structure as the text, or vice versa.

Response: Thanks for the reviewer's valuable suggestion. In the new version, we have adjusted both the Figure 2 and the related text to make them consistent. Please also see the reply to comments #1.

20. Fig 2: Explain colours and frame shapes. Explain which criterion is to be met in "data judging". Explain which explanatory variables are taken from "dataset preparing" to "dataset judging". Rename judging.

Response: In the new version, we rewrite the caption to make it readable.

21. L214: "plenty" as in all possible combinations? Are you stepwise removing or adding variables, or are you trying all different combinations? Please clarify.

Response: The main assumption beneath this regression subset selection approach is that the suppressor variables are associated significantly with each other in regression models, although they may be less correlated with the dependent variables. To be specific, this approach can be conducted with the following steps: (1) using least-squares linear regression to check the potential relationships between SM and explanatory variables; (2) applying a backward stepwise (remove) regression to explore the potential explanatory variables based on the Akaike Information Criterion (AIC); (3) exploiting the best models from all variable combination to identify the important variables impacting SM; and (4) quantifying the relative contributions of each explanatory variable to SM based on the determination coefficient. According to the reviewer's suggestion, we have added the related description in the Supplementary materials.

22. L217: please define "importance criterion"

Response: The "importance criterion" means the determination coefficient.

23. L223: what happens in the case that gaps are present in the variables?

Response: Regarding the gaps presented in these variables, we do not consider further this to avoid introducing additional errors. We have claimed this in the new version.

24. L224: are slope, lat, Lon, aspect and wind removed or not? They are not visible in Figure 3b,c but their removal is not mentioned in the text.

Response: We excluded aspect, slope, wind, latitude, and longitude owing to their low correlations with SM. The EVI, NDVI, and air temperature were also not considered in further application because the EVI and LAI are closely correlated with NDVI, and air temperature is strongly correlated with DTR. We have claimed this in the new version.

25. Eq4: what does subscript p1 mean? What does the "." And the "' "mean in the second equation? Isn't mu(SM_c1) the same as mu(SM_ESA (t_av))? If so, please simplify equations.

Response: Thanks for pointing out this issue. We have revised this in the new version.

26. L254f: please define the difference between "traditional regression-based methods" and "machine learning approaches", since both are regressions, machine learning models do not inherently come with uncertainty estimation (for example, a Random Forest model does not have intrinsically uncertainty estimation and you don't have it in this study) and it is not less likely to overfit with machine learning methods.

Response: Thanks for pointing out this issue. We have rewritten this in the new version, as following,

"Despite being easy to implement and requiring less computational resources, traditional regression-based methods such as generalized linear models and multivariate regression splines generally insufficiently consider the probability density functions in assessing model performance. Machine learning approaches could be much more flexible than conventional parametric models owing to their ability to handle nonlinear relationships and complex interactions."

27. L260 “is feasible to add layer categories” please clarify.

Response: RF is a hierarchical tree diagram, which is based on a nonparametric strategy and offers the opportunity to add a diverse variety of data layers into the model (Breiman, 2001).

28. L293: please clarify how missing values in the explanatory variables are treated within this algorithm.

Response: Considering that a fraction of gaps occur in the satellite dataset (e.g., LST and albedo) and the optimal window may not exist, the maximum values of sw and nd are introduced to terminate this process. On the other hand, regarding the gaps presented in these selected variables, we will not further considered in order to avoid introducing additional errors.

29. Fig 5, caption: please define sw and nd for better readability

Response: Thanks for pointing out this issue. We have revised the related context. The results of the sensitive analysis regarding two maximum values, i.e., the size of the spatial window (sw) and the number of temporal days (nd), for terminating the searching process.

30. L308: please clarify “neglectful variables”

Response: This calibration procedure can potentially correct the bias resulting from neglectful variables such as those are excluded for model establishment (Zhu et al., 2012; Liu et al., 2020a).

31. L311: please introduce acronym GWR before first mention.

Response: The full name of GWR (i.e., geographically weighted regression) is added in the new version.

32. L319: typo “her”

Response: Thanks for pointing out this issue. We have corrected this in the new version.

33. Section 3.4: Is this just a linear regression, applied to the same time window approach as the Random Forest, applied on the residuals from the Random Forest model? Please clarify

Response: We have clarified this in the new version.

34. L322: Please show a plot that shows the relative contributions of the GWR interpolation and the Gaussian Filter smoothing in the reply to this review, as to see that the influence of the latter on the results is smaller than the one of the former.

Response: We also check the accuracy of the models excluding the residual calibration procedure, which is an essential component of the proposed model. Results (Fig. 10) demonstrate that accuracies are lowered by ~9% when removing the residual calibration, underscoring the importance of residual modulation in improving SM reconstruction.

35. L354, 355: “heavy missing issues”, “relative minor conformity” please correct English and clarify meaning.

Response: Thanks for pointing out this issue. We have corrected this in the new version.

36. L356: “consistent pattern” please clarify. Are you arguing they are similar or they have consistent biases? If yes, which? Please describe the results more.

Response: Thanks for pointing out this issue. We have clarified this in the new version, as following,

“Conformity exists between the original and reconstructed SM for most days. A similar pattern in variance and magnitude is also observed for the SM of the monthly average and the selected days, as illustrated in Fig. 5(c); that is, large difference occurs in winter and spring.”

37. Fig7, 8: Please put the corresponding days next to each other to simplify comparison.

Response: According to the reviewer’s suggestion, we have adjusted the Fig.7 and 8 in the new version.

38. L388: I disagree that the values are close to the 1:1 line, but I also think that this is hard to achieve given the spatial gap between point measurements and gridded measurements.

Response: Thanks for pointing out this issue. We have deleted this in the new version.

39. L391: please clarify sentence “in general..”

Response: This sentence has been revised in the new version.

40. L399: NSE is not introduced in Section 3.5. Please add.

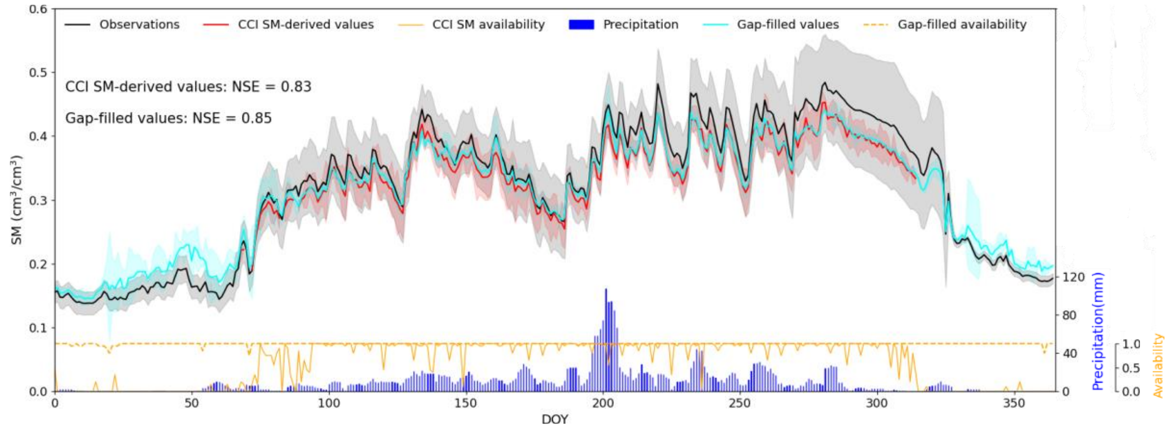
Response: Thanks for pointing out this issue. We have added the related context in this version.

41. L402: please clarify sentence “in general..”

Response: We have removed this word in the new version.

42. Fig9g: please add the fraction of missing values for each day (e.g. similar to precipitation bar plots) such that it can be evaluated how the gap-filling performs with little or many missing values.

Response: According to the reviewer's suggestion, we have added the fraction of missing values for each day.



43. L423 please explain mechanism better

Response: According to the reviewer's suggestion, we add the related context in the new version.

44. L431: again please refrain from simply describing the results as "good" without further analysis (see also general comment above)

Response: Thanks for pointing out this issue. We have revised the related context in this version.

45. L442 typo "in suit"

Response: This is corrected in the new version.

46. L442 "satisfied performance" please correct English

Response: This is corrected in the new version.

47. L446 "severe missing issues" please correct English

Response: This is corrected in the new version.

48. L453 "future compared" please correct English

Response: This is corrected in the new version.

49. L465 since the 9% & 19% increase in accuracy stemming from residual calibration and the spatiotemporal domains, respectively, is an important result that you mention in the conclusions and in

the abstract, it should be more clear in Figure 12. Maybe add a figure with accuracy change per change in the method?

Response: According to the reviewer's suggestion, we redraw this figure.

50. Figure 12, 13, 14: R**2 doesn't have a unit (Accuracy, cm**3/cm**3). Please clarify. For example, add an optimal value to each score (0 for RMSE, 1 for R2) and sort the diagram after scores, not after methods, such that the scores can be directly compared.

Response: In the new version, the original Figure 12, 13 and 14 have been redrawn.

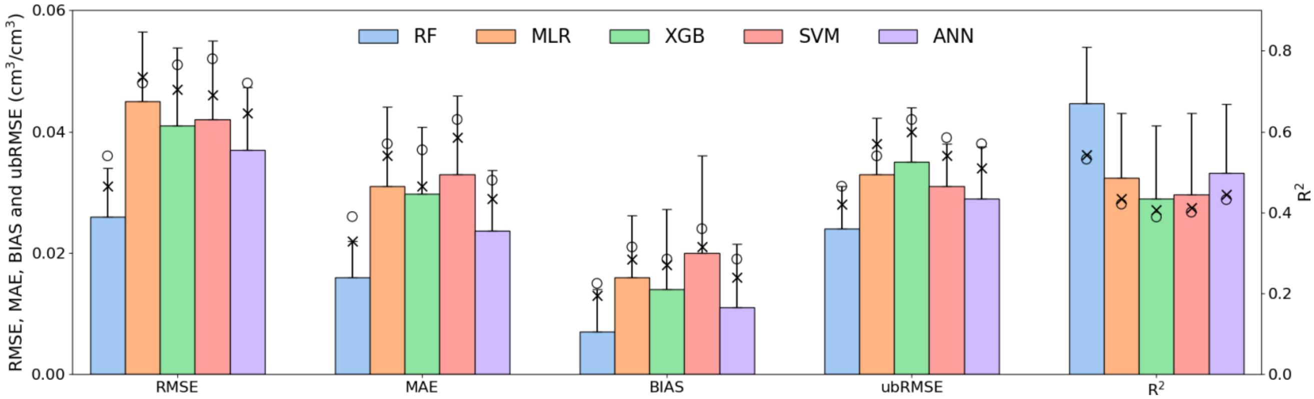


Figure 10: Comparison RF-based model with other models (i.e., MLR, XGB, SVM and ANN). Error bars denote 1σ errors. The symbol 'x' represents the accuracy metrics of models excluding the residual calibration procedure, and the symbol 'o' represents the accuracy metrics of the models that use the global regression rather than regional regression based on the spatiotemporal window searching strategy.

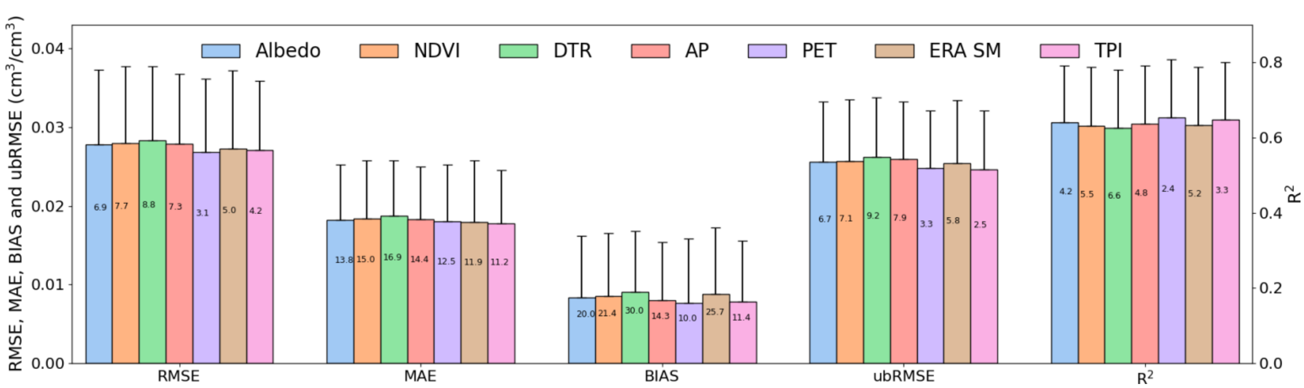


Figure 11: The accuracy of the models removing one variable, i.e., using other six variables in model regression. Error bars denote 1σ errors. The text denotes the relative percentage of the decreased accuracy in comparison to the baseline accuracy using all seven variables.

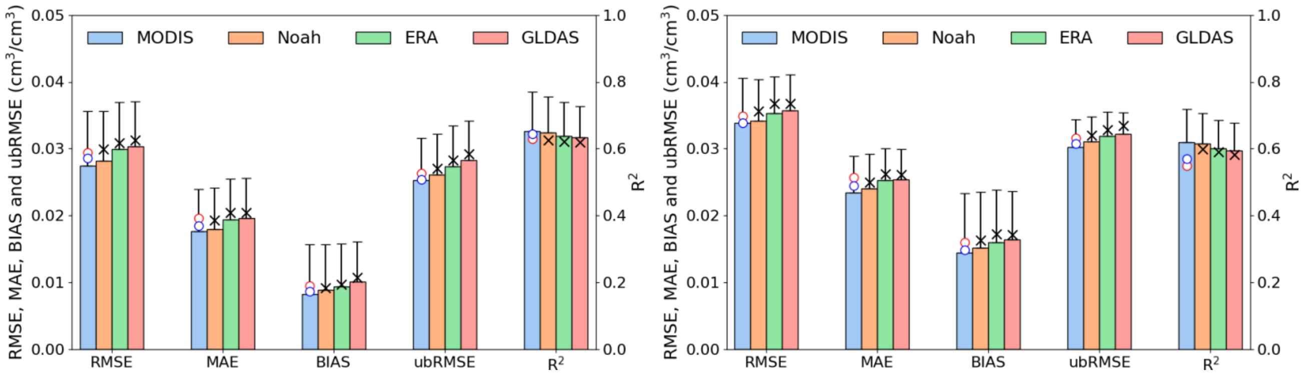


Figure 12: The metrics of models using different DTRs for (a) Northern China (NC) and (b) Southern China (SC). Error bars denote 1σ errors. The symbol 'x' represents the accuracy metrics of the models without DTR correction procedure. The symbol 'o' in red represents the accuracy metrics of the models using GLEAM SM to replace ERA SM, and the symbol 'o' in blue represents the accuracy of the models using Noah SM to replace ERA SM.

51. L514 please clarify where this result is visible. If mentioning percentages of chance in the text, they should be visible in the graphs directly and not from comparing different bar plots visually.

Response: We also check the accuracy metrics of the models without correction procedure. This is also conducted based on the 10-fold cross validation. In comparison with the results obtained using the correction procedure, reduction in accuracy metrics (~4%) occurs when not considering the variable correction procedure. It emphasizes the indispensable contribution of the variable calibration procedures in reconstructing surface characteristics. We have further clarified this in the new version.

52. L532 "has a long sequence" please correct English

Response: This has been corrected in the new version.

53. L534 "more than 90%…" this is not clearly visible in Figure 15

Response: Thanks for point out this issue. We have deleted this sentence in the new version.

54. L535 "comparable accuracy". Some metrics are better, some are worse. Discuss differences and possible reasons!

Response: The accuracy evaluation during 2005-2015 (excluding 2009) is only conducted using the Maqu network, which demonstrates that the reconstructed SM during this period has an acceptable accuracy with the original SM (Table 4) which is comparable to those in 2009. We revised the related context in the new version.

55. L545 Please explain the mechanism better.

Response: Thanks for point out this issue. We have revised the related context in the new version.

56. Table 5: please reorder such that the values are immediately comparable, e.g. the R2 columns next to each other etc

Response: Thanks for point out this issue. The original Table 5 has been adjusted in the new version.

Table 4 Metrics for the gap-filling performance regarding Maqu network for the extended years

Year	R^2		RMSE (cm^3/cm^3)		MAE (cm^3/cm^3)		Bias (cm^3/cm^3)		ubRMSE (cm^3/cm^3)		NSE	
	CCI	gap-filled	CCI	gap-filled	CCI	gap-filled	CCI	gap-filled	CCI	gap-filled	CCI	gap-filled
2008	0.8	0.71	0.11	0.13	0.1	0.13	0.06	0.07	0.06	0.06	0.8	0.81
2010	0.82	0.73	0.1	0.11	0.09	0.11	0.05	0.06	0.06	0.05	0.81	0.83
2011	0.83	0.74	0.09	0.11	0.09	0.1	0.06	0.06	0.06	0.05	0.82	0.84
2012	0.81	0.72	0.12	0.13	0.09	0.12	0.06	0.05	0.05	0.05	0.81	0.82
2013	0.82	0.73	0.09	0.12	0.09	0.13	0.06	0.07	0.05	0.07	0.8	0.82
2014	0.85	0.74	0.09	0.11	0.08	0.09	0.06	0.08	0.05	0.06	0.83	0.85
2015	0.79	0.69	0.12	0.14	0.1	0.12	0.07	0.09	0.07	0.07	0.79	0.81

57. Fig 15: use different colorscale for last column to improve readability. For example, blue to red, for “wetter” to “drier”

Response: Thanks for point out this issue. The original Figure 15 has been adjusted in the new version.

58. Fig 16: one plot per climate zone, not one plot per dataset, such that they are visibly comparable. Also, disaggregate into seasonality and interannual variability to further analyse if both characteristics of the soil moisture dataset are reproduced in the gap-filled version.

Response: Thanks for the reviewer’s suggestion. We have adjusted the original Figure 16. Meanwhile, we also discomposed the time series into to trend-cycle and seasonal component using a Seasonal-Trend decomposition using LOESS (STL). This context has been added in the Supplementary materials.

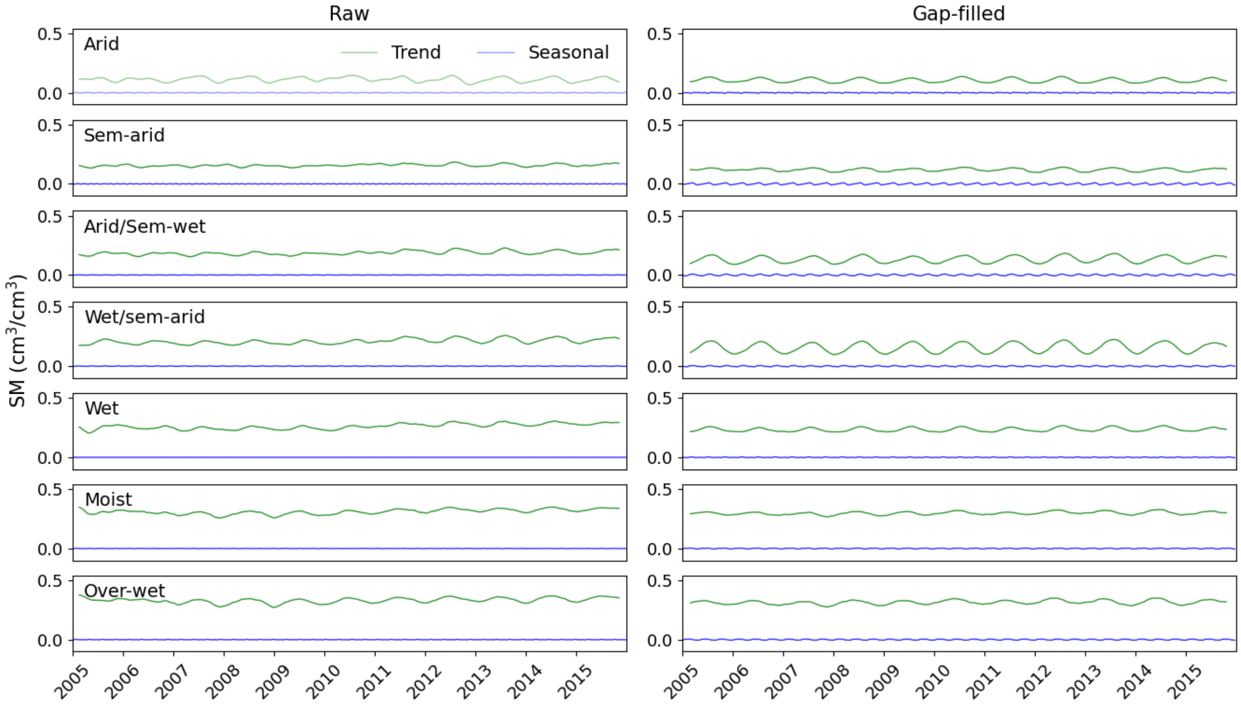


Figure S7. The trend-cycle and seasonal component of raw and gap-filled CCI SM regarding different climate regions during 2005-2015.

59. L576 “study presents” please correct English

Response: This has been corrected in the new version.

60. L585 “especially for areas with large swath gaps” this is not shown in the results but would be very interesting

Response: Thanks for point out this issue. We have deleted this in the new version.

61. L594 “manifest” please correct English

Response: This has been corrected in the new version.

62. L692 “reliable data” too generic

Response: This has been rewritten in the new version.

REFERENCES

Response: Thanks for the reviewer's suggestion. We have tried our best to incorporate these references in the revised version.

Rubin, D. B.: Inference and missing data, Biometrika, 63, 581–592, 1976.

Little, R. J. A. and Rubin, D. B.: Missing Data in Experiments, in: Statistical Analysis with Missing Data, pp. 24–40, John Wiley & Sons,
Ltd, https://doi.org/10.1002/9781119013563.ch2, 2014.

van Buuren, S.: Flexible Imputation of Missing Data, Second Edition, Chapman and Hall/CRC, Boca Raton, 2 edition edn., 2018.

Bessenbacher, V., Gudmundsson, L. And Seneviratne, S.I: CLIMFILL v0.9: A Framework for Intelligently Gap filling Earth Observations, GMD (in review), https://doi.org/10.5194/gmd-2021-164

Dorigo, W., Wagner, W., Albergel, C., Albrecht, F., Balsamo, G., Brocca, L., Chung, D., Ertl, M., Forkel, M., Gruber, A., Haas, E., Hamer, P. D., Hirschi, M., Ikonen, J., de Jeu, R., Kidd, R., Lahoz, W., Liu, Y. Y., Miralles, D., Mistelbauer, T., Nicolai-Shaw, N., Parinussa, R., Pratola, C., Reimer, C., van der Schalie, R., Seneviratne, S. I., Smolander, T., and Lecomte, P.: ESA CCI Soil Mois- ture for improved Earth system understanding: State-of-the art and future directions, Remote Sensing of Environment, 203, 185–215, https://doi.org/10.1016/j.rse.2017.07.001, 2017.

Response to #2

This manuscript explores a RF based approach to fill the spatial gaps in satellite SM observations. The paper is extensive and well organized. The literature review is also extensive, nevertheless it explores studies that are immediately similar to the study to a high degree (i.e. predicts SM from satellite sensors) that there might be some lessons learned in some related studies (i.e. predicts reanalysis SM from model outputs using observed predictors similar to those used in this study) that weren't discussed. Other specific comments are below.

Response: Thanks for your valuable time and constructive comments. We try our best to incorporate them in the new revision. In particular, in the modified version,

- Some references have been enhanced. To be specific for some critical context,

"Li, B., Liang, S., Liu, X., Ma, H., Chen, Y., Liang, T., and He, T.: Estimation of all-sky 1 km land surface temperature over the conterminous United States, Remote Sensing of Environment, 266, 112707, https://doi.org/10.1016/j.rse.2021.112707, 2021.

Li, Q., Wang, Z., Shangguan, W., Li, L., Yao, Y., and Yu, F.: Improved daily SMAP satellite soil moisture prediction over China using deep learning model with transfer learning, Journal of Hydrology, 600, 126698, https://doi.org/10.1016/j.jhydrol.2021.126698, 2021b.

Li, Q., Li, Z., Shangguan, W., Wang, X., Li, L., and Yu, F.: Improving soil moisture prediction using a novel encoder-decoder model with residual learning, Computers and Electronics in Agriculture, 195, 106816, https://doi.org/10.1016/j.compag.2022.106816, 2022b.

Li, L., Dai, Y., Shangguan, W., Wei, N., Wei, Z., and Gupta, S.: Multistep Forecasting of Soil Moisture Using Spatiotemporal Deep Encoder–Decoder Networks, Journal of Hydrometeorology, 23, 337-350, 10.1175/jhm-d-21-0131.1, 2022.

Li, Y., Piao, S., Li, L. Z. X., Chen, A., Wang, X., Ciais, P., Huang, L., Lian, X., Peng, S., Zeng, Z., Wang, K., and Zhou, L.: Divergent hydrological response to large-scale afforestation and vegetation greening in China, Science Advances, 4, eaar4182, doi:10.1126/sciadv.aar4182, 2018.

Long, D., Bai, L., Yan, L., Zhang, C., Yang, W., Lei, H., Quan, J., Meng, X., and Shi, C.: Generation of spatially complete and daily continuous surface soil moisture of high spatial resolution, Remote Sensing of Environment, 233, 111364, https://doi.org/10.1016/j.rse.2019.111364, 2019.

Shangguan, W., Hengl, T., Mendes de Jesus, J., Yuan, H., and Dai, Y.: Mapping the global depth to bedrock for land surface modeling, Journal of Advances in Modeling Earth Systems, 9, 65-88, https://doi.org/10.1002/2016MS000686, 2017.

Li L, Dai Y, Shangguan W, et al. Causality-Structured Deep Learning for Soil Moisture Predictions. Journal of Hydrometeorology, 2022."

- Substantial lessons learned in the model output perspective are added especially in the discussion and conclusion section. To be specific for some critical context,

  "Our study illustrates the merit of identifying a sufficient number of explanatory variables from the integration of satellite observations and model-driven knowledge. This is clearly verified by the fact that the accuracy of reconstructed SM is noticeably reduced when excluding one of each of the participating variables in turn while retaining the remaining variables. The selected variables complementarily reproduce the SM dynamics in addition to capturing the spatial variations, which also implies that the nonlinear correlation between the SM and explanatory variables can be depicted on the spatiotemporal scale. In addition to the conventional variables from optical remote sensing, the essential environmental elements from model-driven knowledge are used to improve the performance of SM reconstruction. Earlier studies have suggested (Li et al., 2021a; Long et al., 2019; Shangguan et al., 2017) that reanalysis datasets and land surface model products could provide spatiotemporally continuous records, indicating the great potential of simulating land surface parameters. Here, we employ a machine learning model and a bias correction procedure for CCI SM simulation, which is expected to leverage the knowledge of the reanalysis dataset and the output from the land surface model in transfer to the CCI SM time series. The reconstructed SM achieves satisfactory accuracy over China, underscoring the importance of spatial coverage and continuity of the environmental factors from model-driven knowledge, and highlighting the need for multiple datasets to be involved in gap-filled models. We further confirm this with an uncertainty analysis showing the feasibility of using alternative data sources of DTR and SM, which is essential on the long-term scales, considering the full coverage characteristic of numerical model simulated products. Nevertheless, because numerical simulation models are generally sensitive to regional surface and climatic conditions, adoption of more effective machine learning models and bias correction strategies, as well as more representative model outputs such as CLDAS and regional numerical models, could be considered in further work (Li et al., 2022a; Li et al., 2022b)."

- The English language usage in this version has been improved deeply by one fluent English researcher that is suggested by the commercial corporation. The detailed modifications can be found in the highlighted text throughout the manuscript.

1. L85 ElSaadani et al. 2021 "Assessment of a spatiotemporal deep learning approach for soil moisture prediction and filling the gaps in between soil moisture observations" discussed in detail the following issues that are relevant to this manuscript:

- Filling SM gaps saptio-temporally using a convlstm ML approach.
- The effect of the number of predictors and time step of prediction on the model performance.

In addition, Q Li et al "Improved daily SMAP satellite soil moisture prediction over China using deep learning model with transfer learning" built on the above work to apply it to SMAP observations while improving the ML convlstm accuracy. Please include the above references for completeness of literature review and lessons learned regarding the predictors and their effect on ML model performance.

Response: Thanks for pointing out this issue. We enhance the references throughout the manuscript to make it more convincible.

2. Table 5 Please separate the two sides of the table properly

Response: Thanks for pointing out this version. The original Table 5 has been adjusted in the new version.

Table Metrics for the gap-filling performance regarding Maqu network for the extended years

Year	R^2		RMSE (cm³/cm³)		MAE (cm³/cm³)		Bias (cm³/cm³)		ubRMSE (cm³/cm³)		NSE	
	CCI	gap-filled	CCI	gap-filled	CCI	gap-filled	CCI	gap-filled	CCI	gap-filled	CCI	gap-filled
2008	0.8	0.71	0.11	0.13	0.1	0.13	0.06	0.07	0.06	0.06	0.8	0.81
2010	0.82	0.73	0.1	0.11	0.09	0.11	0.05	0.06	0.06	0.05	0.81	0.83
2011	0.83	0.74	0.09	0.11	0.09	0.1	0.06	0.06	0.06	0.05	0.82	0.84
2012	0.81	0.72	0.12	0.13	0.09	0.12	0.06	0.05	0.05	0.05	0.81	0.82
2013	0.82	0.73	0.09	0.12	0.09	0.13	0.06	0.07	0.05	0.07	0.8	0.82
2014	0.85	0.74	0.09	0.11	0.08	0.09	0.06	0.08	0.05	0.06	0.83	0.85
2015	0.79	0.69	0.12	0.14	0.1	0.12	0.07	0.09	0.07	0.07	0.79	0.81

3. L143 please check grammar and explain why regular DEM wasn't used

Response: Thanks for pointing out this issue. Earlier studies [1] found that topographic position index (TPI) correlated best with surface variables such as snow depth and soil moisture amongst several other terrain-derived indices, with the strength of the correlation varying as a function of elevation range and topographic complexity in the designated neighborhood. Regarding this index, larger neighborhoods are more likely to reveal larger-scale terrain features such as valleys and ridges, while smaller neighborhoods more likely identify local depressions/fissures [2].

The applicability of TPI can be further corroborated with the Pearson correlation. Our analysis observes that TPI has the higher Pearson's correlation with soil moisture in comparison with DEM (0.317 versus 0.288 in significance percentage), which encourages our work for using TPI rather than the DEM.

In the new version, we have revised the related context.

[1] Cristea N C, Breckheimer I, Raleigh M S, et al. An evaluation of terrain-based downscaling of fractional snow covered area data sets based on LiDAR-derived snow data and orthoimagery. Water Resources Research, 2017, 53(8): 6802-6820.

[2] Shaw T E, Gascoin S, Mendoza P A, et al. Snow depth patterns in a high mountain Andean catchment from satellite optical tristereoscopic remote sensing. Water Resources Research, 2020, 56(2): e2019WR024880.

4. L335 please explain the reasoning behind the separation percentage of 90 10 training testing and how this subset was extracted. Is it random undefined subset or is a certain defined period was extracted and why.

Response: Thanks for the reviewer's valuable suggestions. Evaluating the gap-filled SM with in situ measurements is supposed to produce biases that can be caused by scale mismatching and disaggregation model performance. To account for this, the artificial gaps were created to mitigate potential bias in model performance for any particular gap sequence. Model performance was tested by 10-fold cross validation (CV). The gap-filling accuracy was evaluated by a spatiotemporal 10-fold CV, i.e., randomly holding out 10% of pixels, training the model with the remaining 90% of the pixels, making evaluating on the held-out stations, and repeating this process 10 times.

Previous studies generally implemented regular spatial or temporal 10-fold CV by randomly choosing 10% subset of each band or 10% period of each grid each time. Here, a much stricter spatial and temporal CV procedure [1, 2] was selected in this study by rearranging the pixels during all studied period into one time series and then dropping 10% samples each time (leave-one-year-out-cross-validation) to test the capacity of gap-filling soil moisture. According to the reviewer's suggestion, we will revise the related context in this version.

[1] Meng X, Liu C, Zhang L, et al. Estimating PM2. 5 concentrations in Northeastern China with full spatiotemporal coverage, 2005–2016. Remote sensing of environment, 2021, 253: 112203.

[2] Zhang D, Du L, Wang W, et al. A machine learning model to estimate ambient PM2. 5 concentrations in industrialized highveld region of South Africa. Remote Sensing of Environment, 2021, 266: 112713.

5. Figure 13: please reword the description of panel (a) regarding the text in the figure, does that describe the decrease in performance as a percentage of the original value?

Response: Thanks for pointing out this issue. This denotes the relative percentage of the decreased accuracy of the model with six variables (i.e., excluding one) in comparison with that of a model with seven variables. We have revised the related context in the new version.

6. Figure 15 please explain in writing the effect of the significance level on the accuracy of conclusions and interpretation of the results.

Response: Thanks for pointing out this issue. Owing to the missing satellite retrievals, the CCI SM tends to be overestimated. As shown in Fig. 13(d)-(f), the difference in valid participating SM values causes disparity in calculating the SM trend, i.e., bringing a lower SM trend in most wet regions but a higher SM trend in some dry regions when gap-filled values are introduced. Additionally, most regions with a significant trend demonstrate a lower trend in comparison with the trends of the original SM.

The confidence level of the SM trend is converted from a significance level to a non-significance level for a considerable fraction of the grids. This is more pronounced in wet regions such as northeast, northwest, and southwest parts of China, which are sensitive to monsoon precipitation and ice melting. Our results are corroborated by earlier studies that revealed an overestimation in the trend of missing AOD [1] and albedo [2] when cloudy conditions prevented satellite retrievals. It means that the variations in SM trend are related to changes in the climate variables (e.g., precipitation) and land management activities. According to the reviewer's suggestion, we have revised the related context in the new version.

[1] Zhang R, Di B, Luo Y, et al. A nonparametric approach to filling gaps in satellite-retrieved aerosol optical depth for estimating ambient PM2. 5 levels. Environmental Pollution, 2018, 243: 998-1007.

[2] Gunnarsson A, Gardarsson S M, Pálsson F, et al. Annual and inter-annual variability and trends of albedo of Icelandic glaciers. The Cryosphere, 2021, 15(2): 547-570.

7. Figure 16 is difficult to interpret, please make sure to have a proper legend that makes the figures self-explanatory, especially in the lower panels. Reading the figure caption to understand symbols adds difficulty to the interpretation.

Response: Thanks for pointing out this issue. The original Figure 16 and the related caption have been adjusted in the new version. In addition, we separate the scatters plot of 1-km CCI SM-derived trends against in situ measures into two screen windows, i.e., regarding the trends under significance level ($P<0.05$), and regarding all the trends.

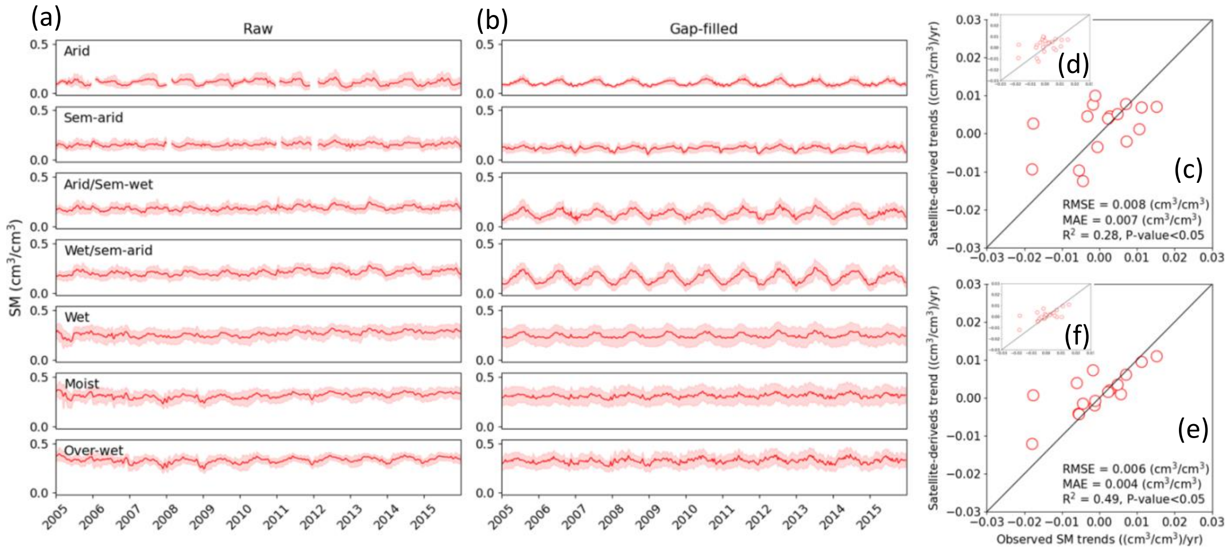


Figure 14: (a) shows the temporal patterns of raw CCI SM regarding different climate regions during 2005-2015, and (b) shows the temporal patterns of gap-filled CCI SM regarding different climate regions. The shaded area in (a) and (b) denotes ±1 standard error. (c) and (d) The scatter plot of 1-km CCI SM-derived trends against in situ measures during 2005-2014, and (c) shows the trends under significance level (P<0.05), while (d) shows all the trends. (e) and (f) The scatter plot of 1-km gap-filled SM-derived trends against in situ measures during 2005-2014, and (e) shows the trends under significance level, while (f) shows all the trends.

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