**"Gap-Free Global Annual Soil Moisture: 15km Grids for 1991–2016" by Mario Guevara et al. Responses to anonymous reviewer #2**

REVIEWER COMMENT: OVERVIEW
The study has developed a gap-filled, and downscaled with topography-derived information, long-term annual (15 km) global soil moisture dataset based on the ESA CCI satellite soil moisture products. The assessment of the dataset with respect to in situ observations has been carried out through annual comparisons as well as in terms of long-term trends (1991-2016).

REVIEWER COMMENT: GENERAL COMMENTS
The paper is mostly well written and clear. The topic of the paper is interesting for the readership of Earth System Science Data as a global scale gap-filled annual soil moisture dataset is surely useful for many applications. However, I believe the paper needs major changes before the publication as several parts are not properly described and other sections need to be improved or summarized. I have listed below my comments with the indication of their relevance.

AUTHORS RESPONSE: We appreciate the reviewer comments, the recognition of the importance of this dataset, and support for the possible publication of this manuscript. We have clarified and improved the description of methods and improved the manuscript following these comments and those from other reviewers.

REVIEWER COMMENT:1) MAJOR: The factors used in the downscaling and gap-filling algorithm should be described in details. Two figures (Figures 2 and 3) are not mentioned in the text. It seems a part is missing. The reader needs to know the details on the methodology employed and which factors have been found to be more important. Which Digital Elevation Model is used?

AUTHORS RESPONSE: In a revised version we have included more information about the prediction factors used in our prediction framework and the source elevation data. The source of the DEM is mentioned in the datasets section of the manuscript.

REVIEWER COMMENT: Additionally, other static factors such as vegetation and soil types are not considered. Why?

AUTHORS RESPONSE: Our initial objective was to test the predictive capacity of topographic terrain parameters derived from a single source of information (elevation), considering that a satellite soil moisture pixel is representative of soil moisture of the spatial configuration of climate and ecological conditions (within each pixel) for a specific period of time.

In the revised version we have included in our prediction framework (as prediction factors) bioclimatic and soil classes static information. We compare the predictive capacity of topographic patterns in relation to these bioclimatic and soil type classes, but we found no significant differences in model performance. Therefore, we conclude that a parsimonious model based on topographic terrain parameters is an alternative approach for downscaling soil moisture while preventing potential spurious correlations (in subsequent analyzes) by adding bioclimatic and soil classes information as prediction factors.

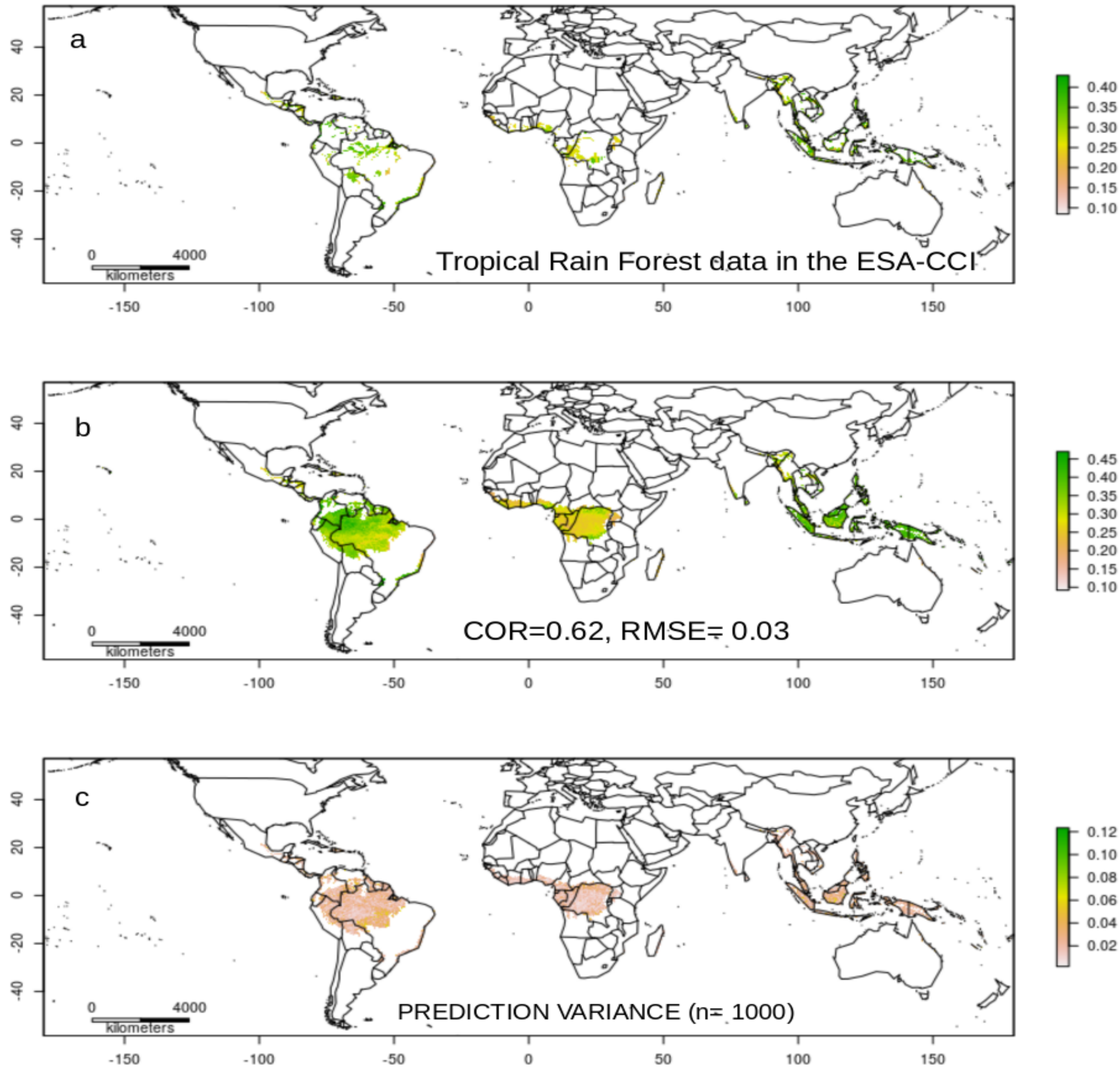


Figure R2_1 Soil moisture across Tropical Rain Forests of the world based on the data available in the ESA-CCI soil moisture product (4.5) for the year 2018 (a). We show the soil moisture prediction (b), the soil moisture prediction variance using only the data available for Tropical Rain Forests (c). Note that the correlation between observed and predicted decreased to 0.62, most likely due to the limited information for modeling these ecosystems, however the root mean squared error is comparable with a model using all global data (e.g., <0.04).

REVIEWER COMMENT: The discussion on the approach employed for downscaling and gap-filling needs to be included in the paper. Why do the authors select such approach?

AUTHORS RESPONSE: We included more information on model selection in the revised version of our manuscript. We used a *kknn* algorithm because it is fast in comparison with other modeling approaches that are computationally more expensive (i.e., deep learning). We do not focus in finding the "best method" for predicting soil moisture, but highlight that the machine (computer-assisted statistical) learning between topographic constraints and satellite soil moisture could benefit the spatial representation of soil moisture grids. Algorithms such as Random Forests or Support Vector Machines are examples of conventional machine learning methods that can also be used as regressors for satellite soil moisture gridded surfaces. We decided to use 'fast and effective' *kknn* to generate a baseline of predictions that can be reproduced in hours (annual 1991-2018) using conventional laptops (i.e., 6GB of RAM) and a flexible framework across multiple users of soil moisture information. We recognize that other forms of statistical learning such as deep learning or ensemble learning could increase the accuracy our predictions. Increasing the accuracy of the *kknn* predictions combining multiple forms of statistical learning (e.g., ensemble learning) could be an emergent objective for future work.

REVIEWER COMMENT: 2) MAJOR: I have found particularly challenging performing gap-filling over dense forest regions in the Amazon and in Congo. Satellite soil moisture data cannot be used in such regions due to dense forest that mask the soil moisture signal. How is it possible to extend the signal there only based on topography?

AUTHORS RESPONSE: There are sparse pixels with soil moisture data across specific areas of the tropical rain forest such as the Amazon or Congo (Figure R2_1a) that are useful for modeling and training soil moisture predictions using our approach (Figure R2_1b). We highlight that our approach is a machine learning algorithm that finds relationships from the provided multivariate space to predict patterns (i.e., spatial gaps). Furthermore, in the revised version we include uncertainty estimates so model outputs could be interpreted based on their spatial uncertainty values.

In the revised version we compare the accuracy of including new prediction factors to account for ecological and climate variability (e.g., presence or absence of bioclimatic features). Soil type information (e.g., harmonized world soil database) was also included to account for the capacity of soil to retain water across these areas with low availability of soil moisture data in the ESA-CCI soil moisture product. Our models were replicated multiple times using different combinations for training and validating models and now we can report a surrogate of model based uncertainty (accounting for the variance of models to multiple data variations) (Figure R2_1c).

REVIEWER COMMENT: I would suggest to perform a more detailed validation in these areas. I strongly suggest to perform a comparison with modelled datasets (e.g., ERA5 soil moisture) to have an assessment of the performance over dense vegetated areas. A similar comment can be done for high latitude areas in which frozen soils and snow completely mask the soil moisture signal. Please perform a detailed validation over these areas, too.

AUTHORS RESPONSE: We have improved our validation exercise across these areas (e.g., tropical forests or high latitude areas) searching for available soil moisture data across the published literature. We find a few sites with available data in a tropical rain forest of southeast Mexico (Vargas et al., 2012) and across tropical forests of Brazil (Saleska, et al., 2013) for a total of 9 new sites across tropical areas (in addition to the original sites available in the ISMN). We found good agreement between our predictions and the ESA-CCI available pixels (only those recognized as pixels of high quality by the ESA-CCI), with field soil moisture estimates (in all cases the correlation between observed and predicted r=>0.8). In addition, using in situ annual precipitation (Bond-Lamberty and Thomson, 2018), we report higher correlation between our soil moisture predictions and in-situ precipitation records, compared with the original ESA-CCI (e.g., from r=0.31 to r=0.38 in the tropics and r=0.40 to r=0.51 in temperate areas). We believe that this is good alternative comparison for validating and interpreting soil moisture predictions as previous studies have described the coupling between soil moisture and precipitation across multiples scales of available soil moisture and precipitation estimates (Koster, et al., 2004, McColl et al., 2017).

REVIEWER COMMENT: 3) MAJOR: The trend analysis is very interesting. However, as above, we need more details on how trends are computed. For instance, in situ stations are available only at some points over the Earth, are the same locations used with the satellite-derived datasets? If not, the comparison is wrong.

AUTHORS RESPONSE: We improved the description of the methods in the revised version of our manuscript. We clarify that the comparison was done at the annual scale (i.e., annual means) using only pixels where there was a spatial match with the sites available in the ISMN.

REVIEWER COMMENT: Similarly, in situ stations are not available every year, and for the full year. How are the data aggregated in time and space? These details are needed. I expect the results are strongly impacted to these choices.

AUTHORS RESPONSE: We aggregated all available records of the ESA-CCI in an annual basis and the resulting yearly means were used to train a model for each year (Table 1 of submitted paper shows the number of pixels for each year). We recognize that there is limited soil moisture field information for validating models and satellite soil moisture estimates across large areas of the world. We used all information within each ISMN station aggregated in an annual basis (> 8000 tables containing several gigabytes of soil moisture information) and each data/year was used to validate the soil moisture predictions also in a yearly basis. We argue that the effect of missing data across in situ measurements is diluted when aggregating all available data at the global scale (i.e., calculating a global mean). We clarify that the comparison was done at the annual scale (i.e., annual means) using only pixels where there was a spatial match with the sites available in the ISMN.

REVIEWER COMMENT: 4) MODERATE: The machine learning downscaling approach provides soil moisture data with a resolution higher than the original ESA CCI product. However, I am always doubtful on these downscaling approaches as instead of resolution it should be higher spatial sampling. The higher spatial resolution should be tested, but I am aware it is very hard to do (I have this comment for all downscaling studies).

AUTHORS RESPONSE: We recognize that there is a compromise between where and when to sample across scales. We also recognize that all global studies are limited with the available information of global networks, and local studies (across multiple ecosystems and regions of the world) are needed to better test satellite soil moisture downscaling approaches. We highlight that our main focus is to provide a downscaled soil moisture product that improves the spatial representation of the ESA-CCI and that is independent of climate- or vegetation-related variables (to avoid potential spurious correlations in further analyzes). That said, the the ESA-CCI satellite soil moisture product showed the lower slightly lower accuracy against field data in the ISMN; thus, supporting the applicability of this approach to downscale satellite-derived soil moisture. In addition, using in situ annual precipitation (Bond-Lamberty and Thomson, 2018), we report higher correlation between our soil moisture predictions and in-situ precipitation records, compared with the original ESA-CCI (e.g., from r=0.31 to r=0.38 in the tropics and r=0.40 to r=0.51 in temperate areas). We believe that this is good alternative comparison for validating and interpreting soil moisture predictions as previous studies have described the coupling between soil moisture and precipitation across multiples scales of available soil moisture and precipitation estimates (Koster, et al., 2004, McColl et al., 2017).

REVIEWER COMMENT: The authors should demonstrate that the downscaled product is able to reproduce features at higher resolutions with respect to the parent ESA CCI product. It is not done in the paper, that's why I believe higher spatial sampling, and not spatial resolution, is more appropriate.

AUTHORS RESPONSE: We found a larger range of soil moisture predicted values compared with the original ESA-CCI soil moisture product. We found a temporal trend at the places of field stations that is more similar between the field data and our predictions compared with the ESA-CCI soil moisture product. Please note that the main purpose of the model is to reproduce the signal of satellite soil moisture using as reference the relationship that it maintains with topographic data. This is a regression problem were the satellite soil moisture measurements (for a specific time across an area, a pixel under a approximately the same vegetation type or general climate condition) are statistically related to multiple quantitative topography surrogates.

We believe that a spatial resampling (e.g., Figure R2_2a) is just a change of spatial resolution by using simple algorithmic approaches across the orthogonal relationship of the variable itself with the latitude and longitude plane. In contrast, our soil moisture predictions (e.g., Figure R2_2b) are replicated and there is a learning process on each iteration in order to maximize the selection of optimal parameters and maximizing the prediction error given a specific spatial resolution defined by the topographic prediction factors. We understand that this represents a conceptual and semantic debate and we believe that we have improved the description of this empirical modeling approach applied to soil moisture in the new version of our manuscript.

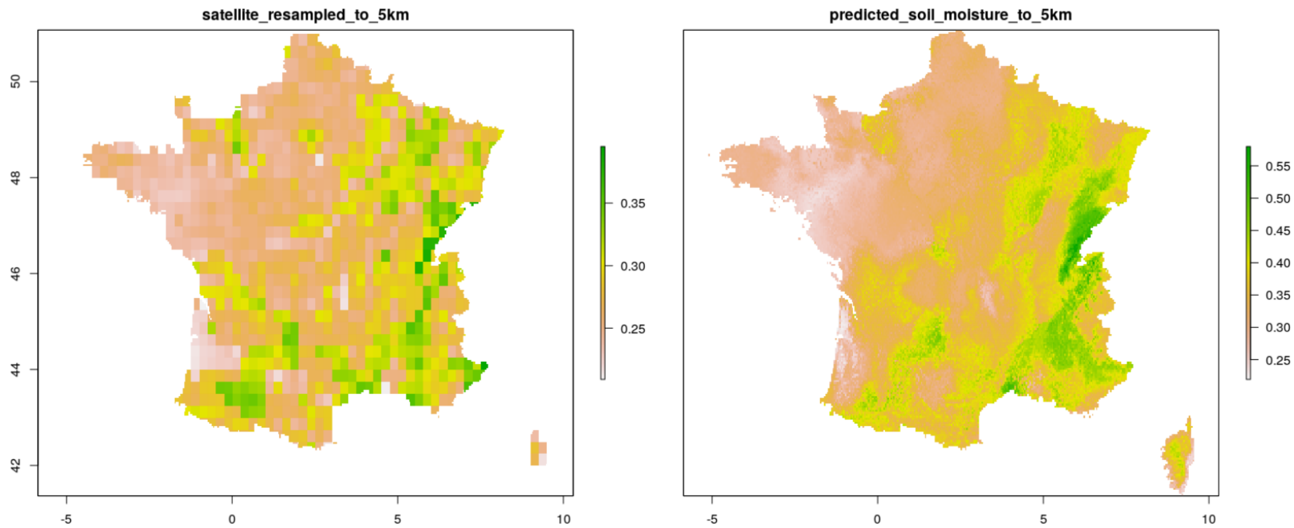


Figure R2_2 Comparison between simple spatial resampling (bilinear) applied to the ESA-CCI product from 27 to 5 km grids (a) and a modeling output using our proposed framework using 5km grids across France (b). We present this example to highlight differences between resampling and prediction using our framework and also the applicability and flexibility across scales. See also Guevara and Vargas 2019.

REVIEWER COMMENT: 5) MODERATE: Several performance scores have been used in the paper. However, I don't think it is necessary to use all of them. The authors should discuss what information each performance score is providing for the assessment of the dataset, not simply to list many numbers. Indeed, Tables 2 and 3 are hard to read and not informative. Please summarize only the more relevant scores in a figure.

AUTHORS RESPONSE: We summarized the description in the accuracy numbers using a quantile plot. We believe that his new figure (Figure R2_3) is useful to visualize and compare differences and similarities between field soil moisture, original ESA-CCI soil moisture and modelled soil moisture. We highlight that in the revised version we include a comparison of the predictive capacity using only terrain parameters and another model including terrain parameters, bioclimatic features and soil type classes. These new results support our conclusion that a parsimonious model only using terrain parameters is a good alternative approach for downscaling satellite-derived soil moisture.

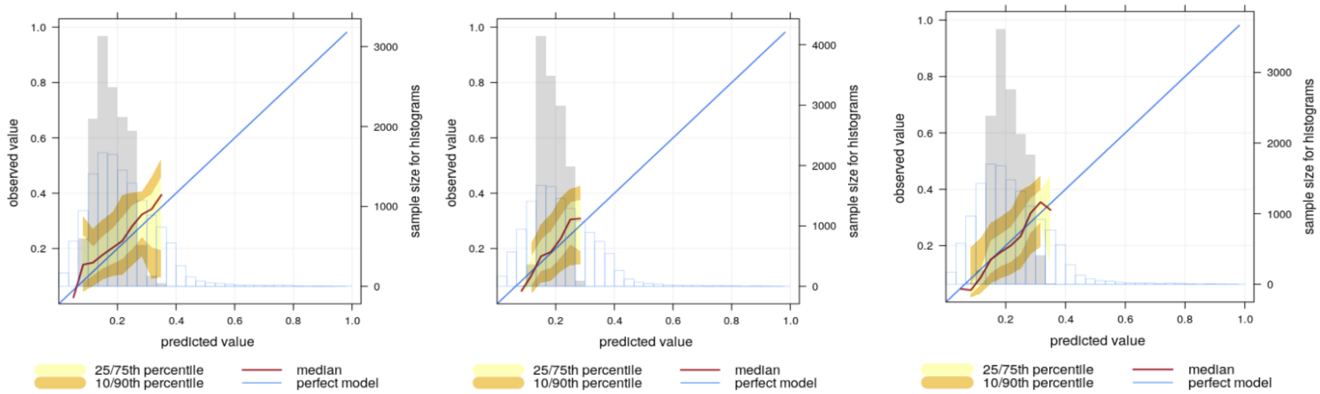


Figure R2_3 Evaluation of soil moisture predictions based on quantiles. The relationship between the ESA-CCI and the ISMN in an annual basis (a). We show the relationship between the ISMN field soil moisture and our predictions based on terrain parameters (b) in relation with a model using bioclimatic and soil type classes as prediction factors (c). Blue line is a perfect model. Blue histogram is from training data and gray histogram are from model predictions.

REVIEWER COMMENT: 6) MAJOR: The range of values of ESA CCI soil moisture products has little value, as the satellite products are rescaled to match the range of variability of modelled soil moisture from GLDAS. Therefore, the range of values is that obtained from GLDAS. For the analysis shown in Figure 4, and similarly for the trend analysis, the soil moisture datasets should be rescaled between the minimum and maximum of each time series and expressed as relative soil moisture (between 0 and 1). Then the data should be aggregated and the range of values and the trends can be assessed.

AUTHORS RESPONSE: We agree with the reviewer and the pixel-wise soil moisture trends detected at the global scale used the downscaled soil moisture predictions are now provided in percentage of change to avoid issues associated with the dimensions of input data. We also report soil moisture trends in percentage of change comparing gridded and field based soil moisture estimates at the places of field stations in the ISMN.

7) MODERATE: I believe the discussion section must be rewritten. General results are mostly discussed, whereas it should be closely related to the results shown in the paper. I believe it should be shorter and better focused.

AUTHORS RESPONSE: We have improved the narrative of our discussion section and main findings in the revised version of our manuscript.

REVIEWER COMMENT: SPECIFIC COMMENT (L: line or lines)
L307: Why the “angle between satellite sensors and the earth surface” is useful for determining soil moisture? It has no sense and I believe it is wrong.

AUTHORS RESPONSE: We meant to say that topography affect the distance between the satellite and the earth surface; therefore, it could be correlated with the satellite soil moisture signal (which is a hypothesis supported with the data analyzed in this study).

REVIEWER COMMENT: RECOMMENDATION

Based on the above comments, I suggest a major revision before the possible publication on Earth System Science Data.

AUTHORS RESPONSE: We appreciate the comments of the reviewer as they have been very useful to improve the overall revised manuscript.

References:

Bond-Lamberty, B.P., and A.M. Thomson. 2018. A Global Database of Soil Respiration Data, Version 4.0. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/1578

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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, Nature Geoscience, 10(2), 100–104, doi:10.1038/ngeo2868, 2017.