Response to reviewers

Line numbers mentioned in this reply refer to our clean version of the revised manuscript.

Reviewer #1

Comments:

This work developed a monthly global long-term satellite radar C-band backscatter data set (CScat) by fusion of ERS-1(C-band), QSCAT (Ku-band) and ASCAT(C-band) observations using a new rescaling method. Maybe the CScat data set has useful in analysis and understanding of some global surface parameters (e.g., vegetation and soil moisture). But the temporal resolution is little low. And, there are some main problems of this manuscript:

Response: We thank Referee #1 greatly for the comments. Due to the covid situation in China, this reply is bit late but never careless: we have carefully considered the comments and revised the manuscript accordingly. Please see below a point-by-point response.

Regarding the temporal resolution, we chose monthly time resolution because this is perhaps the most preferred time scale for studies conducted at the global scale. Some data sets are released with a daily time resolution but daily images hardly complete a full global coverage. We have now explained it in the Introduction and Discussion (lines 117-119).

Also, as stated in the previous manuscript, we will soon release a new version of the CScat data set which has a global coverage, a ~4.5 km resolution, and a 4-day temporal resolution, by merging QSCAT and ASCAT images of the BYU version (https://www.scp.byu.edu/data.html). This point, together with the limitations of the current data set, have been made clearer in Abstract, Introduction and Discussion (lines 60, 120, and 475-485).

1) The signals of Ku-band (13.4GHz) and C-band (5.3GHz) microwave is different. Theoretically, comparing the Ku-band, the X-band and C-band have more similar frequency. Authors choose the Ku-band to fill up the six-year gap of the C-band scatterometer, not choose the X-band, L-band. It is no reasonable explanation here. In addition, authors did not choose data of the same C-band satellite radar data for fusion. It is better using same C-band radar data for fusion. For example, ERS-1/2, ASCAT, Sentinel-1 and GF-3 et al. The results of microwave data merging using the same microwave C-band have greater application significance compared with different microwave bands.

Response: We fully agree that Ku-band and C-band signal dynamics are different, but we believe this is exactly why our research is potentially valuable: we successfully developed an approach to adjust the Ku-band signals into C-band signal dynamics.

Regarding the question why X-band or C-band data were not used for filling the six-year (2001-2007) data gap between ERS and ASCAT, there is no such data at the global scale as far as we know. The only X-band sensor covering the entire period of 2001-2007 is TRMM TMI. Unfortunately, TMI is only available for tropical regions. Since we aimed at producing a global dataset, TMI was not used. For C-band Sentinel-1 and GF-3, they are available since 2014 and 2016, respectively, thus cannot be used to bridge the data gap of 2001-2007. L-band data have an even shorter time span, neither can them be used to fill the six-year data gap (2001-2007) between ERS and ASCAT.

To address your concern, we added a table (Table 1, lines 101-105 in Introduction), which lists the most frequently used satellite microwave data sets, and shows that QSCAT is a good candidate for bridging ERS and ASCAT.

2) For the developed new rescaling method, the comparison analysis in Figure 3 is not enough with CDF method in only two sites. And, Is the new rescaling method developed by authors only applicable to Ku-band correction? Can X-band and L-band data also be fused with C-band using this new rescaling method？

Response: Before replying to this comment, we would like to mention that, thanks to a comment of Referee #3, we now avoid calling our data rescaling method a "new method", as similar approaches have been used by previous research (Brocca et al. 2010

& 2013). The revised manuscript now focuses on producing a new radar data set, rather than a new data scaling method.

Indeed, we showed only two examples in Fig. 3. This is because these two kinds of pixel are very particular: one has a strong trend and the other has sudden changes in signal. In fact, during our calculation, we visually inspected the rescaling results for every 100 of all the pixels. We found that the three methods performed almost equally well in most pixels (per your suggestion, more examples are shown in Fig. R1). However, linear regression and CDF yielded very unnatural results for pixels with a strong signal trend or sudden changes in signal. It's out of these reasons we show only these two kinds of pixels in Fig. 3. To address this concern, we have shown Fig. R1 as Fig. S1 in the revised manuscript.

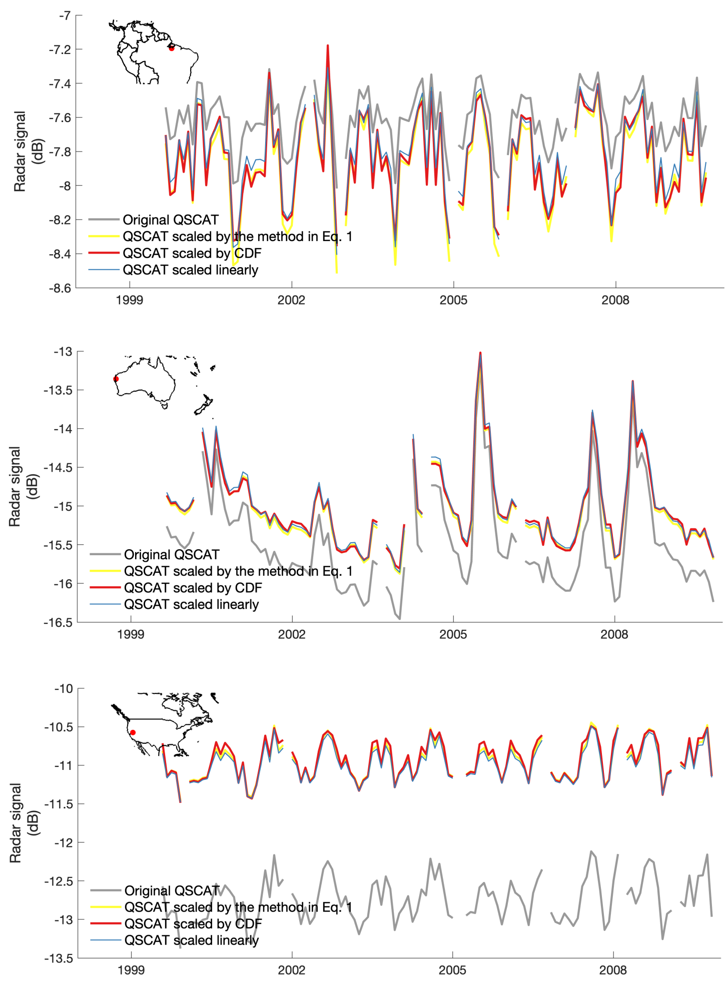

Fig. R1. QSCAT signals rescaled by different methods in different locations of the world.

Regarding the second and the third questions raised here (*And, Is the new rescaling method ….? Can X-band and L-band data also ….?*), we believe there is a misunderstanding between "rescale" and "fuse". Based on our understanding, a rescaling method can scale any time series (irrespective of the radio frequency) into the same scale as long as there are enough overlapping observations. In other words, rescaling only unify the scales of two (or more) time series. Fusing, however, means more than just rescaling: fusing additionally accounts for the signal differences between the scaled signals. In other words, rescale is the first of the two steps of fusing. We sincerely hope this makes sense, and will be glad to exchange more if needed.

3) I think the validation of CScat data set is not sufficient if authors only used ERS-2 data as validation data for CScat. I suggested that the authors consider using the C-band observation data of airborne or other satellite/sensor different ERS-1/2 as comparison data. And, I doubt the reliability of the validation results of CScat data set. Authors used the ERS-1 observation radar signals to correct the Ku-band signals of QSCAT, and used the ERS-2 signals to validate the corrected Ku-band data. Because the satellite parameters and sensor parameters of ERS-1 and ERS-2 are the quite same, the observation radar signals of ERS-1 and ERS-2 are very similar at the same place and time. This may be the reason for the very high correlation coefficient in Figure 9.

Response: We believe there is a misunderstanding here, which is possibly caused by our ambitious use of the word "ERS". In our previous manuscript, we sometimes used "ERS" to refer to "ERS-1", and sometimes to "ERS-2". We apologize and have specified whether it's "ERS-1" or "ERS-2" every time we mention "ERS". Figs. 1 & 2 have been redrawn.

In fact, we did not use ERS-1 to correct the Ku-band signals: ERS-1 scatterometer stopped working in 1996, thus did not overlap with ASCAT. Instead, we used C-band ERS-2 (1996-2001) and ASCAT (2007-2020) to adjust the Ku-band QSCAT (1999-2009) into C-band signal dynamics, based on overlapping observations in the years of 1999-2001 (between ERS-2 and QSCAT) and 2007-2009 (between ASCAT and QSCAT).

To check whether Ku-band QSCAT signals have been well adjusted into C-band dynamics, the best validation data should be a continuous C-band time series extending through our study period—This is exactly what we did with Fig. 9: although ERS-2 stopped working in full mode after 2001, observations are occasionally available for a subset of global pixels until 2011. Comparing our merged radar signal against this long-term but spatially incomplete ERS-2 dataset is the strictest validation we can perform.

Regarding "*the C-band observation data of airborne or other satellite/sensor different ERS-1/2*", we appreciate this suggestion but didn't find such data covering the period of 2001-2007 (during which Ku-band signal was used to bridge the C-band data gap). We would be glad to further test our merged data set if more details can be provided by Referee #1.

4) The English language of manuscript needs to be polished. The abstract of this manuscript is too long. For the introduction of this manuscript, the research background for active microwave fusion or rescaling study is not sufficient. In 110 lines, is there any other studies that show that the Ku-band QSCAT signal can be adjusted to the ERS observations except the author's own research (i.e., Tao et al.,2002b)? I suggest that the abstract and introduction of this manuscript need to be rewritten.

Response: Thank you. As suggested, we have further corrected some grammar errors during this revision. The abstract has also been shortened.

Regarding the Introduction, we very much appreciate the suggestion that more background for fusing active microwave data is needed. Thanks! We have added a new table to specify the sensor details of the most frequently used satellite microwave sensors. From the table (Table 1), it's clear that using QSCAT to fill the 2001-2007 data gap at the global scale is good choice (and perhaps the only choice). For your question "*is there any other studies that show that the Ku-band QSCAT signal can be adjusted to the ERS observations except the author's own research (i.e., Tao et al.,2002b)?*" The answer is yes: recently, Frolking et al. (2022a & b) have been published which merged signals from exactly the same sensors but for global metropolis. Their research therefore confirms that QSCAT is one of the best options for gap-filling the six-year data between the ERS and ASCAT. We have referred to Frolking et al. (2022 a & b) in the revised manuscript (line 104).

Above-mentioned, I am in a difficult position to reject the manuscript for publication

Response: We believe the comments from Referee#1 have largely improved our manuscript, and we hope the revision has address all the raised concerns. Once again, we thank Referee #1 for the helpful comments.

Reviewer #2

Comments:

This work extended the C-band data set to the previously missing period by rescaling the QSCAT Ku-band dataset during 2001-2007. Data-rescaling was used to unify the backscatter values from different sensors and then the machine learning method was used to address the monthly values differences. This is a quite useful dataset for further detecting forest structure and resilience dynamics. I have some minor comments as below:

Response: Thank you greatly for reviewing our manuscript. We apologize for the late reply due to the covid situation in China. We have carefully considered the comments and revised the manuscript accordingly. The suggestion of considering the overfitting issue is especially useful. Thank you!

To compare the linear regression, CDF and new data rescaling method, the author should compare their performances at global scale, i.e. a map showing the pearson r and RMSE pixel by pixel.

Response: Before replying to this comment, we would like to mention that, thanks to a comment of Referee #3, we now avoid calling our data rescaling method a "new method", as similar approaches have been used by previous research (Brocca et al. 2010 & 2013).

Thank you for the suggestion of mapping the Pearson r and RMSE pixel by pixel. We very much appreciate this suggestion but refrain us from showing such a map. Seen from Fig. R2 below, the Pearson r, RMSE, and rRMSE by CDF and linear correction could be even higher than that obtained with the “new scaling method”. However, the scaled signals by CDF and linear correction are obviously less satisfying. Thus, we believe Pearson r and RMSE can be misleading here.

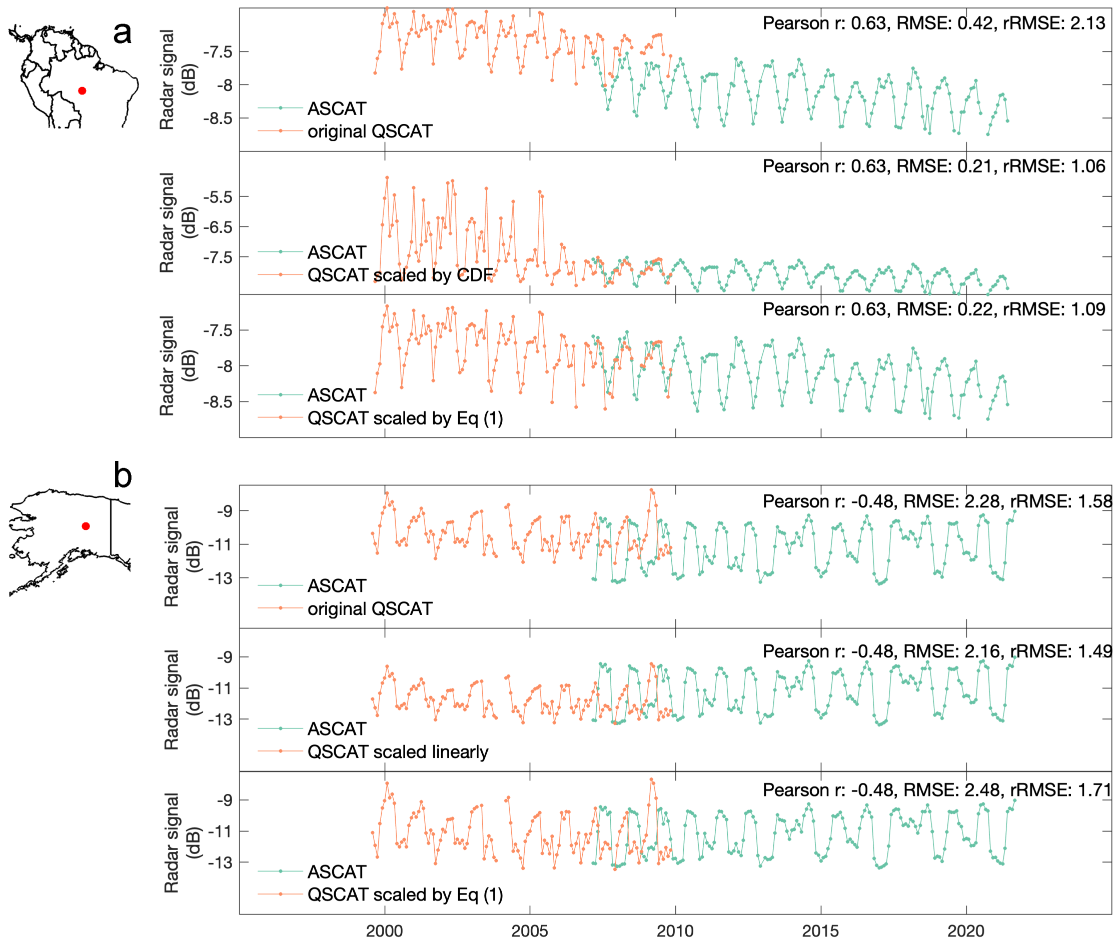

Fig. R2. Same as Fig. 3 in the main text but showing the Pearson r, RMSE, and rRMSE between ASCAT and QSCAT signals in the overlapping period.

In fact, during our calculation, we visually inspected the rescaling results of the three methods for a large number of pixels (every 100 of all the pixels). We found that at the global scale, the three methods performed almost equally well in most pixels (Fig. R1 in responses to Referee #1, also shown as Fig. S1 in the revised manuscript), but linear regression and CDF created very unnatural results for pixels with a strong signal trend or sudden changes in signal. We therefore focused on these two particular kinds of pixels in Fig. 3. This point has been made clearer in the legend of Fig. 3 (lines 716-720).

Similar for Fig 4, the author can show the spatial map of the performance of scaled Ku-band and corrected Ku-band pixel by pixel.

Response: The maps suggested by Referee #2 have actually been shown as Figs. 6 (Pearson r-based assessment), 7 (RMSE-based assessment) & S2 (rRMSE-based assessment). Per your suggestion of checking the overfitting issue below, all these figures have been updated.

It seems that such rescaling method can also apply to other merging tasks. Can you discuss a bit of its potential usage to benefit the big data environmental science field?

Response: As above-mentioned, we now avoid calling our rescaling method a totally new method, because Referee #3 has pointed out that similar approaches have been used by previous research (Brocca et al. 2010 & 2013). However, we followed your suggestion to discuss more the potential usage of the data rescaling method in earth science studies (lines 379-384).

The author could include a table mentioning the specific information of available microwave dataset, i.e. their time and spatial coverage, time and spatial resolution, etc, to prove the uniqueness of constructing the time series over non-overlapped period with QSCAT Ku-band data.

Response: Indeed! Thank you for this very useful suggestion. We now added such a table (Table 1).

As you used the decision tree regression, have you checked whether the over-fit issue exist or not?

Response: Thank you for reminding us of this very important issue. Previously we used the 'fitrtree' function in Matlab without tuning the parameters (i.e., default value of 1 for 'MinLeafSize'). A small value for 'MinLeafSize' means a deep tree, and vice versa. Thus, overfitting could indeed occur due to a small value of 'MinLeafSize'.

Per your suggestion, we now use cross-validation to find the best 'MinLeafSize' value. Cross-validation is a suggested approach by Matlab to overcome the overfitting issue (https://ww2.mathworks.cn/help/stats/improving-classification-trees-and-regression-trees.html), and has been used by previous research (Sankaran et al., 2005; Pekel 2020). We used five-fold cross validation as there are only ~60 overlapping monthly observations between QSCAT and ERS/ASCAT, but we verified that the results were not changed if 10-fold was used. This point has been stated in lines 258-260. Meanwhile, we also followed a suggestion of Referee #3 to include all three climatic variables into one regression tree (instead of building the regression trees separately).

We tuned the parameter pixel by pixel. Taking one pixel in the Tibetan Plateau as an example (Fig. R3 below), the cross-validated errors decrease initially with the increase of 'MinLeafSize', reach its minima when 'MinLeafSize' is around 6, then increase sharply. Previously the depth of the regression tree is 6, but now after cross-validation, the depth becomes 4 (Fig. R4). Fig. R5 further shows the C-band and Ku-band signals before and after signal correction: the Ku-band signals corrected by the optimal tree showed highly similar dynamics with the C-band signals, with a r value of 0.9 (Fig. R5c), and this accuracy is only slightly lower than that created by the "default tree" (0.93, Fig. R5b).

After addressing this comment, all results have been updated, and all related figures (Figs 4-9, S2, S3) have been redrawn. Encouragingly, the new results are highly similar to the old ones, suggesting that the over-fitting issue is not severe in the previous results. We thank Referee #2 once again for this important suggestion!

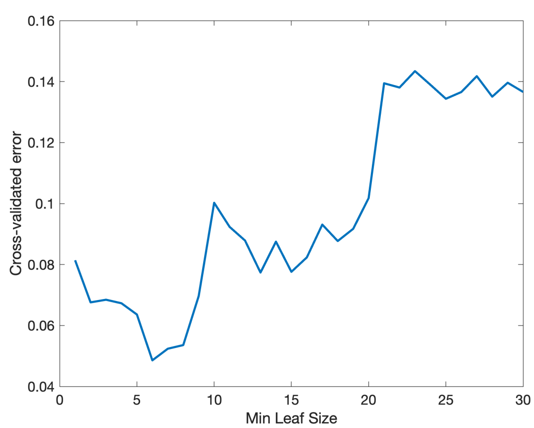

Fig. R3. 'MinLeafSize' parameter *vs* cross-validated errors.

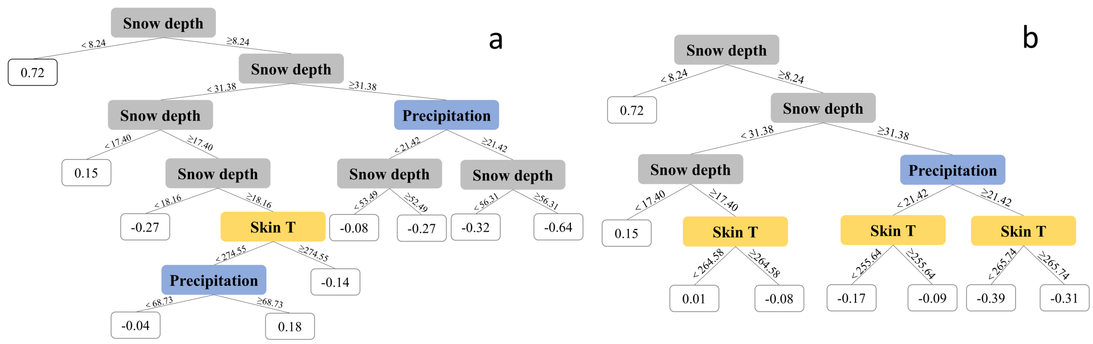

Fig. R4. Comparison between regression tree with (a) default parameters and (b) with optimal ‘MinLeafSize’ parameter.

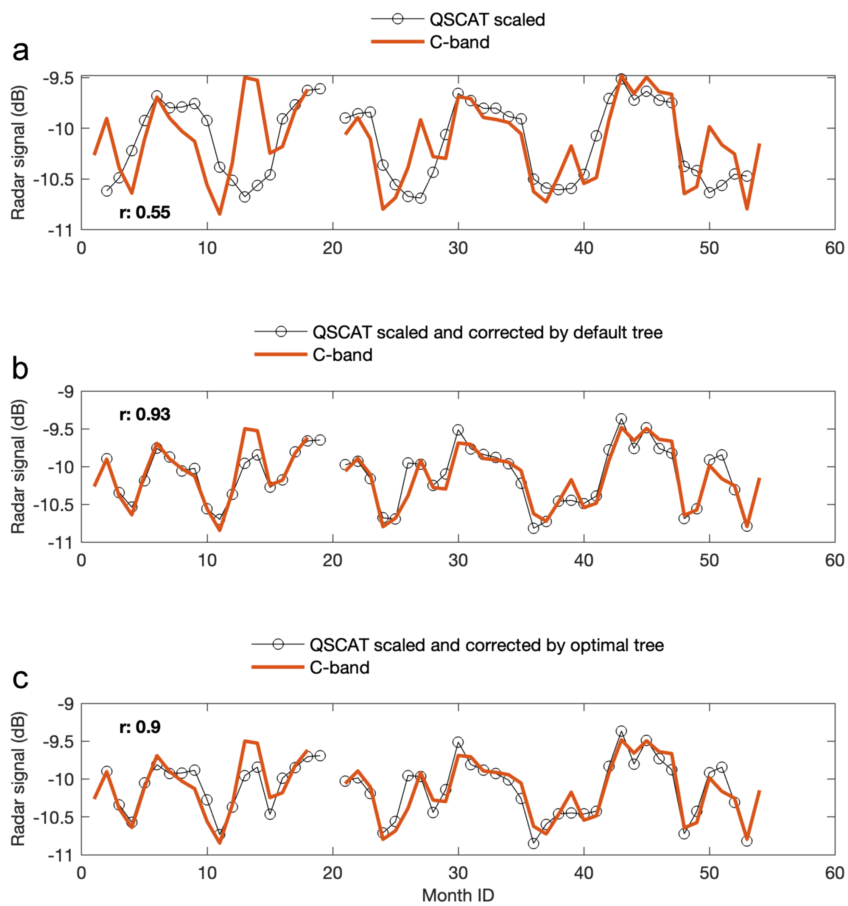

Fig. R5. Performances of the decision tree modelling for correcting the signal differences between C- and Ku- band signals. (a) shows the C-band signal and the scaled Ku-band signal before correction. (b) shows the C-band and Ku-band signal corrected by the decision tree with default parameters. (c) shows the C-band and Ku-band signals corrected by the decision tree with optimal “MinLeafSize” parameter.

For Fig 8, there is large overlap between type 1 and type 2 pixels. If the author just compared the corresponding pearson r values between corrected Ku-band and C-band values to find the appropriate regressor, the type of each pixel can be determined. Why are some pixels assigned by two type?

Response: We apology for this misleading figure. This figure was drawn in GIS and each pixel was shown as a point. Points in GIS have a size; thus their locations appear "overlapping" but actually they do not. We have redrawn this figure (Fig. 8) into a raster map to avoid this misunderstanding.

We hope the revision has addressed all your concerns! We thank you once again for the very helpful comments!

Reviewer #3

Comments:

In this study the authors presented a monthly global C-band backscatter data record by combining ERS (C-band), QScat (Ku-band) and ASCAT (C-band) data for the time period 1992-2021. QScat data has been used to fill a six year gap between the C-band backscatter datasets (1999-2009). For this reason the Ku-band dataset has been rescaled using the overlapping period with ASCAT (2007-2009). The presented rescaling method was found to be robust to both signal trends and sudden changes. Monthly signal differences have been corrected after rescaling based on a decision tree regression. ERA5-land data (monthly rainfall, snow depth and skin temperature) was used to model signal differences in C- and Ku-band. Two types of quality assessments have been carried out. The first one is based on a comparison between the C-band and scaled Ku-band signal on a pixel by pixel bases reporting the distribution of Pearson R, RMSE and rRMSE for the periods 1999-2001 and 2007-2009 before and after the monthly signal correction for 13 regions. The second quality check is using ERS-2 data for the time period 2001-2011 reporting Pearson R for 10 regions. The results overall show that the *rescaling and correction method are doing reasonably job fitting the Ku-band data in the C-band data space generating a homogeneous dataset.*

Response: Thank you for the positive feedback on our manuscript. We have carefully considered each of the suggestions and made revisions accordingly. Please see below a point-by-point response.

Major comments:

1. While it is clear that this "C-band" dataset is one of its kind, I doubt the novelty of the presented "new data scaling method". It is a simple mean-std rescaling and part of "standard data rescaling techniques". See e.g. 10.1201/b15610-21, 10.1016/j.rse.2008.11.011, 10.5194/hess-14-1881-2010

Response: Thank you very much for providing the references. To address this concern, we avoided calling our method a new one, and referred to all the suggested references. Our revised manuscript now focuses on producing a new data set, instead of a new data rescaling method. Figs. 2 & 3 have been redrawn, all related sentences were changed.

2. I can see the importance of long-term C-band radar data, but a monthly temporal resolution is a big disadvantage and perhaps a no-go criteria for certain applications. The study doesn't explain why this temporal resolution has been chosen in the first place and is also not discussed in chaper 4.3. What is the reason? Would it be possible to get a 14-day, 10-day or lower temporal resolution? Please discuss possible applications and limitations of monthly C-band radar data. E.g. how is it possible to describe/separate vegetation and soil moisture (trends), also taking long-term land cover changes into consideration?

Response: We fully agree with you. Monthly resolution is not suitable for local-scale applications which requires frequent observations, such as phenological monitoring. However, we chose the monthly time resolution because: 1) Although it's possible to merge the radar signals at daily time resolution, daily images do not have a full global coverage. 3) Within the limit of our knowledge, monthly resolution is perhaps the most preferred by global scale studies.

Nevertheless, as stated in the previous version of manuscript, we are actively creating data sets with higher spatial and temporal resolutions. We will release a new data set with a full global coverage, ~4.5 km spatial resolution, and ~4-day time resolution, by merging QSCAT and ASCAT images of the BYU version (https://www.scp.byu.edu/data.html).

Regarding separating vegetation optical depth (VOD) and soil moisture from the radar signal, this is feasible with help of the Water Cloud Model. Our coauthors have achieved it taking African ecosystems as a testbed (Liu et al. 2021), and we are working together on extracting VOD from the CScat radar signals at a global scale.

As for land cover changes, radar signals already contain information about land cover types (please see Fig. R6 below: the values differ among land cover types). Besides, time series of VOD have been successfully used to quantify forest biomass loss due to drought and deforestation (Liu et al. 2015; Fan et al. 2019). Thus, we believe once VOD was properly extracted from the radar signal, it can be used directly to indicate land cover changes.

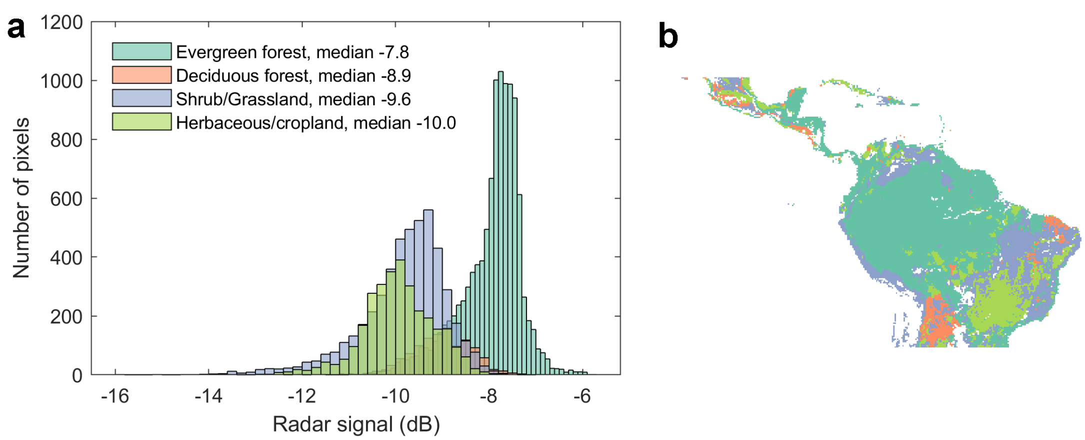

Fig. R6. (a) Histograms of the C-band ASCAT signal (in unit of dB, monthly averaged between 2007 and 2018) for four land-cover types in part of the Neotropics. (b) shows the spatial distribution of the four types of land-cover. Land cover information was taken from the European Space Agency (ESA) Climate Change Initiative (CCI) land-cover map for the year 2015 (maps.elie.ucl.ac.be/CCI/viewer/). This figure is taken from the supplementary of Tao et al. (2022).

In short, to address these concerns, we explained why monthly resolution was chosen in Introduction and Discussion (lines 117-120, 475-485); we mentioned possible applications and especially limitation of the CScat data set (lines 475-477). We also made it clearer that a new data set with higher spatial and temporal resolutions will be released soon (lines 60 in abstract, line 120 in Intro, and 480-485 in Discussion).

3. The manuscript is missing essential background information on decision tree regression. The authors describe that they performed three separate regressions (against monthly rainfall, snow depth and skin temperature) and used MSD to decide on the optimal regression. The term "decision tree regression" is far-fetched and not correct in this context. A decision tree regression would separate the feature space using nodes/leaves thereby selecting the optimal regression/parameter. See e.g. 10.1007/s00704-019-03048-8

Response: Thank you very much for reminding us of Pekel (2020). Following your suggestion, we re-examined our modelling approach, and realized that our way of using decision tree is indeed uncommon. To address this concern, we

1) explained why decision tree is suitable for our study in the Method section (lines 235-248);

2) used decision tree modelling following the practices of Sankaran et al. (2005) and Pekel (2020) as suggested by you;

3) used cross-validation approaches to avoid over-fitting, as Sankaran et al. (2005) and Pekel (2020) did;

4) calculated variable importance using the MATLAB function 'predictorImportance', which "*computes estimates of predictor importance for tree by summing changes in the risk due to splits on every predictor and dividing the sum by the number of branch nodes*" (https://ww2.mathworks.cn/help/stats/compactclassificationtree.predictorimportance.html).

Consequently, all data have been reanalyzed and figures redrawn, but encouragingly, the new results are highly similar to the old ones. This is actually expected: even though with simple single variable linear regression for modelling the signal differences, our previous results in Tao et al. (2022) are highly satisfying. We thank you once again for this very helpful comment, which has substantially improved our manuscript.

Minor comments:

- Title: It is a "C-band" dataset so it should certainly have a C-band signal dynamic. I'd suggest to highlight the fact that a Ku-band dataset is used to fill a gap and create a long-term "C-band" data set.

Response: Following this suggestion, the title of our manuscript has been changed into "*Global long-term satellite radar backscatter data set created by merging C-band ERS/ASCAT and Ku-band QSCAT*".

- p2 - l38: remove "and can be acquired in all weather conditions"

Response: Changed as suggested.

- p2 - l53-54: No unit for RMSE/rRMSE in abstract, is it dB? Also missing in the rest of the article and graphics

Response: The unit for RMSE is dB, but rRMSE is unitless (it's RMSE normalized by the std of signals). We have made changes throughout the paper (lines 269, 784).

- p4 - l102: Metop-SG

Response: Thanks, Metop-SG and a reference (Lin et al. 2016) have been added here (line 99).

- p5 - l131: Please add references

Response: Thanks, references have been added here (lines 132-134).

- p7 - l180: wording

Response: This sentence has been reworded (lines 179-180).

- Figure 4: remove connection of Ku-band time series for the temporal break

Response: We have redrawn this figure as suggested.

- Figure 8: why is there an overlap? shouldn't it be one map indicating type 1,2,3?

Response: We apology for this misleading figure. The same concern was raised by Referee #2. This figure was drawn in GIS and each pixel was shown as a point. Points in GIS have a size; thus their locations appear "overlapping" but actually they do not. We have redrawn this figure into a raster map to address this concern.

- Figure 9: why two different y-axis?

Response: This is because the ERS signals in our CScat data set have been scaled taking ASCAT as a baseline (mentioned in the Method section). We have explained it in the legend of Fig. 9 to address this concern.

- p22 - l450: typo

Response: Thanks, "have" has been changed to "has" here.

On this basis, I found the topic of the paper interesting, but I suggest a major revision and after that reconsider a possible publication.

Response: We hope our revision have addressed your concerns in full. Thank you once again for the very useful suggestions!

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