

## Exploring the combined use of SMAP and Sentinel-1 data for downscaling soil moisture beyond the 1 km scale

The authors test the possibility of downscaling SMAP coarse soil moisture to the sub-kilometer resolution using Sentinel-1 SAR data. This paper is interesting and the topic is suitable to HESS. However, I have several major comments the authors should seriously consider.

Dear reviewer, we thank you for thoroughly reading our manuscript and your helpful comments that we believe considerably improved the quality of the revised version of the manuscript. We have added our replies to the reviewer comments and suggestions in *italic* below.

Major comments:

1. This paper directly disaggregates the SMAP coarse soil moisture at 9 km to high resolution using Sentinel-1 SAR backscattering coefficients. It should be noted that the method tested in this paper is based on the assumption of a near-linear relationship between radar backscatter  $\sigma_0$  pp and soil moisture  $\theta$  at different scales. In order to estimate the parameter  $\beta$ , a time regression is performed under the assumption that the soil roughness and vegetation conditions do not change greatly over a specified temporal window. Meanwhile, the parameter  $\beta$  is NOT invariant in time and space and it depends on vegetation cover and type as well as surface roughness. Therefore, a moving window of  $\beta$  estimation should be adopted when applying this downscaling algorithm to a long time period and the length of time window should be carefully determined. In this study, about 377 images of synchronized SMAP and Sentinel-1 were obtained during the period of January 1, 2017 to May 31, 2019. However, this paper did not describe how to determine the parameter  $\beta$ . In Page 15 Line 445, a temporal window of 40 data points was used to derive seasonal  $\Gamma$ . To derive  $\beta$ ?

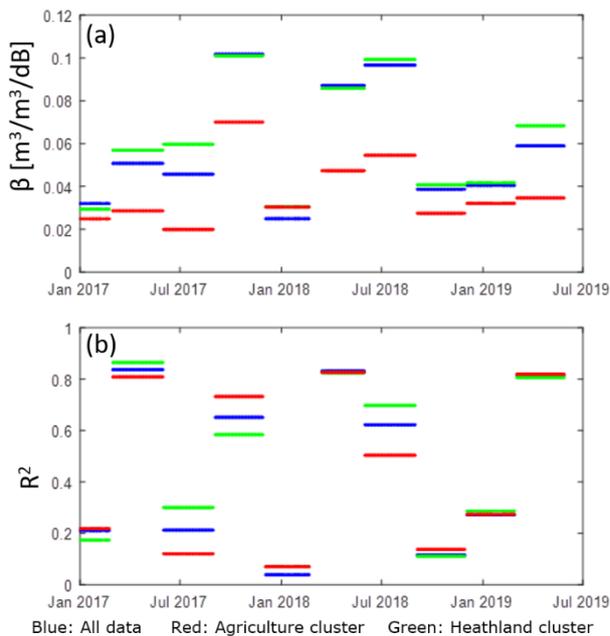
**Reply:** *We thank the reviewer for the valid comment. We do agree that  $\beta$  is also influenced by soil roughness and vegetation conditions and hence varies in principal in space and time. One of our major objectives is to test whether the downscaling algorithm can be improved by introducing spatial varying (land use cover dependent) downscaling parameters ( $\beta$  and  $\Gamma$ ). In order to take the spatial variability into account we performed the cluster analysis and used this to estimate a land cover dependent  $\beta$  value. The cluster analysis is based on the temporal variation in mean and std. of Sentinel backscatter (both VV and VH).*

*We decided to apply a time invariant (constant)  $\beta$  because the vegetation and surface roughness barely change in the heathland and evergreen pine forest. Of course there is a change in vegetation and roughness in land cover class of agriculture due to land management. However, the crop yield is relatively constant and changes in biomass relatively small which has been studied by Andreasen et al. (2020). Moreover, time series of VV and VH (e.g. Figure 5) show the opposite trend as would be expected if the backscatter signal would be dominated by vegetation and surface roughness. We would expect that a higher amount*

of vegetation would enhance the volumetric backscatter, both for co- and cross polarization (e.g. Rosenqvist, 2018). However, what we observe is a reduction of the backscatter signal in the growing and peak vegetation periods (spring and summer). On the other hand, in these periods soil moisture is low due to relatively high temperature and evapotranspiration. This trend is mostly observed in the land cover class agriculture, while less visible in the heathland and almost not significant in the forest. Therefore, we believe that applying a time invariant, but spatially varying  $\beta$  is a valid assumption for our study area, representing a classical Danish rural setting.

Inspired by the reviewer's comment and also by the first comment of reviewer 2 we performed a seasonal  $\beta$  estimation in order to evaluate if a time varying  $\beta$  would be essential to consider. The following figure shows (a)  $\beta$  estimated over an interval of 3 month\* (Dec-Feb, Mar-May, Jun-Aug, Sep-Nov, representing the seasons in Denmark) and (b) the respective  $R^2$ .

\* except for the first interval, starting with January (2 month interval).



What we can conclude from this analysis is that there might be a slight seasonality in  $\beta$  with low values in winter and higher values in summer (figure a). However, if we only consider the  $\beta$ -value with acceptable  $R^2$  of above 0.5 (figure b), this trend might not be significant. To estimate a robust time variant  $\beta$ , a dynamic in the range throughout the year would be needed, but what we see is a relatively constant  $\beta$  value, except for the summer. Hence, it is rather difficult to achieve a good estimation of correlation when there is only little variation in the data (during the rest of the year). On the other hand, we observe that particularly the  $\beta$  estimates for the agriculture cluster (red) deviate significantly from the other data (all=blue and heathland=green). This supports our approach in estimating spatial varying (land cover dependent) but time invariant  $\beta$ .

*We agree with the reviewer that both the incidence angle correction and  $\beta$  estimation add to the uncertainty of the downscaled product. We acknowledge these comments and will expand the discussion in the manuscript to emphasize these aspects.*

2. Page 14 Line 425-426: The soil moisture derived by CRNS shows a good linear correlation with Sentinel-1 VV and VH backscatter at a resolution of 100 m and 200 m at the agricultural and heathland site. A good linear correlation between radar backscatter and soil moisture was observed in this study, which is the foundation of the downscaling algorithms. However, this good correlation may be caused by seasonal vegetation variations as indicated in Line 427-429. Please do more analyses to prove that the good correlation between radar backscatter and soil moisture was not induced by vegetation changes.

**Reply:** *We understand the concern of the reviewer about the impact of vegetation on the correlation between CRNS and Sentinel backscatter. We believe that the good correlation between CRNS and Sentinel backscatter is soil moisture dominated at the heathland and agricultural site because:*

- *There is little correlation between CRNS and backscatter in the forest where we believe that the Sentinel (C-band) backscatter is dominated by volume scattering of the pine trees and does barely penetrate to the soil.*
- *There is a high correlation in the heathland where the low vegetation is relatively constant over the seasons. Hence, temporal changes in backscatter are due to soil moisture, which is supported by the good correlation to CRNS signal.*
- *We can observe a good correlation also in the agriculture even though the biomass and vegetation cover changes, as a result of land management. We believe that changes in backscatter are dominantly driven by soil moisture because we observe lower backscatter values in spring/summer during the growing and peak. If the backscatter would be highly influenced by these vegetation changes, we would expect a positive correlation between backscatter and vegetation (higher backscatter signals coinciding with higher vegetation). However, we observe the opposite. Therefore we believe that the backscatter value in the agriculture is mostly influenced by soil moisture.*
- *Previous studies (Andreasen et al., 2020) about the CRNS method in the same area showed that the amount of biomass (8.42t/ha) and its seasonal change in the agriculture are rather small and hence the CRNS signal is mostly representative for soil moisture in this area. The reason for this is that the amount of water in the crop is small compared to the amount of water stored in the rootzone.*

*Taking all these points into account, we believe that the strong correlation of backscatter and CRNS is due to soil moisture changes and only insignificantly influenced by vegetation. We will add a condensed version of this line of arguments to the manuscript.*

3. Page 15 Table 5: This table lists eight types of  $\beta$  and  $\Gamma$  combinations. However, the reviewer

cannot follow how the  $\beta$  and  $\Gamma$  were estimated and the differences between different experiments. Please make more explanations.

**Reply:** Thank you for the comment. We will try to clarify it further below and we will add this more detailed explanation to the manuscript in the Supplemental Material.

To investigate whether the downscaling product can be improved by introducing land use cover dependent downscaling parameters ( $\beta$  and  $\Gamma$ ), we performed these eight different downscaling tests. Hereby we combined either:

- one constant value for  $\beta$  (space and time invariant), estimated as:  $\theta_{SMAP}/VV$
- or three constant values for  $\beta$  (time invariant), one for each land use cover, estimated as:  $\theta_{SMAP}/VV_{cluster}$  (compare Table 4 and Supplemental Material Fig. S3)

with

- one constant value for  $\Gamma$  (space and time invariant), estimated as:  $\delta VV_{mean}/\delta VH_{mean}$
- or three constant values for  $\Gamma$  (time invariant), one for each land use cover, estimated as:  $\delta VV_{cluster\_mean}/\delta VH_{cluster\_mean}$
- or one time-varying  $\Gamma$  (space invariant), estimated as:  $\delta VV_{mean}/\delta VH_{mean}$  applying a moving window of 40
- or three time-varying  $\Gamma$ , one for each land use cover, estimated as  $\delta VV_{cluster\_mean}/\delta VH_{cluster\_mean}$  applying a moving window of 40

4. Page 15 Table 4: This study estimated cluster dependent parameters  $\beta$  and  $\Gamma$ . The parameter of  $\beta$  was obtained from linear regression of soil moisture  $\theta_{coarse}$  at coarse resolution and averaged backscatter within this coarse pixel. However, the soil moisture  $\theta_{coarse}$  represents the average soil moisture condition. How can the  $\theta_{coarse}$  be related to backscatters of different land cover types? Please clarify it and make more explanations.

**Reply:** We follow the reviewer's comment and will explain further how we derive the spatially varying  $\beta$ . Commonly,  $\beta$  relates to the sensitivity of soil moisture to co-polarization radar backscatter ( $\sigma_{VV}$ ) and can be estimated as the slope of a linear regression of  $\frac{\theta_{SMAP}}{VV_{coarse}}$  time series. For the land cover dependent  $\beta$  we used the mean and std. of VV and VH time series at different resolutions, e.g. 100 m resolution, in a k-means clustering and derived three clusters at the specific (e.g. 100 m) scale spatially distributed over the entire study area. These three clusters represent the three dominant land use/cover types (heathland, agriculture and forest). The cluster dependent  $\beta$  was consequently estimated based on the linear regression of the time series  $\frac{\theta_{SMAP}}{VV_{cluster\ mean}}$ . For example for cluster 1,  $\beta$  was estimated based on the time series of spatial mean of the backscatter signal (VV) of all Sentinel pixels in cluster 1 within the

corresponding SMAP pixel  $\frac{\theta_{SMAP}}{VV_{cluster1\ mean}}$ . The distribution of the clusters and the mean and std. of the backscatter signal are shown in figure 4 in the manuscript.

We will add this explanation is a condensed version to the manuscript to clarify how  $\beta$  was derived.

Other comments:

1. Table 1 and Figure 3 can be merged, with R2, bias and RMSE putting in the scatter plots.

**Reply:** Thank you for this suggestion. We will combine Table 1 and Figure 3.

2. Page 5 Line 210-211: The Ahlergaarde catchment is covered by 21 SMAP pixels. Please indicate the 21 SMAP pixels in Figure 1 with grids. Are the SMAP pixels in resolution of 9 km by 9 km or 36 km by 36 km?

**Reply:** We thank the reviewer and understand his/her wish. Since we are using mainly the average of the 21 pixels, we would not like to include the grid in the main manuscript. If the reviewer and editor think it would be useful we would of course add a figure to the supplemental material showing the grid of the SMAP coverage at the study area. The resolution of the 21 SMAP pixel used in our study is the 9km EASE-grid. We will add a sentence in the manuscript to make it more clear.

3. Page 6 Line 230-233: For a deeper investigation of the spatial pattern information content of the Sentinel-1 data, an unsupervised data driven k-means cluster analysis is performed based on four parameters, the mean and the standard deviation of both the VV and the VH backscatter. How were the mean and the standard deviation values calculated, over temporal variations or spatial variations of radar backscatter? Please clarify.

**Reply:** We thank the reviewer for the comment and explain further how the cluster analysis was performed. The mean and std. were calculated over temporal variation of the Sentinel (VV and VH) backscatter, which were used for the clustering that resulted in three clusters that are associated with the different land use types as illustrated in figures 4, 5 and 6. We will clarify this aspect in the manuscript.

4. Page 11 Line 375: Heath in Table 2 should be Heathland.

**Reply:** Thank you for the comment, we will change as suggested.

References:

Andreasen, M., Jensen, K. H., Bogena, H., Desilets, D., Zreda, M., & Looms, M. C. (2020).

Cosmic Ray Neutron Soil Moisture Estimation Using Physically Based Site-Specific Conversion Functions. *Water Resources Research*, 56(11), 1–20.  
<https://doi.org/10.1029/2019WR026588>

Rosenqvist, A. (2018). A Layman's Interpretation Guide to L-band and C-band Synthetic Aperture Radar data. In *CEOS* (Issue 2). <http://ceos.org>