The manuscript by Meyer et al., 2021 presented an interesting study in estimating high-resolution soil moisture via the combination of SMAP L3 soil moisture and Sentinel 1 backscatter data. I recommend that the authors address the following comments before considering the paper for publication.

Dear reviewer we thank you for your profound reading and the constructive 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.

1. Soil moisture at sub-kilometre is indeed in high demand by many regional and local applications. Combination of radiometer and SAR data is definitely valuable and provides a promising way to improve spatial resolution. One major concern is the strong combined effects of incidence angle, biomass and surface roughness on the backscatter. The studies applied a simple methods to calibrate the incidence angle and made a key assumption that ð›½ is invariant in time and space. What impacts of such assumption can influence on the downscaled soil moisture? Furthermore, is that possible to conduct a sensitivity analysis to investigate such impacts?

Reply: *We thank the reviewer for his/her valid comment and understand his/her concerns about the incidence angle correction and assumption used for* β *estimation.*

For the incidence angle correction we followed the standard approach that is discussed in Mladenova et al. (2013) *and applied for a similar purpose in* He et al. (2018)*:* $\sigma^0_{ref} = \frac{\sigma^0_{\theta_i} \cos^n(\theta_{ref})}{\cos^n(\theta_i)}$*. Hereby the exponent n is roughness dependent and varies between 0.2 and 3.4* (Mladenova et al., 2013)*.* He et al., (2018) *evaluated a value of n=2 as suitable for a similar application as in this study. In our study area, the mean incidence angle of Sentinel-1 is 36.87° (min 30.25° and max 41.74°). Early on in our study we compared VV and VH time series with and without incidence angle correction, using an exponent of 2. We could see that the correction has a higher effect on VV than on VH. We evaluated that a correction with the exponent of 2 is feasible because it improves the time series by reducing the noise but still showing a dynamic behavior. We do acknowledge that this choice might introduce uncertainty and that applying different exponents might have even further improve our results. However, an extended analysis of the impact of incidence angle correction was out of the scope of our study.*

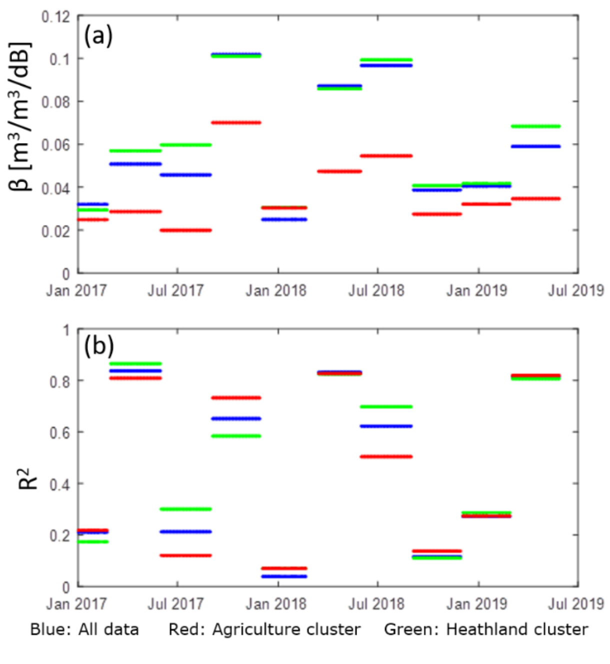
As we understand the concern of the reviewer about the β *estimation is similar to comment 1 raised by reviewer 1, we hope that we already there answered satisfactorily. For an easier reading we add our reply to reviewer 1 here again:*

*"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 (*β and Γ). *In order to take the spatial variability into account we performed the cluster analysis and used this to estimate a land cover dependent* β*. 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) β *because the vegetation and surface roughness barely change in the heathland and evergreen pine forest. Of course in the agriculture due to land management there is a change in vegetation and roughness, 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 enhanced the volumetric backscatter, both in co- and cross polarization* (e.g. Rosenqvist, 2018). *But, 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 agriculture while less visible in the heathland and almost not significant in the forest. Therefore, we believe that applying a time invariant, but spatial varying* β *is a valid assumption for our study system.*

Inspired by the reviewer's comment and also by the first comment of reviewer 2 we performed a seasonal β *estimation in order to evaluate if a time varying* β *would be essential to consider. The following figure shows (a)* β *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 β *with low values in winter and higher values in summer (figure ,a). However, if we only consider the* β *-value with acceptable* R^2 *of above 0.5 (figure , b), this trend might not be significant. On the other hand, we observe that particularly the* β *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* β*."*

The reviewer is right that both the incidence angle correction and β *estimation add to the uncertainty of the downscaled product. We will emphasize these aspects in the discussion of our manuscript.*

2. CRNS data was used as a reference to evaluate satellite-based soil moisture. Since CRNS neutron is also influenced by vegetation water content, did you calibrate such impacts in deriving volumetric soil moisture? The CRNS also has variable spatial and vertical footprints. Not sure if the direct comparison with satellite surface soil moisture is appropriate. Is that possible to consider such representative errors in your evaluation?

Reply: *We thank the reviewer for his/her valid comment and will explain the CRNS data set in detail. A short version of the explanation will be added to the manuscript.*

The influence of the vegetation water content on the CRNS estimated soil moisture is low. In the Heathland and pine forest, there is very limited change in vegetation cover. At the agricultural site the amount of biomass is relatively low (8 t/ha consisting of ~15% cellulose and 85% water, Andreasen et al., 2020). Andreasen et al. (2020) also tested the impact of the vegetation cover on the CRN intensity using field measurements of neutrons at two energy ranges and neutron transport modeling (Monte Carlo N-Particle code version 6, MCNP6) of the agricultural field site. Their analysis showed very little impact of the vegetation cover compared to bare soil conditions (Andreasen et al., 2020, Figure 4).

The second concern of the reviewer relates to the variability in spatial and vertical footprints. We do agree with the reviewer that the CRNS footprint varies in space and time. However, it should be noted that the sensor sensitivity is highest in the close vicinity of the probe (86% within a radius of 200m) and decreases exponentially with distance from the sensor. The CRNS sensors were installed at three different land use/cover types in 2013/2014 and data collection is still ongoing. The location of the sensors has been carefully chosen. They are set up in a way that they are in the same soil type and placed far enough from the next land use/cover type to prevent influence/mixture of different LUC signals. Furthermore, Ahlergaarde catchment is situated on a glacial outwash plain, and the study area is characterized by homogeneous soil (sandy and stratified soil with similar chemical composition). Therefore, we do not expect changes in the vertical and horizontal footprint area to affect the CRN signal significantly. A network of capacitance probes (please note that this network is not the same as used in our manuscript, but specifically set up to validate/compare the CRNS estimates), TDR measurements and soil probes are placed/taken strategically in the vicinity of the CRNS sensors. The long time series of CRNS estimated soil moisture has been shown to be very robust in comparison to the average of these measurements (Andreasen et al., 2020)*. The same data set has been successfully used to improve the closing of the water balance by* Denager et al. (2020)*.*

The CRNS estimates of soil moisture are subject to uncertainties, but we believe that at this stage and for our purpose the method is better than any other available technology, and particularly because the spatial scale is similar to the envisaged downscaled soil moisture product.

3. Another comment is regarding the validation of your downscaled soil moisture. As authors described, small modifications to the downscaling approach can induce significant changes in spatial patterns, it is therefore challenging to identify the best approach. I agree with such statement, but also want to ask how to distinguish noise and real soil moisture patterns? Direct comparison with CRNS might not sufficient due to the scale mismatch and high diversity of soil properties. In addition, can you give some practical advice or outlook on how to generate sub-kilometre soil moisture products, which can be used for fine-scale applications?

Reply: *Thank you for the comment. We understand the concern of the reviewer and try to explain our approach. We believe that the application of CRNS soil moisture estimates, in addition to more conventional capacitance probes measurement constitute a major improvement for validation of remotely sensed and downscaled soil moisture products. The biggest advantage is the similar scale of horizontal sensitivity of the downscaled product and the CRNS which is in the order of few hundreds meter. To minimize the impact of noise we smoothed the Sentinel backscatter, spatially (a minimum aggregation to 20 m) and temporally, by applying a moving average of five images. Moreover, meaningful trends in the time series are visible that follow the season and the expected soil moisture. By validating against different independent ground measurements (CRNS and capacitance probes), each of them of course has advantages and disadvantages, we try to enhance the reliability of our approach and results. One of our main challenge was to get a reliable data set for validation. In our study area the capacitance probe time series had many gaps. Moreover, we think that the CRNS does not have as bad a mismatch in scale as other soil moisture products, e.g. capacitance probes.*

We fully agree with the reviewer that one of the major challenge in current soil moisture research is the differentiation between noise and soil moisture and the different scales of downscaled product and validation data. We hope that the application of new technologies, e.g. roving CRNS, can address these issues in the future.

Our advice for future research in this area includes getting a high quality dataset in the same scale for validating of the downscaled product. This could be achieved e.g. by enlarging the study area so that more CRNS stations can be used (e.g. it exist a network of about 50 CRNS stations across Europe). The use of such a network for calibration of the downscaling parameters β and Γ *might be successful and hence improve the algorithm substantially.*

4. In cluster analysis, 20m, 100m, 1000m were selected and analysed. What is the criterial to choose these scales? For the downscaled soil moisture, 100 m is presented as "the downscaled sub-kilometre" product. Does it mean it is the tradeoff between quality and resolution?

Reply: *We thank the reviewer for this remark. Actually, we performed the whole analysis with many different resolutions between 20 m and 1000 m. The objective is to investigate the sub kilometer scale because previous studies aimed for the 1km scale. For the perspective in applying the downscaled soil moisture for catchment hydrological questions, a resolution in the hundreds meter is favorable. Moreover, the CRNS footprint lies in the 100-200 m resolution. In order to be concise in our results we choose to mainly show the 100 m results in detail and occasionally show also the 20 m and 1000 m results, but not the 50 m, 200 m, 400* *m, 500 m and 800 m which we had also performed. Hence, the 100 m resolution is not a trade of, as the 200 m may look similarly meaningful. However, from our results we can clearly see, that at the 1000 m resolution a lot of valuable information is lost, e.g. compare figures 4, 6 and 8. The choice of showing the 100 m resolution results from the purpose (future application in hydrological modelling), available ground data (CRNS with a footprint of 100-200 m) and aiming for conciseness.*

5. Remote the comma in the title.

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

6. Caption figure 4: c is backscatter and d is db.

Reply: *Thank you for the comment. We will double check to be sure there is no mistake.*

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