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OPTIMAL SPATIAL RESOLUTION OF SENTINEL-1 SURFACE SOIL MOISTURE EVALUATED USING INTENSIVE IN SITU OBSERVATIONS

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ABSTRACT

Space-borne SAR instruments can provide backscatter on a high spatial resolution, and with the introduction of the Sentinel-1 satellites, these can co-exist with relatively high temporal resolutions. Here, we use a combination of active microwave Sentinel-1 and optical Sentinel-2 data in the MULESME algorithm to estimate soil moisture on a field in Southeastern Luxembourg. Satellite data were compared to data gathered in the field and semi-continuous measurements from a nearby permanent station. Our results indicate that the accuracy of MULESME soil moisture estimates increases with a decrease in spatial resolution, but that this increase stagnates rather soon after the first few spatial aggregations, thus confirming the value of high resolution data. Future endeavours will focus on the analysis of soil moisture variation in time, compared to soil moisture measurements from a nearby permanent station.

Index Terms— Soil moisture, Sentinel-1, MULESME

1. INTRODUCTION

With the arrival of more and more space-borne instruments that can estimate soil moisture, both the spatial and temporal resolution of these estimates is improving. The Sentinel-1 constellation (S1), carrying a C-band SAR instrument, provides backscatter data at a very high resolution, which can in turn be used to estimate soil moisture. The backscatter data is provided on a $\pm$ 20x20 m^2 resolution with revisit times of three days over Europe. This makes that data from this satellite constellation is extremely well suited for multi-temporal algorithms, where the roughness is assumed to remain constant within a number of consecutive acquisitions.

Regardless of the high native resolution of the S1 acquisition, retrievals are affected by noise from the SAR instrument. To reduce this so-called speckle noise, multi-looking (i.e. spatial averaging) can be applied, at the cost of spatial resolution. This leads to reported resolutions of final products of 100 [1], 500 [2, 3] or 1000 [4, 5] meters, which are still useful for applications such as hydrological and crop modelling [6]. In this study, we look for ways to provide accurate soil moisture estimates at a higher spatial resolution, making use of readily available data from the S1 and Sentinel-2 (S2) satellites. In the best case, the 20 meter native resolution backscatter data could translate to soil moisture estimates in the same resolution. At such scales, the combined high spatial and temporal resolution of the soil moisture estimates could be useful for e.g. precision agriculture.

Validation of remotely sensed soil moisture is a well-known issue [7]. First of all, reference data with the correct spatial and temporal resolution on large scales is near to impossible to find. Though high resolution data can be gathered in dedicated field campaigns, field reference data often consist of point data and thus lack spatial representativeness when compared to gridded satellite data, [7]. Moreover, due to the heterogeneity of soil moisture in both space and time, even reference data cannot be considered to be “ground truth”. As such, uncertainties are difficult to quantify. Additionally, there are several trade-offs which occur when estimating soil moisture using remotely sensed data. For instance, high temporal soil moisture resolution usually coincides with low spatial resolution data and vice versa [8, 7]. Another important trade-off exists between spatio-temporal resolution and accuracy of the soil moisture estimates [7].

Here, we try to identify an adequate spatial resolution for S1 based soil moisture estimation, considering the trade-off between product resolution and accuracy. We use the uncertainty of the soil moisture estimate as a guide parameter, and focus on how product accuracy depends on factors such as soil wetness, and characteristics of the vegetated canopy. To this end, we compare S1 soil moisture estimates to both in situ data and global reference data sets with a lower spatial resolution.

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2. METHODS & DATA

The S1 satellite constellation carries a C-band Synthetic Aperture Radar (SAR) which measures the amount of the signal scattered back to the satellite from the Earth's surface, with a temporal resolution of 3 days over Europe [9]. The amount of backscatter is dependent on the dielectric constant of the soil surface and can therefore be used to estimate surface soil moisture (SSM) [10], the water content in the top few cm of the soil. However, the backscatter coefficient is also sensitive to soil roughness and vegetation.

Optical data can be used to counter the effect of vegetation on soil moisture estimates. Combining S1 and S2 data is not uncommon, as both spatial and temporal resolution are comparable. This combination is applied in several different empirical or machine learning based approaches [11], such as linear regression [12], artificial neural network [13, 14], support vector regression [4], or multi-temporal approaches [15, 2, 5, 16]. In this last approach, the roughness sensitivity is countered by assuming that the roughness remains constant over the considered time period. The change detection algorithm used in this study is the MULESME algorithm [2]. It is an algorithm well-suited for operational performance and by default provides soil moisture estimates on a 500 x 500 m^2 resolution [2].

Remotely sensed surface soil moisture data used in this study were obtained by applying the MULESME algorithm [2] on S1 backscatter data. Data were obtained from two different descending (morning) overpasses throughout 2020, but processed separately in the algorithm. From March 2020 until present, a field campaign was performed in Southeastern Luxembourg on 24 different days coinciding with S1 overpasses. Each measurement day consisted of 5 TDR measurements on each of the 72 sampling locations on a regular grid with 20 m spacing (Figure 1), as well as 12 volumetric soil samples distributed over the field. A nearby setup of permanent soil moisture probes at the Elvange-Burmerange station additionally provided continuous measurements of soil moisture at different depths, from 10 to 60 centimetres.

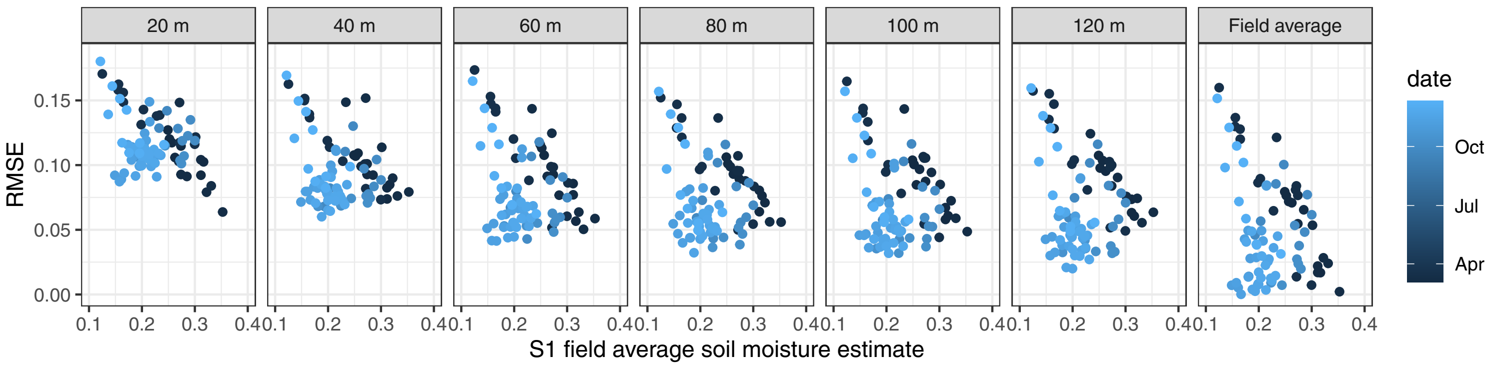
The MULESME algorithm was run on a spatial resolution of 20 x 20 m^2 with 5 consecutive S1 backscatter images at a time, as this was found to be the optimal number based on a trade-off between accuracy and computation time [2]. NDVI images from the S2 satellite were used to provide an estimate of the vegetation water content to the algorithm. The algorithm makes a temporal average of the S2 data on the S1 sensing date when no S2 data is available on that specific day. A Corine land cover map and a local slope map (SRTM) were also included. As such, every algorithm run results in five soil moisture content (SMC) maps and five uncertainty maps, which can be used for further processing. A moving window was applied on the input data, such that for each consecutive run, one new backscatter image replaced the oldest one. In the end, this approach resulted in five SMC and uncertainty maps for each S1 overpass.

Fig. 1. Field campaign setup near Elvange, in Southeastern Luxembourg. The 72 points show the locations at which TDR and volumetric soil samples were taken.

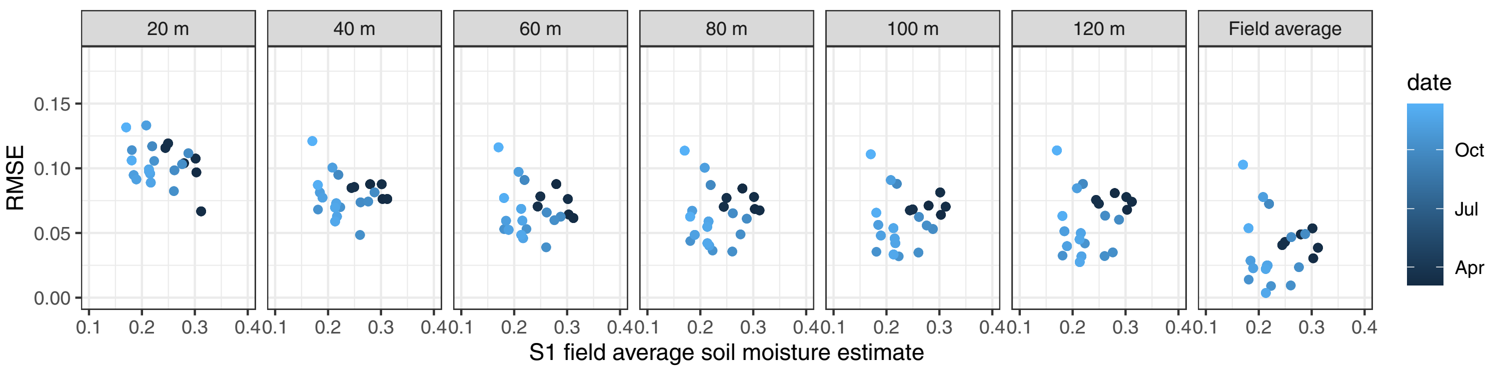
To remove the most uncertain SMC estimates, the uncertainty map was used as a mask on the SMC map, as suggested by [2]. The 20 m resolution SMC map was then aggregated to several lower spatial resolutions: 40, 60, 80, 100 and 120 m. Additionally, a field average, based on the 20 m map, was computed over the testing field (Fig. 1). For each overpass, all five available SMC maps, resulting from the moving window approach, were averaged to get the most complete view of the SMC on a specific date. Finally, both the separate and the averaged soil moisture estimates were compared to the different reference data sets, as mentioned earlier, to estimate the accuracy of the S1 SMC data.

3. RESULTS & DISCUSSION

Figure 2 shows the Root Mean Square Error between the S1 MULESME soil moisture estimates and the TDR soil moisture content gathered in the field. A clear decrease is visible in the RMSE between different resolutions, especially in the first two aggregation steps, from 20 to 40 and from 40 to 60 meters. The field average shows the lowest difference between SMC values gathered in the field and estimated from backscatter data. The results in Figure 2 also show that a



(a) Output for all separate algorithm results



(b) Output for average per date

Fig. 2. Field average Root Mean Square Error (RMSE) between the TDR values gathered in the field and MULESME soil moisture estimates on different resolutions. A color scale is included to distinguish between timing of the measurements over the year. Figure (a) shows the result for all separate algorithm outputs, whereas (b) shows the result of averaging all outputs for the same dates.

clear improvement on soil moisture estimates can be made when all outputs for a specific date are averaged, as was done to create the results in Figure 2b. The RMSE is clearly lower in these plots than in the plots in Figure 2a. The set-up that leads to lowest RMSE is a combination of averaging in time and space, shown in the most right plot of Figure 2b. Here, most RMSEs are below 0.10 and a majority falls below the 0.05 threshold.

That lower resolutions provide a better estimate of soil moisture is not a new finding. However, the field average, that showed the lowest RMSE, is still at a much higher resolution than the scales of 500 x 500 m^2 and 1 x 1 km^2 that are common in these types of studies. We will therefore continue studying this process to see whether it is possible to get field outlines from S2 images and use these to average soil moisture in those fields. Judging from the difference between the temporal moving average and the original algorithm results, it seems that an improvement can be expected when a spatial moving average is applied. It is yet to be seen whether or not this is in fact the case. Moreover, as the decrease in RMSE does not seem to be linear with a decrease in spatial resolution, we will study the possibility of estimating within-field soil moisture variation using a combination of S1 and S2 data. Such and more hypotheses will be tested in the near future.

4. CONCLUSION

Based on a combination of active microwave S1 and optical S2 data, we showed the potential of high-resolution spaceborne soil moisture estimates. Our results indicated that the accuracy of MULESME soil moisture estimates increases with a decrease in spatial resolution, but that this increase stagnates rather soon after the first few spatial aggregations, thus confirming the value of high resolution data. Future endeavours will focus on the analysis of soil moisture variation in time, compared to the soil moisture measurements from the permanent station. The uncertainty of the TDR data will be considered, as well as the uncertainty of the S1 soil moisture estimates. Additionally, the data discussed here will be compared to other reference soil moisture data sets, such as those from the ESA CCI, the SMOS satellite constellation, and the GLDAS.

5. REFERENCES

[1] Q. Gao, M. Zribi, M. J. Escorihuela, and N. Baghdadi, “Synergetic Use of Sentinel-1 and Sentinel-2 Data for Soil Moisture Mapping at 100 m Resolution,” *Sensors*, vol. 17, no. 9, pp. 1966, Sept. 2017, Number: 9.

[2] L Pulvirenti, G. Squicciarino, L. Cenci, G. Boni, N. Pierdicca, M. Chini, C. Versace, and P. Campanella, “A surface soil moisture mapping service at national (Italian) scale based on Sentinel-1 data,” *Environmental Modelling & Software*, vol. 102, pp. 13–28, Apr. 2018.

[3] A. Al-Yaari, J. P. Wigneron, W. Dorigo, A. Colliander, T. Pellarin, S. Hahn, A. Mialon, P. Richaume, R. Fernandez-Moran, L. Fan, Y. H. Kerr, and G. De Lannoy, “Assessment and inter-comparison of recently developed/reprocessed microwave satellite soil moisture products using ISMN ground-based measurements,” *Remote Sensing of Environment*, vol. 224, pp. 289–303, 2019.

[4] X. Bai, B. He, X. Li, J. Zeng, X. Wang, Z. Wang, Y. Zeng, and Z. Su, “First Assessment of Sentinel-1A Data for Surface Soil Moisture Estimations Using a Coupled Water Cloud Model and Advanced Integral Equation Model over the Tibetan Plateau,” *Remote Sensing*, vol. 9, no. 7, pp. 714, July 2017, Number: 7.

[5] B. Bauer-Marschallinger, V. Freeman, S. Cao, C. Paulik, S. Schaufler, T. Stachl, S. Modanesi, C. Massari, L. Ciabatta, L. Brocca, and W. Wagner, “Toward Global Soil Moisture Monitoring With Sentinel-1: Harnessing Assets and Overcoming Obstacles,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 57, no. 1, pp. 520–539, Jan. 2019, Conference Name: IEEE Transactions on Geoscience and Remote Sensing.

[6] E. Tebbs, F. Gerard, A. Petrie, and E. De Witte, “Chapter 19 - Emerging and Potential Future Applications of Satellite-Based Soil Moisture Products,” in *Satellite Soil Moisture Retrieval*, Prashant K. Srivastava, George P. Petropoulos, and Yann H. Kerr, Eds., pp. 379–400. Elsevier, Jan. 2016.

[7] A. Gruber, G. De Lannoy, C. Albergel, A. Al-Yaari, L. Brocca, J. C. Calvet, A. Colliander, M. Cosh, W. Crow, W. Dorigo, C. Draper, M. Hirschi, Y. Kerr, A. Konings, W. Lahoz, K. McColl, C. Montzka, J. Muñoz-Sabater, J. Peng, R. Reichle, P. Richaume, C. Rüdiger, T. Scanlon, R. van der Schalie, J. P. Wigneron, and W. Wagner, “Validation practices for satellite soil moisture retrievals: What are (the) errors?,” *Remote Sensing of Environment*, vol. 244, pp. 111806, July 2020.

[8] L. Brocca, L. Ciabatta, C. Massari, S. Camici, and A. Tarpanelli, “Soil Moisture for Hydrological Applications: Open Questions and New Opportunities,” *Water*, vol. 9, no. 2, pp. 140, Feb. 2017, Number: 2.

[9] Copernicus Space Component Mission Management Team, “Sentinel High Level Operations Plan (HLOP),” Tech. Rep., European Space Agency, 2018.

[10] J. Cihlar and F. T. Ulaby, “Dielectric properties of soils as a function of moisture content,” Tech. Rep. NASA-CR-141868, The university of Kansas Center for Research, Inc., 1974.

[11] C. Ma, X. Li, and M. F. McCabe, “Retrieval of High-Resolution Soil Moisture through Combination of Sentinel-1 and Sentinel-2 Data,” *Remote Sensing*, vol. 12, no. 14, pp. 2303, Jan. 2020, Number: 14.

[12] A. Amazirh, O. Merlin, S. Er-Raki, Q. Gao, V. Rivalland, Y. Malbeteau, S. Khabba, and M. J. Escorihuela, “Retrieving surface soil moisture at high spatio-temporal resolution from a synergy between Sentinel-1 radar and Landsat thermal data: A study case over bare soil,” *Remote Sensing of Environment*, vol. 211, pp. 321–337, June 2018.

[13] S. Paloscia, S. Pettinato, E. Santi, C. Notarnicola, L. Pasolli, and A. Reppucci, “Soil moisture mapping using Sentinel-1 images: Algorithm and preliminary validation,” *Remote Sensing of Environment*, vol. 134, pp. 234–248, July 2013.

[14] M. El Hajj, N. Baghdadi, M. Zribi, and H. Bazzi, “Synergic Use of Sentinel-1 and Sentinel-2 Images for Operational Soil Moisture Mapping at High Spatial Resolution over Agricultural Areas,” *Remote Sensing*, vol. 9, no. 12, pp. 1292, Dec. 2017.

[15] N. Pierdicca, L. Pulvirenti, and C. Bignami, “Soil moisture estimation over vegetated terrains using multitemporal remote sensing data,” *Remote Sensing of Environment*, vol. 114, no. 2, pp. 440–448, Feb. 2010.

[16] M. Hornacek, W. Wagner, D. Sabel, H. Truong, P. Snoeij, T. Hahmann, E. Diedrich, and M. Doubkova, “Potential for High Resolution Systematic Global Surface Soil Moisture Retrieval via Change Detection Using Sentinel-1,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 5, no. 4, pp. 1303–1311, Aug. 2012, Conference Name: IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing.