

# REMOTE SENSING OF SOIL MOISTURE FOR AGRICULTURAL AREAS USING SPATIAL AND TEMPORAL HIGH-RESOLUTION SENTINEL-1 SAR TIMESERIES IN GOOGLE EARTH ENGINE

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## Abstract

The retrieval of soil moisture information with spatially and temporally high resolution from Synthetic Aperture Radar (SAR) observations is still a challenge. By using multi-orbit Sentinel-1 C-band timeseries, we present a novel approach for estimating volumetric soil moisture content for agricultural areas with a temporal resolution of one to two days, based on a short-term change detection method. By applying an incidence angle normalization and a Fourier series transformation, the effect of varying incidence angles on the backscattering signal could be reduced. Using the spatial regression between co- and cross-polarized SAR signal, the vegetation scattering contribution was estimated and used for vegetation correction of the related backscatter ratios. The retrieving algorithm was implemented in a cloud-processing environment, enabling a global and scalable application. Validated against eight in-situ CRNP stations across the Rur catchment (Germany) as well as six capacitance station at the Apulian Tavoliere (Italy) site at 0.025 m and 0.1 m soil depth for the years 2018 to 2020, the method achieves a correlation of  $R = 0.63$  with an unbiased Root Mean Square Error of  $0.063 \text{ m}^3/\text{m}^3$ .

## Introduction

By using 60 % to 90 % of the totally available water, agricultural systems are the main consumers of freshwater resources on global scale. Being heavily affected by the increasing impacts of climate change on the available water resources, detailed knowledge about soil moisture, being a key parameter in the agricultural sector, is therefore crucial for mitigating these effects on both local and regional scale. Nevertheless, high resolution surface soil moisture data for regional and local monitoring (down to precision farming level) are still challenging to obtain. This knowledge gap can be filled by using Synthetic Aperture Radar (SAR) satellite missions. Providing a cloud- and weather independent monitoring of the Earth's surface, SAR observations are suitable for regional and local soil moisture monitoring, but with a global extent.

## Objective & Study Area

While the increasing resolution and the total number of current and future SAR recordings (e.g. Sentinel-1, Advanced Land Observing Satellite-2 (ALOS-2), NASA-ISRO SAR (NISAR), Radar Observing System for Europe - L-Band (ROSE-L)) will contribute to an improvement of soil moisture estimation in general, the computational costs as well as the local memory capacity on the other hand become a limiting factor in processing the vast load of data. Here, on demand cloud-based processing services are one way to overcome this challenge. This is especially interesting as most of the severely affected regions have limited access to computational resources. In this regard, we developed an automated workflow for estimating soil moisture, established within the cloud-processing platform Google Earth Engine (GEE), using temporal and spatial high-resolution Sentinel-1 timeseries. The main innovations are the development of approaches to account for multiple incidence angles and a dynamic vegetation cover. The method is validated on the Rur catchment, which is located in the federal state of North-Rhine Westphalia in the West of Germany and dominated by crop cultivation (sugar beet, maize, winter cereals) in the north and pastures and forest of deciduous and coniferous trees in the south. It is furthermore evaluated on the Apulian Tavoliere site in southern Italy, dominated by cereal crops.

The following datasets are used for the estimation and evaluation of soil moisture:

- Dual-polarized (VV + VH) Sentinel-1A and Sentinel-1B scenes
- The Coordination of Information on the Environment Land Cover (CORINE) dataset
- The OpenLandMap Dataset for field capacity and soil texture
- Eight cosmic-ray neutron probing (CRNP) stations, spatially distributed on agricultural areas within the Rur catchment as well as six capacitance stations at the Apulian Tavoliere site

## Methodology

The soil moisture estimation workflow is completely implemented in the cloud-processing platform Google Earth Engine (GEE) and can be divided into two major parts: (1) Preprocessing of Sentinel-1 SAR data and (2) soil moisture estimation using the alpha approximation method. In a first step, non-agricultural areas are masked, using the CORINE dataset as well as a focal median filter with a radius of 50 m is applied for speckle reduction. Using a multi-orbit SAR timeseries, the effect of alternating incidence angles on the backscattering signal is addressed by normalizing each scene to a reference incidence angle of  $40^\circ$ , using scene-based linear regression. In addition, the timeseries is transformed into a Fourier series excluding frequencies smaller than 15 days, matching with the Sentinel-1 revisit time of 12 days.

Due to its comparable short wavelength of 6 cm, C-band is sensitive to the vegetation cover in both co- and cross-polarization, as its penetration through canopy is limited. This leads to a varying bias in soil moisture information within the individual backscattering signals in both temporal and spatial dimension during the vegetation period. In terms of the first-order radiative transfer model, the total backscattering signal can be written as the sum of the bare soil component and the vegetation affected scattering component. The changing ratio of both components during the growing cycle in fact leads to an underestimation of soil moisture increase and overestimation of soil moisture decrease during vegetation period compared to non-vegetation period. As the bare soil factor is reducing with increasing vegetation, the vegetation influence on the backscattering ratio is growing. To address this issue, we use a linear regression between the backscatter ratios, derived from of each consecutive image pair, and the regression slope parameter  $\beta$ , calculated from spatial regression of a moving window with a kernel size of  $3 \times 3$  pixel between co- and cross-polarized channel, as an indicator for vegetational presence.

Applying a change detection approach on the adapted timeseries, changes in backscattering signal between two consecutive images can be related to changes in soil moisture, as the temporal variability of it is highest compared to other surface parameters. Thus, the ratio of two consecutive co-polarized backscattering signals can be expressed as function of soil dielectric constants and incidence angle. The resulting underdetermined linear equation system can be solved, using a starting value derived from the OpenLandMap field capacity dataset, assuming that the soil is fully saturated in the winter period. The conversion from soil moisture to dielectric constant and vice versa is done using the OpenLandMap soil texture dataset.

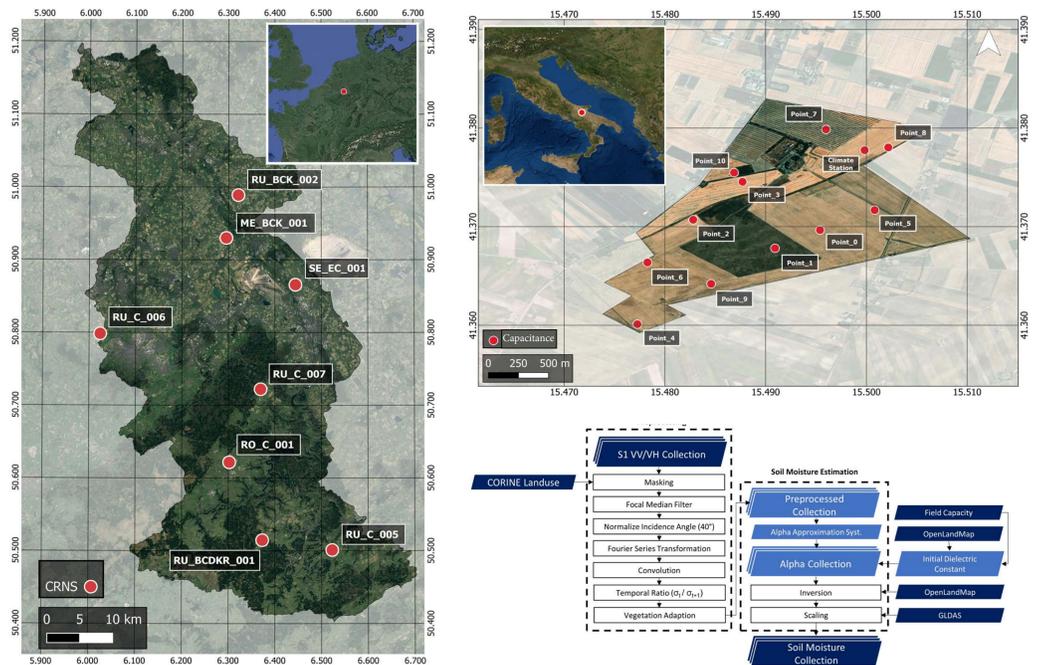


Figure 1: Overview of the input datasets for the Rur catchment (left) and Apulian Tavoliere (upper right) as well as workflow of the soil moisture estimation algorithm (lower right), which can be divided into two main blocks: Preprocessing (1) and soil moisture estimation (2).

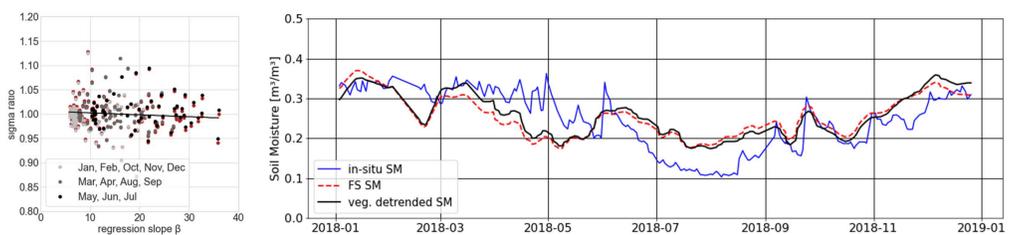


Figure 2: Comparison between vegetation corrected and original backscatter ratios for the CRNP station SE\_C\_001 (left) as well as comparison between vegetation corrected and non-corrected estimated soil moisture to in-situ measured soil moisture (right)

## Results

Applying the vegetation adaption only at the crop dominated sites, an overall  $R$  of 0.64,  $R^2$  of 0.40 and  $\text{uRMSE}$  of  $0.060 \text{ m}^3/\text{m}^3$  at the Rur catchment, as well as an overall  $R$  of 0.64 (0.60),  $R^2$  of 0.41 (0.36) and  $\text{uRMSE}$  of  $0.063 \text{ m}^3/\text{m}^3$  ( $0.067 \text{ m}^3/\text{m}^3$ ) at the Apulian Tavoliere site at 0.025 m (0.1 m) soil depth are achieved. No major difference in the performance can be observed regarding the in-situ measurement instrument, measuring either point (capacitance) and areal (CRNP) values, and no major discrepancy is observed at the different soil depths of 0.025 m (capacitance), 0.1 m (capacitance), and 0.1 m to 0.7 m (CRNP). Evaluating the final soil moisture output over all three years and both test sites, the method achieves a  $R = 0.63$ , a  $R^2 = 0.39$  and an  $\text{uRMSE} = 0.063 \text{ m}^3/\text{m}^3$ .

## Discussion

While the incidence angle normalization led to an alignment of the mean backscattering values between individual orbits, the effect of incidence angle is still present in the individual backscattering signal distribution. By using the Fourier series transformation, dismissing frequencies lower than the revisit time of the Sentinel-1 A and Sentinel-1 B, the change in backscattering signal caused from varying incident angles can be analytically excluded, resulting in higher correlation as well as reduced  $\text{uRMSE}$  at most individual CRNP and capacitance stations. Adding the newly developed vegetation correction, further increase of the correlation between estimated and in-situ measured soil moisture can be observed, but mainly at the crop dominated stations. Here, further research in adapting the proposed vegetation correction to meadow dominated areas is needed, as currently the method tends to overestimate soil moisture decrease within the non-vegetation period at these locations.

## Conclusion

Each of the applied pre-processing steps significantly increased the overall fitness of the estimated soil moisture, both in terms of correlation coefficient as well as  $\text{uRMSE}$ . By establishing the soil moisture retrieval algorithm within a cloud-processing environment, the SAR-based soil moisture estimation takes a step towards a globally applicable, weather independent and user-specific solution. Using the newly developed vegetation adaption, soil moisture estimation from Sentinel-1 time series could be further improved, especially for the relevant field of agricultural management.

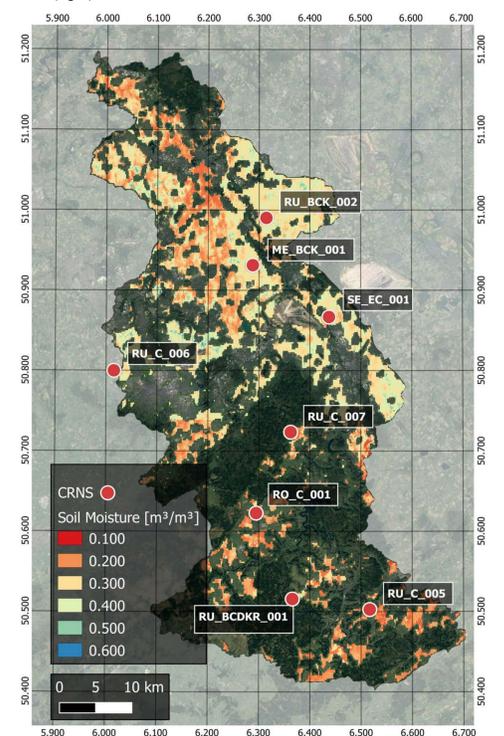


Figure 3 : Soil moisture map for the Rur catchment for 1<sup>st</sup> June 2020

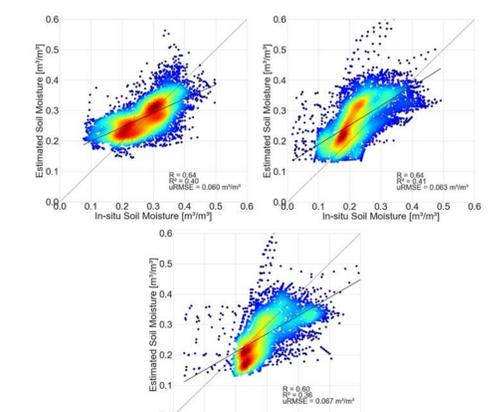


Figure 4 : Density scatter plot between estimated and in-situ measured soil moisture from all eight CRNP stations (upper left) and all six capacitance stations for 0.025 m (upper right) and 0.1 m soil depth (lower) for the period 2018 to 2020

## Major References

- Balenzano, A.; Mattia, F.; Satalino, G.; Davidson, M. (2011): Dense Temporal Series of C- and L-band SAR Data for Soil Moisture Retrieval Over Agricultural Crops. In IEEE J. Sel. Top. Appl. Earth Observations Remote Sensing 4 (2), pp. 439–450. DOI: 10.1109/JSTARS.2010.2052916
- Jagdhuber, T.; Baur, M.; Akbar, R.; Das, N.; Link, M.; He, L.; Entekhabi, D. (2019): Estimation of active-passive microwave covariation using SMAP and Sentinel-1 data. In Remote Sensing of Environment 225 (6), pp. 458–468. DOI: 10.1016/j.rse.2019.03.021.