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ESTIMATING SOIL MOISTURE PROFILES BY COMBINING P-BAND SAR WITH HYDROLOGICAL MODELING

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ABSTRACT

A joint approach for estimating vertically continuous soil moisture profiles by combining P-band SAR polarimetry with soil hydrological modeling is proposed. The approach compares the decomposed soil scattering component from remotely sensed P-band SAR observations of NASA's Airborne Microwave Observatory of Subcanopy and Subsurface (AirMOSS) mission with an ensemble of simulated counterparts based on the hydrological model HYDRUS-1D and the soil scattering model multi-layer small perturbation method (SPM). From the best fit between remote sensing and soil modeling, the most probable soil moisture profile can be retrieved. Estimated soil moisture profiles at individual monitoring stations across the U.S. are compared to *in situ* measurements, as well as the European ReAnalysis (ERA5) land and AirMOSS L4 products. Pearson's coefficient of determination between estimated and auxiliary products prove the overall feasibility of the proposed method with respective R^2 of 0.92, 0.95, and 0.87.

***Index Terms*—** SAR, polarimetry, soil moisture profile, AirMOSS, HYDRUS-1D, multi-layer SPM

1. INTRODUCTION

Soil moisture contributes to the characterization of the Earth's weather and climate [1], influencing land-atmosphere exchanges [2]. Especially the vertical distribution and variability of the soil moisture with depth have direct impact on the land-atmosphere coupling (e.g., evapotranspiration) and the heat and water exchanges [3]. Microwave remote sensing proved to be a useful tool for estimating soil moisture at large spatio-temporal scales. Up to now, most soil moisture retrieval methods are able to estimate moisture from microwave observations near the soil surface (L-band) [4] or at the subsurface (P-band) [5]. These methods provide a single moisture value for the vertical integral from the soil surface until the penetration depth of the respective microwaves. However, in principle, the P-band radar backscatter time series are able to provide information on the soil moisture dynamics in time, space and depth. Thus, by combining remote sensing with hydrological modeling, a new method for estimating the soil moisture variability across the vertical soil column, i.e. the soil moisture profiles, is proposed in this research study. Specifically, remotely sensed soil information from P-band synthetic aperture radar (SAR) observations at high resolution are combined with approximate solutions for soil moisture variabilities from hydrological modeling. By doing so, the proposed method estimates soil moisture profiles with improved accuracy, enhancing already existing soil moisture profile products based on retrieval methods like simple polynomial shape fitting, e.g., [6].

2. DATA SOURCES

In this study, fully polarimetric SAR observations at a center frequency of 430 MHz (P-band) of NASA's Airborne Microwave Observatory of Subcanopy and Subsurface (AirMOSS) mission are employed [7]. The airborne mission was conducted between 2012-2015 across multiple monitoring sites in North and Central America, all covering an area of ~100 × 25 km at ~90 m resolution [7]. The proposed approach is analyzed and validated at eight individual monitoring stations within six AirMOSS campaign sites across the continental U.S., enabling the investigation of variable climates, vegetation covers and soil conditions. Further, estimated soil moisture profiles are compared and validated with *in situ* measurements from the US Climate Reference Network (US-CRN) network [8], the European ReAnalysis (ERA5) land product from the European Centre for Medium-Range Weather Forecasts (ECMWF) [9], and the project AirMOSS L4 mission product [10]. Since all these validation and comparison products only provide moisture values at discrete soil depths (symbols in Fig. 1), their profiles are estimated by applying a polynomial function of 2nd degree combining the discrete values.

3. METHOD

The approach begins with decomposing polarimetric P-band SAR observations from the AirMOSS campaign [7] into the individual scattering mechanisms (soil, dihedral, vegetation) by applying the revised hybrid decomposition method from [5]. In this way, the influence of vegetation-only or double-bounce scattering is eliminated from the total SAR signal and only the soil scattering component, represented by the data-based polarimetric scattering angle α_s^{SAR}, is considered for soil moisture profile estimation. The reader is referred to [5] for more details on the hybrid decomposition method and the removal of the vegetation scattering components from the total SAR signal.

Second, the HYDRUS-1D model [11] is used to simulate an ensemble of soil moisture profiles (number of layers fixed to 101) based on varying initial assumptions, e.g., the profile depth or the soil matrix potential. HYDRUS-1D computes the one-dimensional water flow in variably saturated soils by solving a modified version of the Richards' equation [11]. Every simulated soil moisture profile is then used to model the corresponding backscatter coefficient σ_{PQ}^{o} by employing the multi-layer small perturbation method (SPM), which simulates backscattering from multi-layered soils [12]. These modeled σ_{PQ}^{o} are then used to calculate the model-based scattering angle α_s^{Model} [13] for every simulated profile.

Lastly, the best fit between observed α_s^{SAR} and simulated α_s^{Model} determines the final, most representative, continuous soil moisture profile. Sensitivity analyses showed that always the global minimum can be found (no multiple solutions). Further, the best fit deviates at least 1.75 % from the second best and higher best fits (one distinct solution).

4. RESULTS

Results are presented here exemplarily for the monitoring station Stillwater 2 W within the AirMOSS campaign site MOISST in Oklahoma, USA. This station is characterized by the landcover classes grassland or herbaceous, as well as a temperate climate with mild summers (Cfa) [14].

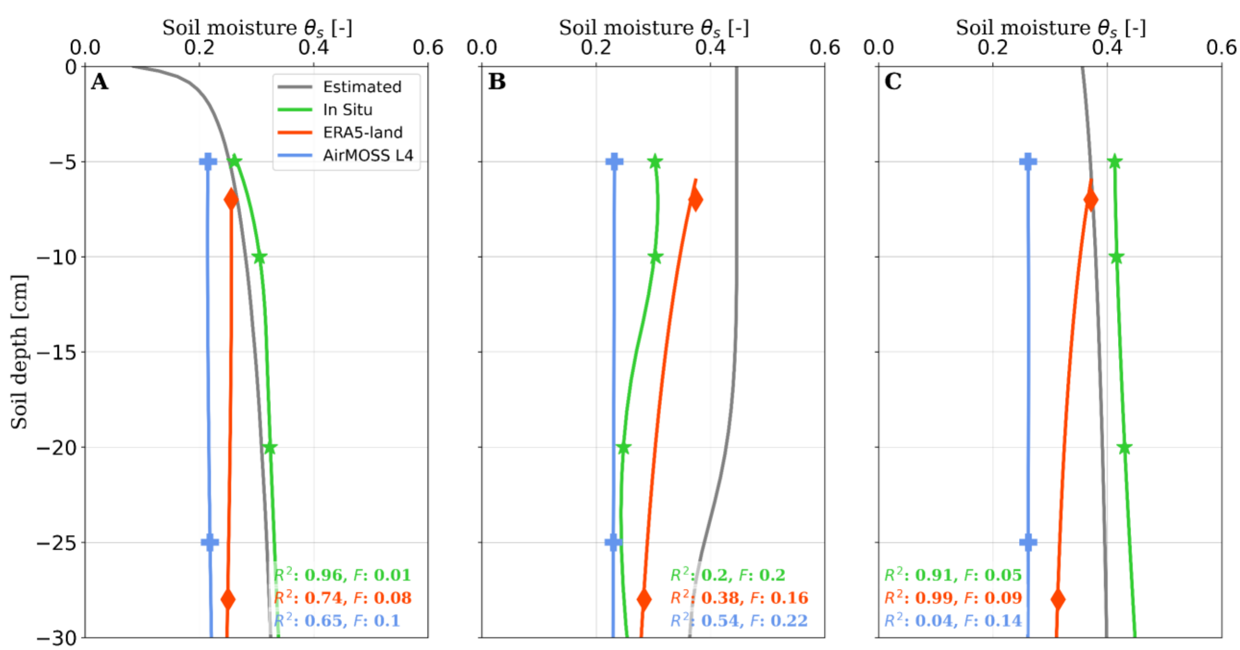

Fig. 1. Estimated soil moisture profiles for individual dates at AirMOSS monitoring station Stillwater 2 W, OK, USA, in comparison with auxiliary soil moistures products. R^2 [-] is the correlation coefficient and F [-] is the Fréchet distance [15]. A: drying soil on 10/21/2014, B: rewetted soil (after small rain event in the week before) on 07/16/2013, C: rewetted soil (after three consecutive rain days before acquisition) on 06/17/2013.

In Fig. 1 three individual profile plots (A, B, C) represent typically occurring soil moisture profiles (shape & level) at individual dates, depending on prior precipitation events and soil conditions. The estimated soil moisture profiles are compared with *in situ* measurements from US-CRN, as well as the ERA5-land and the AirMOSS L4 products.

The estimated profile in Fig. 1A shows increasing values with increasing soil depth since no precipitation occurred at least more than seven days prior to the recording date and hence, the soil constantly dries out from the soil surface towards deeper layers. Fig. 1B shows a typical soil moisture profile when smaller precipitation events occur prior to the recording date (here in total 31.9 mm in the week before). The soil moisture values decrease with increasing soil depth since the water infiltrates from top downwards to deeper layers.

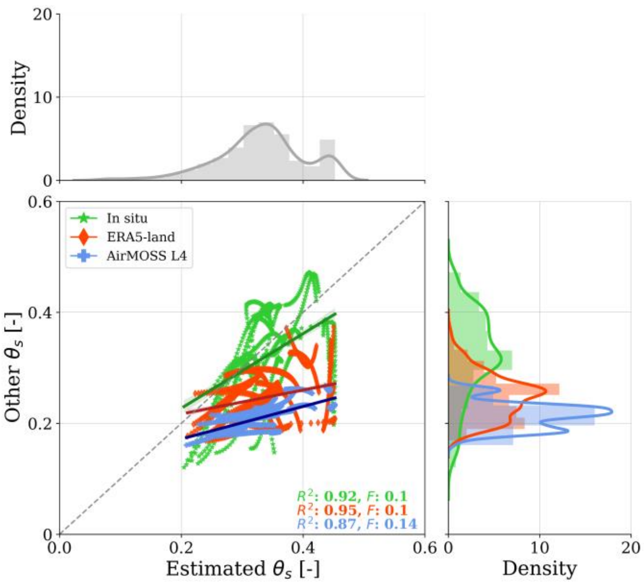

Fig. 2. Comparison of estimated soil moisture values between 2013-2015 for soil depths from 0 cm to -30 cm with auxiliary soil moistures products at the monitoring station Stillwater 2 W, OK, USA (36°7.05´N, 97°5.7´W). R^2 [-] is the correlation coefficient and F [-] is the Fréchet distance [15].

Thereby, the depth of the inflection point varies depending on infiltration rate and time since rain pulse. Finally, Fig. 1C shows almost no variability with depth in the estimated soil moisture profile. Here, the profile is almost static at 38.6 vol.% since in total 66.5 mm of rain occurred within three consecutive days prior to the recording date (saturated conditions).

Analyzing all results at this site for all campaign dates between 2013 to 2015 (in total 19), correlation coefficients between estimates and *in situ* values of 0.92, ERA5-land values of 0.95, and AirMOSS L4 values of 0.87 are achieved (Fig. 2). The higher R^2 between estimates and ERA5-land values can be explained by the smaller value range compared to *in situ* observations as indicated by the probability density functions (PDFs) at the edges of to the scatterplot. The Fréchet distance, accounting not only for the difference in absolute values but also the profile shape similarity, is highest with AirMOSS L4 values (F = 0.14), compared to *in situ* and ERA5-land values (both with F = 0.1), showing lowest similarity in absolute values and profile shapes. This is because AirMOSS L4 values show the smallest value range of all ranging from 0.18 to 0.26 and with the PDF peaking at 0.22. In contrast, estimated moisture values cover a much broader value range between 0.17 and 0.43 with highest density of values at 0.32, similar to *in situ* measurements (between 0.12 and 0.45, and highest density at 0.27). ERA5-land shows the second smallest value range varying between 0.18 and 0.39, with the PDF peaking between the one of *in situ* values and AirMOSS L4 values at 0.24.

Overall, results show that retrieved estimates fit most to *in situ* measured soil moistures with high R^2, lowest F and the regression line closest to the 1:1 line (Fig. 2).

5. SUMMARY AND CONCLUSION

In this study, a combined approach of remote sensing and soil hydrological modeling is presented to estimate vertically continuous soil moisture profiles. The approach is tested based on the polarimetric P-band SAR observations of the AirMOSS mission [7] and the models HYDRUS-1D [11] for soil hydrology as well as the multi-layer SPM [12] for soil scattering. The comparison of remote sensing and soil modeling is performed on the level of the soil scattering angle. The main reason, among others, is that this way only soil scattering has to be simulated since vegetation effects on the P-band SAR observations are removed before the comparison. Further, a variable model set-up is used with varying initial assumptions on certain input parameters in order to diminish potential model errors. Here, actual remotely sensed SAR observations constrain the selection of the most appropriate hydrological model simulation.

This combined approach provides the ability of estimating vertically continuous and physically more realistic soil moisture profiles. Other approaches mainly apply a polynomial fitting of certain degree to few known moisture measurements at discrete soil depths to obtain a vertical moisture profile, which is, however, physically unrealistic due to profound simplifications of reality. Further, *in situ* soil moisture sensors need a certain measuring volume of soil to provide realistic measurements. Hence, most *in situ* measurements are only available below 5 cm soil depth. Here, the proposed approach can provide information on the soil moisture variability and discontinuity also in the upper part of the soil, from the soil surface until 30 cm depth (approximate penetration depth of P-band SAR observations).

Exemplarily results at the monitoring site Stillwater 2 W in Oklahoma, USA, show high correlations and low Fréchet distances between estimated soil moisture profiles and auxiliary data (*in situ* measurements, ERA5-land reanalysis & AirMOSS L4 mission products). Further, since the soil moisture profile shapes constantly coincide with actual hydrological circumstances (e.g., climate regimes, precipitation), the feasibility of the proposed method is confirmed. In the end, this method enables the potential to indicate soil moisture variability across the vertical soil column and improve, e.g., the forecast skill of weather and climate models.

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