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SIMULTANEOUS RETRIEVAL OF SURFACE ROUGHNESS PARAMETERS FROM COMBINED ACTIVE-PASSIVE SMAP OBSERVATIONS

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ABSTRACT

Soil roughness strongly influences processes like erosion, infiltration, moisture and evaporation of soils as well as growth of agricultural plants. An approach to soil roughness based on active-passive microwave covariation is proposed in order to simultaneously retrieve the vertical RMS height (s) and horizontal correlation length (l) of soil surfaces from simultaneously measured radar and radiometer microwave signatures. The approach is based on a retrieval algorithm for active-passive covariation including the improved Integral Equation Method (I^{2}EM). It is tested with the global active-passive microwave observations of NASA's Soil Moisture Active Passive (SMAP) mission. The developed roughness retrieval algorithm shows independence of permittivity for $\varepsilon_s > 10$ [-] due to the covariation formalism. Results reveal that s and l can be estimated simultaneously by the proposed approach since surface patterns of non-vegetated areas can be assessed on global scale. In regions with sandy deserts, like the Sahara or the outback in Australia, determined s and l confirm rather smooth to semi-rough surface roughness patterns with most frequent vertical RMS heights smaller 3 cm and corresponding higher horizontal correlation lengths (> 8 cm).

Index Terms— radar, radiometer, RMS height, correlation length, covariation, I^{2}EM

1. INTRODUCTION

Soil roughness as a boundary property between the pedosphere and the atmosphere is an essential variable in numerous physical processes which are related to water, energy and nutrient flux and exchange [1]. It plays an indispensable role in soil moisture sensing from active and passive microwave techniques, one of the key state variables in the global water cycle having significant impact on the global weather and climate system [2]. Due to their critical role in land surface dynamics, both soil moisture and soil roughness affect the brightness temperature TB_P [K] and backscatter $|S_{PP}|^2$ [dB] characteristics of natural surfaces measured by radiometers and radars, respectively. While TB_P can be expressed as a function of soil moisture, soil roughness and effective surface temperature for bare soils [3], $|S_{PP}|^2$ is only dominated by surface soil moisture and soil roughness for the case of bare soils [4], at polarization P, respectively. In the last decades, soil roughness is regarded as a subordinate variable in the field of microwave remote sensing despite its importance in several environmental applications such as land surface modeling for soil erosion [1]. The two fundamental parameters which describe the soil surface roughness in the microwave domain are the standard deviation of the surface height variation (or RMS height) denoted by s [cm] with its related autocorrelation function (ACF), and the surface correlation length denoted by l [cm]. In order to estimate s and l concurrently and independently of permittivity, we link active and passive microwave signatures through their covariation.

2. DATASET

Global data from NASA's Soil Moisture Active Passive (SMAP) mission launched in 2015 is applied for this study. We used the SMAP L1B Radar Half-Orbit Time-Ordered low resolution backscatter $|S_{PP}|^2$ [5], the SMAP L1C Radiometer Half-Orbit Time-Ordered Brightness Temperature TB_P [6], the physical soil temperature T and soil moisture extracted from the SMAP L3SM_P products [7], all posted on a 36 km Equal-Area Scalable Earth-2 (EASE-2) grid [8, 9]. The period of study with SMAP data covers the months from 04/14/2015 to 07/07/2015 until the failure of the SMAP radar sensor [9].

For filtering of the retrieval results for non-vegetated areas we used the vegetation optical depth (VOD) posted on a 36 km EASE-2 grid from the SMAP dataset processed with the multi-temporal dual-channel retrieval algorithm (MT-DCA) [9], and the surface condition quality flags for snow and frozen ground from the SMAP L3 Radiometer Global and Northern Hemisphere Daily 36 km EASE-Grid Freeze/Thaw State [10].

3. METHODS

In order to combine microwave measurements from radar and radiometers independently of permittivity, their covariation with soil moisture is utilized [11, 12, 13]. We introduced the formulation for active-passive covariation already in [13]. The basic of this method are the data-based β_{P-PP}^{Data} (cf. sec. 3.1.1.) and the model-based β_{P-PP}^{Model} (cf. sec. 3.1.2.) covariation parameters for simultaneous retrieval of surface roughness parameters s and l [13].

3.1. Formulation of Active-Passive Microwave Covariation

The fundamental formulation of active-passive microwave covariation is based on Kirchhoff's law of energy conservation and derived in [12]. The covariation-based retrieval formulation includes the emissivity E_P [-] and backscattering $|S_{PP}|^2$ [-] characteristics of bare surfaces and is proposed here for active-passive surface roughness retrieval at L-band. The relationship between the backscattering coefficient of the radar ($|S_{PP}|^2$) and the emissivity ($E_P = TB_P/T$) based on brightness temperatures TB_P [K] of the radiometer is functionally linear and can be expressed by the two parameters α and β, with α [-] being the intercept and β_{P-PP} [-] being the slope of a linear regression (1) [8].

$$TB_P/T = \alpha_{P-PP} + \beta_{P-PP} * |S_{PP}|^2 \quad (1)$$

For bare soils the intercept α_{P-PP} is 1, due to the fact that vegetation is absent [12].

Based on (1), the P-polarized covariation parameter can be calculated for model as well as data with (2), which stems from [11] and [14]. It is the inversion of the active-passive covariation forward model for bare soils presented in [12]:

$$\beta_{P-PP} = \frac{E_P - 1}{|S_{PP}|^2} = \frac{\frac{TB_P}{T} - 1}{|S_{PP}|^2}, \quad (2)$$

with T [K] as physical surface temperature mostly from about the top 5 cm of the soil.

Thus, the slope β_{P-PP} describes the covariation between emissivity and backscatter for bare soils due to soil roughness. One data-related restriction of this formulation is that both sensor, radar and radiometer, need to have the same spatial resolution in order to observe the roughness on the same scale. Plus, since microwave-retrieved soil surface roughness is dependent on the wavelength of the observation system, s and l are estimated in units of wavelength and subsequently need to be scaled by the wave number $k = 2\pi/\lambda$ to the unit of meters.

3.1.1. Data-based Retrieval of covariation

The data-based covariation parameter β_{P-PP}^{Data} [-] for polarization P is calculated according to (2). As input parameters for active-passive microwave signatures (TB_P, T and $|S_{PP}|^2$) we used the datasets from the SMAP mission (cf. 2.).

3.1.2. Definition of Forward Model for covariation

The model-based covariation parameter β_{P-PP}^{Model} [-] for respective polarization P, calculated with the proposed covariation-based retrieval algorithm (2), is dependent on s and l. We defined a range of values for the surface roughness parameter s from 0.05 cm to 10 cm in 0.1 cm steps, and l from 1 cm to 21 cm in 1.0 cm steps. Besides s and l, input parameter for active-passive microwave signature simulations is the permittivity ε_s, retrieved from soil moisture information by a pedo-transfer function like [15]. The β_{P-PP}^{Model} can be calculated assuming differing ACFs – Gaussian, exponential or n-exponential. Results presented here are determined assuming a Gaussian ACF.

Within the first presentation of this active-passive retrieval algorithm in [13], the covariation parameter β_{P-PP}^{Model} is the ratio of Fresnel and Bragg roughness loss terms. However, sensitivity analyses revealed unsatisfying results for the retrieval of surface correlation length l. The reason could be the missing incoherent part of surface scattering within the Fresnel roughness loss term. Hence, we revised our approach for simultaneous retrieval of s and l and used the I^2EM for simulations of active and passive microwave bare soil interactions. The reason for employing the I^2EM is its physics basis and analytical formalism for backscatter and emissivity based on s and l, frequency, incident angle and permittivity [16, 17]. Due to its analytical formalism, I^2EM is preferred over more computationally intensive numerical methods such as the Numerical Maxwell Model in 3-D (NMM3D) [17].

3.2. Estimation of Surface Roughness Parameters s and l

As described in [13], we determine the best fit between model- and data-based covariation parameters in order to estimate s and l. Hence, we calculate the differences for horizontal as well as vertical polarizations and add up the respective results for both polarizations. We then receive a look-up-table (LUT) with the dimensions of the pre-defined ranges of roughness parameters s and l. The position of the global minimum of the LUT corresponds to the best-fitting values for s and l [13].

4. RESULTS

4.1. Sensitivity analyses on permittivity with I2EM

Permittivity ε_s, along with roughness parameters s and l, is an input parameter in the I^2EM for calculation of backscatter and emissivity. In order to determine the influence of ε_s on surface roughness parameter retrievals we conducted several sensitivity analyses. For instance, we compared the full range of physically possible permittivity values with the calculated model-based covariation parameter β_{P-PP}^{Model} for both polarizations. As depicted in Figure 1, results show that for higher permittivity values the β_{P-PP}^{Model} is at constant level and only exhibits changes for ε_s approximately lower than ten. Hence, with increasing ε_s the I^2EM computed backscatter and emissivity are more and more insensitive to permittivity which in turn applies to the I²EM-based retrieval of s and l.

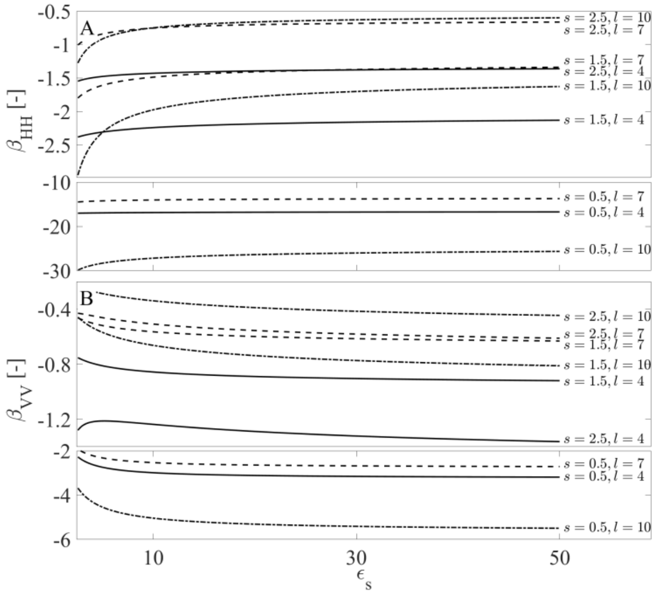

Figure 1. Influence of permittivity $\boldsymbol{\varepsilon_s}$ on model-based covariation parameter $\boldsymbol{\beta_{P-PP}^{Model}}$ from backscatter and emissivity values of I²EM assuming a Gaussian ACF. (A) Results for $\boldsymbol{\beta_{H-HH}^{Model}}$, (B) Results for $\boldsymbol{\beta_{V-VV}^{Model}}$; Model input parameters: vertical RMS height of 0.5 cm, 1.5 cm and 2.5 cm, horizontal correlation length of 4 cm, 7 cm and 10 cm.

4.2. Global surface roughness retrieval with SMAP data

Figure 2 illustrates the retrieval results for s and l calculated with the proposed covariation-based approach assuming a Gaussian ACF. Pixels with VOD > 0.12, or with more than one day covered by snow or frozen ground during the investigation period, or with > 5 % water fraction are masked out to guarantee analyzes exclusively for bare soils.

Results for surface roughness parameter s are in the range from 0.05 cm to 7 cm with most frequent heights (~60.3 %) between 0.05 cm to 4 cm. In Figure 2A the smallest RMS heights are found within the Sahara whereas largest heights are reached at the edges of the Sahara or in Australia due to sparse vegetation (e.g. shrublands). Results for surface roughness parameter l are between 1 cm and 21 cm with most lengths (~75.4 %) from 2 cm to 6 cm. Lowest horizontal correlation lengths are estimated, for instance, in the Sahara or in the southern part of Australia. Highest lengths can be found in the north western part of Australia as well as in Kazakhstan and Mongolia (cf. Fig. 2B).

By taking a closer look at both roughness parameters, results show opposed retrievals for vertical RMS heights and horizontal correlation lengths. This means, in regions with smallest RMS-heights the corresponding correlation lengths are largest, and vice versa. Furthermore, retrieval results for s and l indicate rather smooth surface structures in regions with deserts, like the Sahara in Africa, the outback in Australia or the northern part of the Gobi in Mongolia, and rather rough surface structures at the edges of deserts, like south of the Sahara or the outback.

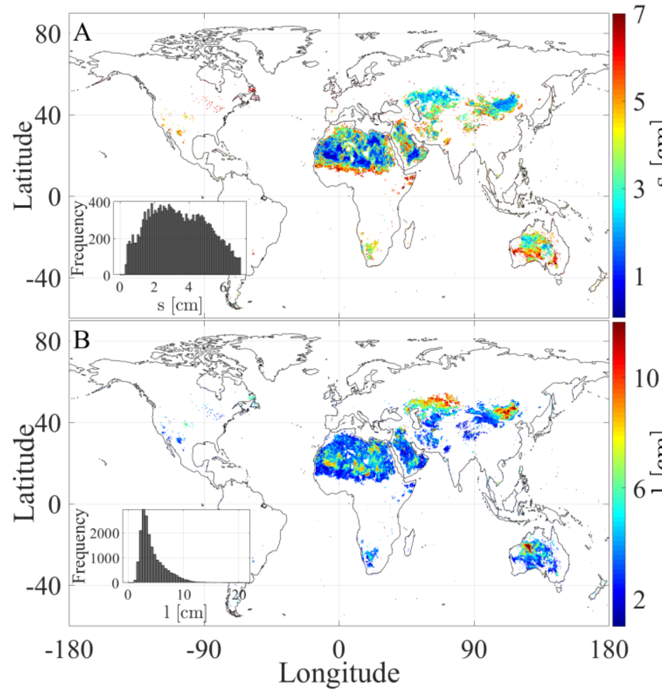

Figure 2. Global time-averaged (April-July 2015) results for estimated surface roughness parameters $\boldsymbol{s}$ (A) and $\boldsymbol{l}$ (B) assuming a Gaussian ACF and using SMAP active and passive microwave observations. Inset shows histogram of the estimated parameter.

Final sensitivity analyses based on comparisons of initial and retrieved values for surface roughness parameter s and l with varying deviation on the I²EM computed input parameters confirmed the feasibility and accuracy of the proposed covariation-based approach with correlations between input and output s-values from 77 % to 98 %.

Compared to the presented surface roughness results for s and l in [13], further analyses revealed that the revised covariation-based approach proposed in this study outperforms the initially introduced retrieval algorithm in [13] (based on Fresnel and Bragg roughness loss terms) especially regarding the estimation of the horizontal correlation length.

5. CONLCUSION

In this study, we presented a covariation-based retrieval algorithm to simultaneously determine surface roughness parameters (s, l) from combined polarimetric radar and radiometer microwave signatures of the SMAP mission.

The analyses for regions with bare soils on the globe confirm that s and l can be calculated simultaneously over large sparsely until non-vegetated areas, compared to field-based techniques, and for each individual active-passive acquisition pair (no time series needed). Admitting, this requires nearly identical spatial resolutions for radar and radiometer acquisitions in order to observe roughness at the same scale. The utilization of the covariation parameter β_{P-PP} combined with the forward model I^{2}EM to retrieve s and l concurrently provides the advantage of a quasi-permittivity-independent algorithm for non-arid soils ($\varepsilon_s >$ 10 [-], cf. Fig. 1). Furthermore, the model basis (I^{2}EM) of the approach enables the application of varying autocorrelation functions (ACF). Hence, calculations for s and l can also be performed for an exponential or n-exponential ACF and will be further investigated.

Despite the rather coarse resolution of the SMAP datasets (~36 km) the retrieval results for s and l can be used as larger-scale indicators of global soil surface patterns. In regions with rather smooth surface structures, like sandy deserts (e.g. parts of Sahara or Gobi), the estimated surface roughness parameters are also indicating rather smooth surface structures with small vertical RMS heights and corresponding higher horizontal correlation lengths.

Further add-on studies are the extension of the active-passive covariation algorithm also for vegetated areas as well as the retrieval of global soil moisture maps incorporating the retrieved surface roughness parameters.

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