AN ALTERNATIVE ROUGHNESS PARAMETERIZATION FOR SOIL MOISTURE RETRIEVALS FROM PASSIVE MICROWAVE OBSERVATIONS

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ABSTRACT

The usefulness of L-band radiometer observations for the retrieval of near-surface soil moisture has already been demonstrated in many studies. Unfortunately, the ability to estimate soil moisture from these remotely sensed observations is hampered by the infeasibility to characterize the roughness of the soil surface. Given the difficulty to measure *in situ* soil roughness parameters, improved methodologies to estimate these parameters from observed quantities is a prerequisite to retrieve high quality soil moisture maps from passive microwave observations. This research focusses on an alternative methodology to estimate soil roughness parameters used in the L-band Microwave Emission of the Biosphere model.

1. INTRODUCTION

Given the significant influence of soil moisture on a variety of hydrological processes, the observation of this variable is of key importance to better understand the cycle of water in its environment. Moreover, information on soil moisture is of key importance to improve hydrological model simulations, which are often used in flood forecasting schemes.

The usefulness of remotely sensed information on soil wetness in a hydrological modelling framework has already been shown by several researchers (e.g. [1, 2]). Recently, the interest in passive microwave systems to retrieve soil moisture has grown rapidly. One of the major advantages of passive microwave systems with respect to active microwave sensors is their ability to cover large areas of the Earth during one overpass, resulting in a high temporal resolution. The drawback of these sensors is the relatively poor spatial resolution, which causes that the measured signal results from a variety of land cover types within the observed pixel. This heterogeneous nature of the observed scene imposes major challenges on the modelling of the observed signal and the validation of the retrieved surface variables [3].

Since its launch in 2009, the SMOS-satellite (Soil Moisture and Ocean Salinity) [4] provides global maps of brightness temperatures at a nominal resolution of 43 km, observed using an L-band 1.4 GHz 2D interferometer. Given the capability of SMOS to observe the Earths surface at different incidence angles, these observations can be used to retrieve several surface variables at once [5], depending on the number of brightness temperature observations and their quality [6]. The retrieval of surface variables, such as soil moisture, is based on the inversion of the L-MEB (L-band Microwave Emission of the Biosphere) model [7]. Due to the significant influence of soil roughness on passive microwave observations, the parameterization of this variable is of key importance to obtain high quality estimates of soil moisture. Unfortunately, the relationship between the roughness parameters of the L-MEB model and physical roughness parameters such as the correlation length or the RMS-height, is not well known. Moreover, measurements of physical roughness characteristics in the field are highly uncertain and time consuming. In order to circumvent the potential problems inherent to roughness measurements in the field, and the problem of relating these observations to the parameters used in the L-MEB model, roughness parameters can be calibrated, resulting in effective roughness parameters. For the retrieval of near-surface soil moisture from active microwave observations, this technique has already shown its large potential. A variety of techniques have been developed to estimate effective roughness parameters prior to the soil moisture retrieval, resulting in improved soil moisture estimates from active microwave observations [8, 9, 10].

Similar to active microwave observations, many studies have investigated the potential of the effective roughness parameter technique for soil moisture retrieval from passive microwave observations. Most of the studies found that the main roughness parameter used in the L-MEB model is impacted by the soil moisture content in a linear way [11, 12]. The dependence of this roughness parameter on soil moisture has been explained by a dielectric roughness induced by the spatial heterogeneity of moisture in the soil, which causes local variations in the dielectric properties. However, the linear relationship between the roughness parameter and soil moisture is not yet well understood and its robustness, especially under vegetated surfaces, needs to be further assessed. The main objective of this study is to investigate an alternative parameterization of soil roughness to increase the quality of soil moisture retrievals from passive microwave observations. This paper will present the results obtained from an airborne dataset of passive microwave observations.

2. DATA AND STUDY AREA

During the first phase of this study, an extensive dataset of airborne microwave observations is used together with ground validation data collected in Australia. Further research will focus on the transferability of the tested methodologies to SMOS data acquired at different sites over the world.

The data used in this study was collected during the SMAPEx campaigns, conducted in the Murrumbidgee catchment (subcatchment of the Murray Darling basin) located in the south eastern part of Australia. Data was collected during three intensive field campaigns held in 2010 and 2011. Each campaign was conducted during a different season to collect data under a variety of land surface and environmental conditions. A detailed description of the dataset can be found in Panciera et al. [13] with only the relevant information provided here.

During each flight day, passive microwave observations were collected over an experimental study site of approximately 34x38 km. The selected study site is dominated by low vegetation (agricultural crops and (grazed) grasslands) and has a low topography, which makes it an ideal location for remote sensing studies. Observations of brightness temperature were collected using the PLMR (Polarimetric L-band Multibeam Radiometer), flown at an average height of ± 3 km, resulting in a pixel size of approximately 1 km. Measurements were made at incidence angles of $\pm 7°$, $\pm 21.5°$ and $\pm 38.5°$ at a frequency of 1.413 GHz. During each flight, volumetric samples of soil moisture were collected on a regular grid with 250 m spacing at specific locations in the study area. In addition, vegetation samples, including LAI (Leaf Area Index), VWC (Vegetation Water Content), vegetation height *etc.* were taken at representative locations in the study site, and a detailed land cover classification of the study area was created. Leaf area indices were extracted from MODIS imagery to obtain site-wide observations of LAI, rather than point observations. Meteorological data, including soil temperature at different depths, air temperature and precipitation were also collected at several locations in the study site. These data were interpolated using IDW (Inverse Distance Weighting) to obtain gridded estimates of soil and air temperature.

3. RETRIEVAL OF SURFACE VARIABLES

3.1. L-MEB model

A detailed description of the radiative transfer model used can be found in Wigneron et al. [7]. Here only the most important aspects of the model are highlighted. The L-MEB model is based on a simplified solution of the zero-order radiative transfer equation. The brightness temperature at polarization p and incidence angle θ, upwelling from a rough, vegetated surface ($Tb_{\mathrm{p}}(\theta)$) can be simulated using:

$$Tb_{\mathrm{p}}(\theta) = (1-\omega_{\mathrm{p}}(\theta))(1-\gamma_{\mathrm{p}}(\theta))(1+\gamma_{\mathrm{p}}(\theta)r_{\mathrm{p}}(\theta))T_{\mathrm{gc}} + (1-r_{\mathrm{p}}(\theta))\gamma_{\mathrm{p}}(\theta)T_{\mathrm{gc}} \quad (1)$$

where ω_{p} is the vegetation scattering albedo, γ_{p} is the vegetation attenuation factor depending on the vegetation optical depth (τ_{p}), r_{p} is the reflectivity of a rough soil and T_{gc} is an effective composite temperature, calculated from the effective soil temperature (T_{g}) and the effective canopy temperature (T_{c}). The parameter r_{p} is related empirically to the reflectivity of a bare smooth soil (r^*_{p}, i.e. the Fresnel reflectivity) using:

$$r_{\mathrm{p}}(\theta) = \left[(1-Q_{\mathrm{rp}}(\theta))\, r^*_{\mathrm{p}}(\theta) + Q_{\mathrm{rp}}(\theta) r^*_{\mathrm{p}}(\theta)\right] \exp\left(-H_{\mathrm{rp}}(\theta)\cos^{N_{\mathrm{rp}}}(\theta)\right) \quad (2)$$

where Q_{rp} accounts for the influence of the soil roughness on polarization mixing, H_{rp} is another roughness parameter and N_{rp} models the dependence of soil roughness on incidence angle. In this study, Q_{rp} is assumed to be equal to 0 with N_{rp} a constant depending on the land cover type observed. Furthermore, H_{rp} is assumed to be independent on polarization and thus denoted as H_{r}.

Several parameterizations of H_{r} have been proposed in literature. Lawrence et al. [14] and Mialon et al. [15] for instance attempted to link H_{r} to some physical roughness parameters such as the RMS-height and the correlation length. Other studies observed a decreasing linear trend of the roughness parameter with soil moisture (e.g. [12, 16, 17, 18]). The dependence of H_{r} on soil moisture has been explained by a dielectric roughness, induced by the spatial heterogeneity of moisture in the soil. When the soil is saturated, water is almost homogeneously distributed in the soil reservoir and the roughness is entirely determined by the height variations of the soil surface. However, when the soil dries out, water is withheld at preferential locations in the soil, causing a heterogeneous distribution of water which induces variations in the dielectric properties of the soil reservoir. These variations

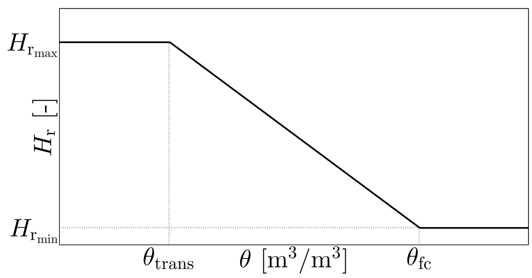

Figure 1. Decreasing trend of the roughness parameter (H_{r}) as a function of soil moisture (θ).

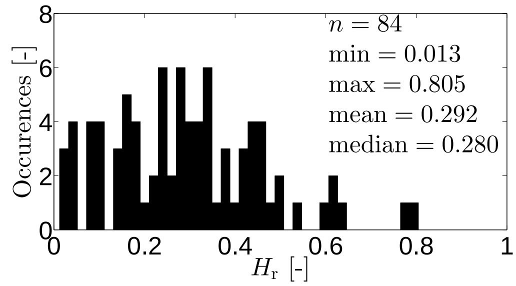

Figure 2. Histogram of the retrieved roughness parameters (H_{r}) for the entire dataset.

increase the dielectric roughness of the soil, while the physical roughness of the soil is not altered during this process.

The idea of increasing dielectric roughness with decreasing soil moisture is also used in the SMOS soil moisture retrieval algorithm [6] and is illustrated conceptually in Fig. 1. This figure shows the decreasing trend of the roughness parameter with soil moisture (θ) between the transitional soil moisture content (θ_{trans}) and the field capacity (θ_{fc}) of the soil. θ_{trans} and θ_{fc} can be calculated based on the clay fractional content, the sand fractional content and the bulk density of the soil [6]. Fig. 1 shows that for soil moisture values exceeding θ_{fc} or undershooting θ_{trans}, the roughness parameter is assumed to be constant. The values of the minimum ($H_{\mathrm{r_{min}}}$) and maximum ($H_{\mathrm{r_{max}}}$) roughness parameter are a function of the soil and vegetation properties.

3.2. Inversion method

Given the capability of the L-MEB model to simulate brightness temperatures at different incidence angles, the model can be used to retrieve surface variables from multi-angular, passive microwave observations. Surface variables can be estimated from a set of passive microwave observations by minimizing the difference between the modelled and the observed brightness temperatures. To this end, a simplex algorithm [19] is used to minimize the following cost function:

$$Co = \sqrt{\frac{\sum_{i=1}^{n} (Tb_i - Tb_i^*)^2}{n}} \tag{3}$$

where Co is the cost, n is the number of observations, and Tb_i and Tb_i^* are the observed and simulated brightness temperatures at a given incidence angle and polarization respectively. Eq. 3 simply represents the RMSE (Root Mean Squared Error) between the observed and simulated brightness temperatures over all incidence angles and polarizations. It should be noted here that several authors have modified the cost function to incorporate *a priori* knowledge on the values of the variables to be retrieved. However, no *a priori* information is assumed here, which justifies the use of Eq. 3 to retrieve unknown variables of interest.

3.3. Retrieval of H_{r}

The methodology outlined in Section 3.2 was used to retrieve roughness parameters for the dataset presented in Section 2. To this end, all passive microwave observations were mapped on a predefined grid with 1 km resolution. For each grid cell, a variety of brightness temperature observations were available at different incidence angles and for both horizontal and vertical polarizations. This set of brightness temperatures was used to retrieve the roughness parameter for the given grid cell. Taking into account the relatively small spatial resolution of the predefined grid, each grid cell was assumed to have homogeneous land cover. Moreover, to obtain a consistent dataset, only pixels classified as grasslands were considered. Average soil moisture values of a grid cell were calculated by taking into account all volumetric measurements located inside the grid cell. All other parameters of the L-MEB model necessary to simulate brightness temperatures were taken from default values reported in literature [7, 16].

Fig. 2 shows a histogram of the retrieved values of H_{r}. It is clear from this figure that the retrieved values of the roughness parameter are restricted between 0.013 and 0.805. The mean value of 0.292 is somewhat lower than the frequently used default value of 0.5 for grasslands [12]. However, it should be noted that the retrieved values are highly dependent on the parameterization of other variables in the radiative transfer model, such as the vegetation optical depth. Also, site specific properties such as the physical roughness of the soil surface and the vegetation can have a significant influence on the retrieved values of H_{r}. Nevertheless, the estimated values of the roughness parameters fall within acceptable limits of the values frequently reported in literature for similar vegetation covers (e.g. [16]).

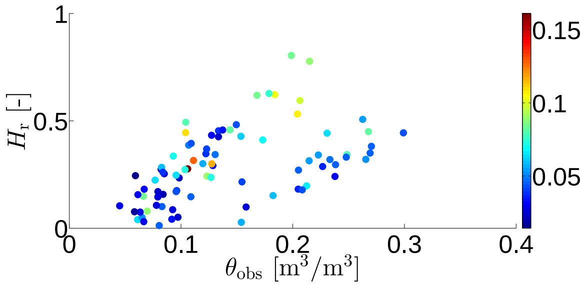

Figure 3. Plot of the retrieved roughness parameters (H_r) as a function of the average soil moisture within a given grid cell (θ_obs). The colours indicate the standard deviation of soil moisture observations within the grid cell.

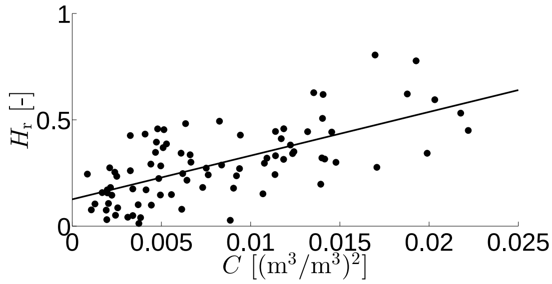

Figure 4. Plot of the retrieved roughness parameters (H_r) as a function of the average soil moisture multiplied with the standard deviation (C). The best linear fit is shown as a black line.

4. MODELLING FRAMEWORK FOR H_r

4.1. Dependence of H_r on soil moisture characteristics

Several studies have used the negative linear dependence of H_r on soil moisture to get an estimate of the roughness parameter necessary to retrieve soil moisture. Fig. 3 shows the relationship between the retrieved roughness parameters and the average soil moisture within a given grid cell. Colours indicate the standard deviation of soil moisture values within the pixel. It is clear from Fig. 3 that there exists a positive correlation between the retrieved roughness parameters and the average soil moisture, which strongly contradicts with most of the results reported in literature. Panciera et al. [20] did observe a similar behaviour for clay soils and for soil moisture values below 0.2-0.3 $\mathrm{m}^3/\mathrm{m}^3$. Despite the fact that a different soil texture is observed in this study (loamy soils), the positive trend is observed for the same soil moisture values. However, it should be noted here that a comparison between the results of different studies is difficult because of the difference in scale. Most of the studies used data obtained at field scale (e.g. [12, 18]) or high resolution airborne data (e.g. [20, 16, 17]), in comparison with the relatively large scale data which is used here ($\pm$1 km airborne data).

From Fig. 3 it can be seen that there is also an influence of the soil moisture variability on the roughness parameter. In general, an increase of H_r with soil moisture variability can be observed. This observed trend is in agreement with the idea of dielectric roughness at small scale. When the large scale variability of soil moisture within a grid cell is high, an additional amount of roughness will be experienced. In contrast, the roughness decreases as the large scale variability of soil moisture decreases. Therefore, Fig. 3 suggests that a combination of the average soil moisture and soil moisture variability should be used to parameterize soil roughness at large scale.

Figure 4 shows the dependence of the retrieved roughness parameters on the coefficient C, which is the product of the average soil moisture value (μ_SM) and the standard deviation (σ_SM). It is clear that a positive correlation exists between H_r and C (a correlation coefficient (R) of 0.661 was obtained), which indicates that a linear regression between H_r and C can be used to parameterize soil roughness in the L-MEB model. The following roughness model was fitted to the data used in this study:

$$H_\mathrm{r} = 20.543C + 0.126 \tag{4}$$

The dependence of H_r on C suggests that, within the limits of the soil moisture values observed in this dataset, H_r increases with both μ_SM and σ_SM. This means that pixels with low values of μ_SM can still exhibit high roughness values when the large scale variability of soil moisture is high and *vice versa*.

4.2. Parameterization of σ_SM

Fig. 4 shows that the main roughness parameter of the L-MEB model can be estimated by using a simple linear regression (see also Eq. 4). The linear model makes use of both μ_SM and σ_SM to get an estimate of H_r. Since μ_SM is often the main variable of interest when surface variables are retrieved from passive microwave observations, this relationship should be used in an iterative retrieval algorithm. However, the large scale variability of soil moisture within a given pixel is not known and therefore needs to be estimated during the retrieval of μ_SM. To this end, the dependence of σ_SM on μ_SM is used. Several studies have shown that a dependence between the mean soil moisture within a given extent and the observed soil moisture variability exists. Famiglietti et al. [21] studied this relationship on an extensive dataset and across different scales. The following exponential function was proposed:

$$\sigma_\mathrm{SM} = k_1 \mu_\mathrm{SM} \mathrm{exp}\left(-k_2 \mu_\mathrm{SM}\right) \tag{5}$$

with k_1 and k_2 two best fit parameters. Multiplying Eq. 5 with μ_SM gives the coefficient used to estimate H_r:

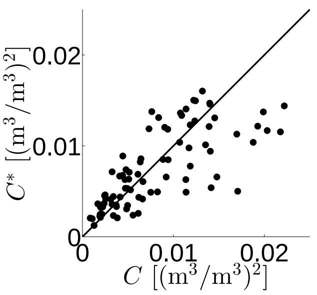

Figure 5. Scatter plot of the estimated values (C^*) against the observed values of C.

$$C = k_1 \mu_{\mathrm{SM}}^2 \exp\left(-k_2 \mu_{\mathrm{SM}}\right) \tag{6}$$

For a scale of 800 m, which matches closest to the scale of 1 km used in this study, a value of $k_1 = 0.884$ and $k_2 = 5.807$ was reported in Famiglietti et al. [21]. These two values were optimized using the data from this study and were slightly adjusted to $k_1 = 0.763$ and $k_2 = 4.896$. To assess the ability of Eq. 6 to simulate C, a cross validation of the model was carried out. Fig. 5 shows a scatter plot of the simulated values (C^*) against the observed values of C. Overall, the model performs relatively good which is confirmed by the calculated RMSE and correlation coefficient of 0.0037 (m^3/m^3)^2 and 0.74 respectively. Despite the small underestimation of high C values, which can be observed in Fig. 5, Eq. 6 is used in this study to predict values of C, which in turn can be used to estimate the value of H_{r}.

5. PERFORMANCE OF THE ROUGHNESS MODEL

To assess the performance of the roughness model presented in Section 4, soil moisture values were retrieved for the entire dataset. Three different approaches were considered:

- *Case 1:* Multi-angular soil moisture retrieval using a constant value of $H_{\mathrm{r}} = 0.5$ (default value reported in literature).
- *Case 2:* Multi-angular soil moisture retrieval using a constant value of $H_{\mathrm{r}} = 0.28$ (median of the retrieved roughness parameters for the dataset in this study).
- *Case 3:* Multi-angular soil moisture retrieval using the roughness model presented in Section 4.

Figs. 6, 7 and 8 show scatter plots of the retrieved soil moisture (θ_{ret}) against the observed soil moisture (θ_{obs}) for the three approaches considered. Table 1 summarizes some statistics (Root Mean Squared Error (RMSE), Mean Estimation Error (MEE) and the correlation coefficient (R)) of the different retrievals. Fig 6 shows that the use of a constant roughness parameter of 0.5 results in a strong overestimation of the observed soil moisture, which is confirmed by the positive bias shown in Table 1. This could be expected given the results shown in Fig 2. As can be seen from this figure, the bulk of the retrieved roughness parameters has a value below 0.5. This means that the predefined value of 0.5 is too high in most of the cases. Given the positive correlation between the soil roughness parameter and the simulated brightness temperatures, an overestimation of soil moisture will thus be obtained.

As can be seen from Fig. 7, the overestimation of the observed soil moisture can be strongly reduced by decreasing the value of H_{r}. Using a value of 0.28 results in a remarkably lower bias, which is shown in Table 1. The negative sign of the MEE suggests that a slight underestimation of the soil moisture can be observed. Fig. 7 shows that this is especially true for high soil moisture values and some intermediate soil moisture values. Low soil moisture is still overestimated given the too high roughness parameter for these observations. Table 1 shows that the second retrieval approach gives better results in terms of the listed statistics, which could be expected.

Fig. 8 shows a scatter plot of the soil moisture retrievals using the proposed roughness model. As can be seen from this figure, relatively good results are obtained. Unfortunately, a slight overestimation of high soil moisture values can be observed, which is reflected in a positive, however small, bias (see Table 1). This is mainly due to a small overestimation of the value of C for high soil moisture measurements, which results in an overestimation of the roughness parameter (see also Eq. 4). As was already shown in Fig. 5, high values of C were mainly underestimated, which results in an underestimation of H_{r}, which in turn decreases the retrieved soil moisture. This can be observed in Fig. 8 where some intermediate soil moisture values ($\theta_{\mathrm{obs}} = \pm 0.2$ m^3/m^3) are underestimated. These are the soil moisture observations related to the highest roughness parameters, which can also be observed in Fig. 3. However, it should also be noted here that the same soil moisture observations are also underestimated with each of the methods considered. This is due to the use of a too low roughness parameter for these measurements. As can be seen from Table 1, the third retrieval case gives rise to a slightly higher value of the RMSE compared to the one obtained in the second retrieval case. However, the obtained RMSE is still below 0.05 m^3/m^3, while a comparable correlation coefficient and MEE is obtained.

The results show that the proposed roughness model has a good potential to retrieve high quality soil moisture maps from passive microwave observations. However, the model to estimate the large scale soil moisture variability used in this study should be reassessed to obtain better estimations of the coefficient C. This means that the parameters from the model of Famiglietti et al. [21] should be optimised based on a more extensive dataset for the study area. However, alternative models to estimate

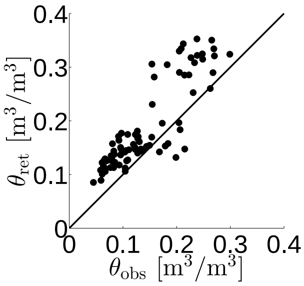

Figure 6. Scatter plot of the retrieved soil moisture (θ_{ret}) vs. the observed soil moisture (θ_{obs}) for the retrieval with a constant roughness parameter equal to the default value reported in literature.

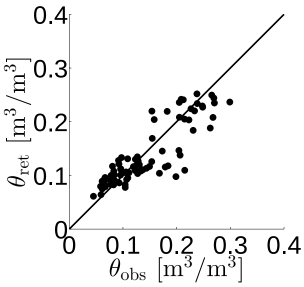

Figure 7. Scatter plot of the retrieved soil moisture (θ_{ret}) vs. the observed soil moisture (θ_{obs}) for the retrieval with a constant roughness parameter equal to the median of the roughness parameters obtained for the dataset used in this study.

the large scale soil moisture variability can also be considered. The use of copula models is probably a promising technique to estimate the soil moisture variability for a given extent. However, sufficient data is a prerequisite to fit a good copula model to the data.

6. CONCLUSION

The main goal of this study was to assess the performance of an alternative roughness parameterization which can be implemented into the L-MEB model. Several studies have shown that there exists a negative linear relationship between the main roughness parameter of the L-MEB model (H_{r}) and the average soil moisture within the observed scene. However, most of the studies made use of radiometer data at relatively small scales (tower radiometer data or high resolution airborne data). This study makes use of an extensive airborne data set of passive microwave observations at large scale (pixel sizes of approximately 1 km). Results show that a positive correlation exists between the roughness parameter and the average soil moisture value within the pixel. Furthermore, the roughness parameter is also driven by the soil moisture variability within the observed scene. Therefore, linking the roughness parameter to a combination of the average soil moisture and soil moisture variability within the extent, seems a promising approach to estimate the value of H_{r}. The results presented in this paper show that this methodology is able to get a qualitative estimate of the roughness parameter, necessary to retrieve high quality soil moisture maps from passive microwave observations.

Table 1. Some statistics of the soil moisture retrievals presented in Fig. 6, 7 and 8.

	Case 1	*Case 2*	*Case 3*
RMSE $[\mathrm{m}^3/\mathrm{m}^3]$	0.060	0.033	0.045
MEE $[\mathrm{m}^3/\mathrm{m}^3]$	0.044	-0.006	0.005
R [-]	0.863	0.867	0.854

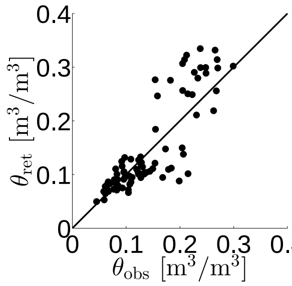

Figure 8. Scatter plot of the retrieved soil moisture (θ_{ret}) vs. the observed soil moisture (θ_{obs}) for the retrieval case where the roughness parameter is estimated using the proposed roughness model.

Despite the promising results obtained with the presented roughness model, a fixed roughness equal to the median of the retrieved roughness parameters, obtains better results. However, it is believed that the quality of the soil moisture retrievals can be enhanced if a different approach is used to estimate the large scale soil moisture variability. Therefore, future research should mainly focus on alternative methodologies to estimate the variability of soil moisture observations within a given extent. Also the transferability of the presented model to spaceborne data from the SMOS satellite should be assessed. Furthermore, the effectiveness of the model should be validated on other extensive data sets collected over different land cover types and a large range of soil moisture values.

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