# UNCERTAINTY OF EFFECTIVE ROUGHNESS PARAMETERS CALIBRATED ON BARE AGRICULTURAL LAND USING SENTINEL-1 SAR

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## ABSTRACT

Uncertainty of roughness parameters has effect on soil moisture retrievals with backscatter models from Synthetic Aperture Radar observations. The uncertainty of soil moisture retrievals is important information for the usability of these estimates. In this paper we introduce a methodology to estimate the uncertainty of effective roughness parameters in the Integral Equation Method surface backscatter model, using a Bayesian Markov Chain Monte Carlo approach. Using Sentinel-1 imagery we demonstrate the methodology for a selected field, showing the posterior uncertainty distributions of the roughness parameters, and the effect on the backscatter model simulations and soil moisture inversions. The estimated total uncertainty of the soil moisture retrievals with the optimum parameter set is 0.043 $m^3/m^3$, which is slightly higher than the root mean square error of 0.040 $m^3/m^3$ of the retrievals compared to in situ soil moisture measurements.

***Index Terms*—** Effective roughness parameters, uncertainty, soil moisture, Sentinel-1.

## 1. INTRODUCTION

Soil moisture is a central hydrological state variable. Estimates of surface soil moisture are interesting for various applications, for example weather and climate predictions, flood forecasting and water management, and agriculture [1], [2]. Besides, soil moisture information has potential to improve land process models via data assimilation [1]. Synthetic Aperture Radar (SAR) satellite observations can be used to retrieve soil moisture information at field scale [2], [3].

Previous studies have acquired better results by viewing the roughness parameters in backscatter models as 'effective roughness parameters' obtained by model calibration, rather than obtained by field estimates [3]–[5]. Generally, the effective roughness parameters are considered as deterministic parameters. However, this does not acknowledge the uncertainty as a result of calibration with a limited number of observations, radiometric uncertainty in backscatter observations and uncertainty in reference soil moisture measurements, variations in space and time, and deficiencies of the backscatter model. An estimate of the uncertainty of the model parameters can be used to quantify the uncertainty of soil moisture retrievals [6], which is important information to assess the reliability and usability of the soil moisture retrievals. In addition, this information can benefit the assimilation of soil moisture information into land process models [3], [6]. For this reason, Lievens et al. [3] argued that more research is required on the quantification of soil moisture retrieval uncertainty. De Lannoy et al. [6] used a Bayesian Markov Chain Monte Carlo approach to estimate the uncertainty of parameters in a radiative transfer model reproducing SMOS L-band passive microwave observations.

In this paper we introduce application of the DiffeRential Evolution Adaptive Metropolis (DREAM) toolbox to calibrate the Integral Equation Method (IEM) and estimate the uncertainty of the effective roughness parameters at field scale. We show results of this methodology with Sentinel-1 SAR imagery for a selected field with bare soil conditions in autumn and winter.

## 2. CALIBRATION OF IEM

To model the bare soil backscatter we employed the frequently used physically-based surface backscatter model IEM [7]. Surface roughness is parameterized by the root mean square surface height ($s$), the autocorrelation length ($c_l$), and the autocorrelation function. We used the exponential autocorrelation function, which is generally viewed as most applicable to smooth (agricultural) surfaces [4], [8].

The effective roughness approach, as introduced by [5], uses backscatter observations and soil moisture measurements to calibrate one or both of the roughness parameters. Subsequently, the calibrated roughness parameters are used to retrieve soil moisture from other observations and/or on other fields. It is often assumed that the roughness parameters are time-invariant [4]. For the calibration we used the Matlab package DREAM, developed by [9]. By implementing a Bayesian Markov Chain Monte Carlo simulation method, DREAM finds an optimum parameter set (the 'maximum a posteriori', MAP), and posterior uncertainty distributions of the roughness parameters and the error model parameters. To obtain the posterior parameter distributions, the Bayesian approach combines the prior probability of a parameter set (adopted

**Table 1:** Specifications for the relative orbits of Sentinel-1 for the selected field, including the Spearman's rank correlation coefficient $r_s$ between Sentinel-1 observations and soil moisture measurements at 5 cm depth, for the period from 1 November 2016 to 23 March 2017.

| Polarization | VV | | | | VH | | | |
|---|---|---|---|---|---|---|---|---|
| Relative orbit | 15 | 37 | 88 | 139 | 15 | 37 | 88 | 139 |
| Pass direction | Ascending | Desc. | Ascending | Desc. | Ascending | Desc. | Ascending | Desc. |
| Projected incidence angle | 34.6° | 35.5° | 42.9° | 43.6° | 34.6° | 35.5° | 42.9° | 43.6° |
| Correlation $r_s$ with soil moisture, before filtering | 0.85 | 0.69 | 0.84 | 0.41 | 0.17 | 0.50 | 0.19 | 0.27 |
| Correlation $r_s$ with soil moisture, after filtering | 0.85 | 0.70 | 0.86 | 0.44 | 0.17 | 0.49 | 0.15 | 0.30 |
| Number of images after filtering | 16 | 13 | 17 | 14 | 16 | 13 | 17 | 14 |

from expectations about the parameters prior to calibration) and the likelihood of a parameter set based on the model performance with respect to observations. If the Bayesian calibration is statistically valid, the estimated residual errors are of similar magnitude as the actual errors of model simulations [6]. We applied DREAM with a Gaussian likelihood function and a homoscedastic error model without autocorrelation. We set the number of chains at 10, and used 2000 generations with a burn-in period of 50% (in total 20000 model runs). The validity of these assumptions is examined in section 4.

## 3. DATA

### 3.1. Sentinel-1 imagery

Copernicus Sentinel-1 satellite imagery over land are made at VV and VH polarization, C-band (5.405 GHz), with a pixel spacing of 10 m × 10 m and a radiometric accuracy (3σ) of 1 dB [10]. Over the selected study area in the Netherlands (see section 3.2), images are acquired in the relative orbits 15, 37, 88 and 139.

We used the Sentinel Application Platform (SNAP) to pre-process Level-1 Ground Range Detected Sentinel-1 images collected in the Interferometric Wide Swath (IW) mode: the pixel values were calibrated to radar backscatter, reprojected and corrected for distortions due to topographical variations and tilt of the satellite sensor using the SNAP Range Doppler Terrain Correction tool, and speckle noise was suppressed by a 5 × 5 median filter. Subsequently, the backscatter values were averaged over selected agricultural fields. Thereafter, we filtered the images for the presence of frozen soil, wet snow cover and a wetting front between the surface and 5 cm depth.

### 3.2. Case study

The selected field to demonstrate the application of DREAM to calibrate IEM is adjacent to a continuous soil moisture monitoring station that is part of the Twente network [11] and operational since 20 May 2016. This agricultural field has an area of 3.7 hectare. In 2016 and 2017 it was used for growing maize. Outside the growing season the field was bare. We calibrated the effective roughness parameters on the pre-processed and filtered Sentinel-1 observations and the soil moisture measurements at 5 cm depth, for the bare soil conditions from 1 November 2016 (after harvesting) to 23 March 2017 (before ploughing and sowing). Following i.a. [4], [12], [13], time-invariant roughness parameters can be assumed during this period, because no cultivation of the land has taken place and there has been an intense rain event of 45 mm after the harvesting (18-21 October 2016). The soil moisture content gradually increases from 0.21 $m^3/m^3$ to 0.47 $m^3/m^3$, so the roughness parameters are calibrated over a wide range of soil moisture conditions.

## 4. RESULTS AND DISCUSSION

Table 1 lists the Spearman's rank correlation coefficients between the Sentinel-1 observations and the soil moisture measurements at the selected field for the relative orbits of Sentinel-1. Generally, the filtering improves the correlation between the Sentinel-1 observations and the soil moisture measurements.

In the ascending orbits the Sentinel-1 satellites measure with a look angle of 15° with respect to the row direction and in the descending orbits with a look angle of 5° w.r.t. row direction. Due to these different look angles on an anisotropic surface, the roughness will be different for the ascending and the descending orbits. The images made in the ascending orbits with VV polarization show the highest correlation with soil moisture. Therefore, we demonstrate the calibration procedure with the VV observations made in the ascending orbits. With the combination of orbits 15 and 88 we calibrated over varying incidence angles (34.6° and 42.9° respectively, see Table 1). Based on an initial calibration round, we filtered an additional 4 images which were unexpected outliers (29 images left for calibration).

Figure 1 shows that many combinations of $s$ and $c_l$ lead to approximately the same model performance, as expressed by the root mean square error (*RMSE*). For bare and sparsely vegetated agricultural fields, effective roughness heights between 0.3 cm and 1.4 cm have been found by [3], [12]–[14]. We defined the parameter search space (and the prior distributions) as uniform distributions with ranges $s = [0.1, 2.5]$ and $c_l = [0.1, 50]$.

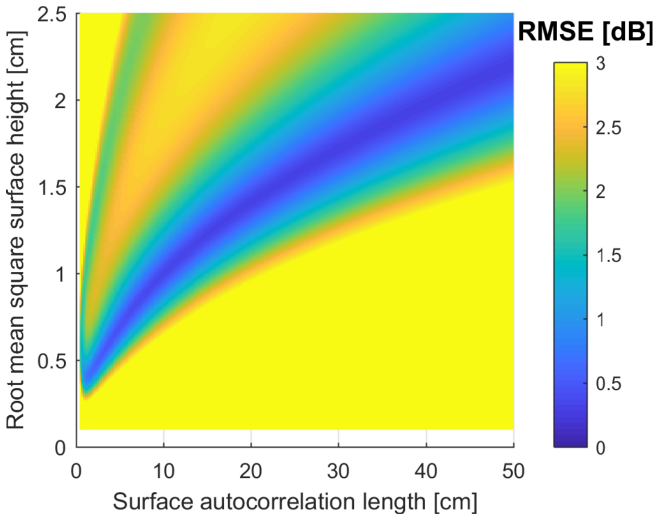


**Figure 1:** *RMSE* [dB] between simulated and observed backscatter for combinations of *s* and $c_l$. The optimums are within the dark blue band, having a *RMSE* of ~0.30 dB.

After 500 generations the Gelman-Rubin convergence diagnostic $\hat{R}$ is below 1.2, which is the threshold that indicates convergence of the chains [9]. Thus, the number of generations and the burn-in period are sufficient. The diagnostic test in figure 2a shows that the residual variance is not dependent on the magnitude of the simulated backscatter, meaning that the homoscedastic error model appropriately describes the residual variance. In figure 2b the residuals follow the line that is expected for a Gaussian distribution. Figure 2c shows that the autocorrelation of residuals remains within the 95% significance interval, confirming that the residuals are uncorrelated.

Figure 3 shows that the posterior parameter distributions follow the area of good performance in figure 1, which indicates that DREAM is able to reproduce this spectrum. Figure 4 shows the resulting total simulation uncertainty (parameter unc. + additive error), the simulation uncertainty as a result of parameter uncertainty and simulations with the MAP parameter set, also see [9]. The *RMSE* of both the MAP simulations and the median of the simulations is 0.30 dB. The observation coverage of the total simulation uncertainty confidence interval is 96.6%, which is close to the expected 95%. The parameter uncertainty is relatively small compared to the total uncertainty. Although the posterior parameter distributions in Figure 3 seem rather wide, the uncertainty as a result of parameter uncertainty is limited because the posterior parameter distributions are highly correlated and the parameter combinations result in approximately the same outcomes. The ratio $s^2/c_l$, as introduced by [15], is approximately 0.1 among all the posterior parameter combinations (figure 3).

The *RMSE* of soil moisture retrievals with the MAP parameter set is 0.040 m³/m³. The estimated residual standard deviation (0.31 dB) of the MAP parameter set converts into an average total retrieval uncertainty of 0.043 m³/m³ (standard deviation). The retrieval uncertainty as a result of

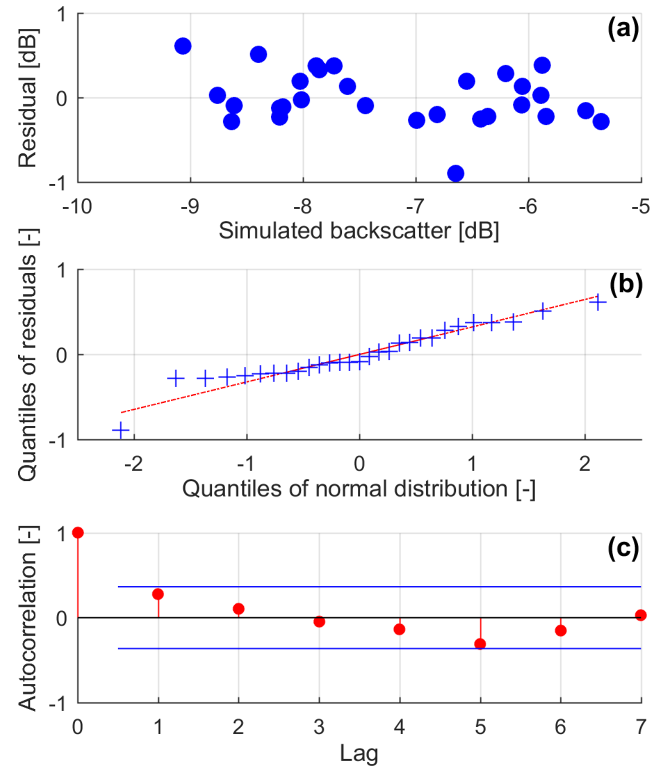


**Figure 2:** Residual analysis of the median of the simulations after Bayesian calibration with a Gaussian likelihood function and a homoscedastic and uncorrelated error model. **(a)** Residuals against simulations, **(b)** quantile-quantile plot of the residuals, **(c)** autocorrelation coefficients of the residuals with 95% significance levels.

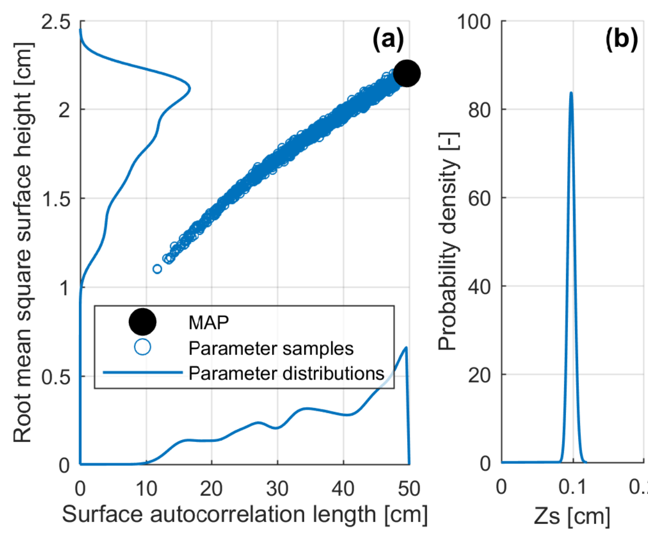


**Figure 3: (a)** Posterior distributions of the roughness parameters (Spearman's rank correlation is 0.99) and **(b)** Posterior distribution of *Zs* ($s^2/c_l$).

parameter uncertainty is on average 0.0086 m³/m³. The uncertainty is larger at higher soil moisture conditions, because of the lower sensitivity of backscatter to soil moisture at higher soil moisture conditions.

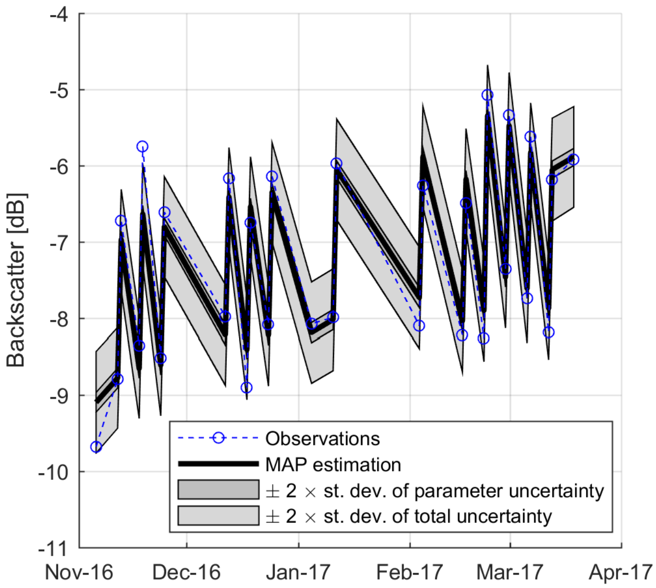


**Figure 4:** IEM MAP simulations and confidence intervals as a result of parameter uncertainty and total simulation uncertainty.

## 5. CONCLUSION AND FUTURE WORK

The presented Bayesian calibration methodology enables to estimate the uncertainty of the effective roughness parameters and the total uncertainty of model simulations. The validity of the underlying assumptions is demonstrated for a selected field with bare soil conditions. The *RMSE* of soil moisture retrievals with the optimum parameter set is 0.040 $m^3/m^3$, while the standard deviation of the estimated total retrieval uncertainty is 0.043 $m^3/m^3$. Thus, the estimated total uncertainty slightly overestimates the *RMSE*.

The ultimate objective is a method that can produce region-wide soil moisture maps accompanied with retrieval uncertainty. Future work may focus on:

- A further investigation of the assumptions made regarding the likelihood function and error model.
- Generating parameter sets for both the ascending and descending orbits to account for the effect of look angle on roughness.
- Validating for other periods and other fields with similar land cover.
- Use of a radiative transfer model that describes vegetation, extending the model's applicability to the growing season.
- Multi-temporal field measurements of roughness that could be used to further investigate the assumption of time-invariant roughness.

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