ASSESSMENT OF THE IMPACT OF UNCERTAINTY ON MODELED SOIL SURFACE ROUGHNESS ON SAR-RETRIEVED SOIL MOISTURE UNCERTAINTY

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ABSTRACT:

Soil moisture retrieval from SAR images using semi-empirical or physically-based backscatter models requires surface roughness parameters, generally obtained by means of *in situ* measurements. However, measured roughness parameters often result in inaccurate soil moisture contents. Furthermore, when these retrieved soil moisture contents need to be used in data assimilation schemes, it is important to also assess the retrieval uncertainty. In this paper, a regression-based method is developed that allows for the parameterization of roughness by means of a probability distribution. This distribution is further propagated through an inverse backscatter model in order to obtain probability distributions of soil moisture content. About 70% of the obtained distributions are skewed and non-normal and it is furthermore shown that their interquartile range differs with respect to soil moisture conditions. Comparison of soil moisture measurements with the retrieved median values results in a root mean square error of approximately 3.5 vol%.

1 INTRODUCTION

Soil moisture is a key variable in various earth science disciplines such as hydrology, meteorology and agriculture. The models that are mostly used in these disciplines generally require spatially distributed soil moisture as an input. As the microwave backscattered signal from a bare soil surface is partly influenced by the soil moisture content, radar remote sensing can be used to meet these high spatial resolution requirements. Currently, only active microwave sensors, of which the Synthetic Aperture Radar (SAR) is the most common imaging configuration, are able to capture small-scale soil mositure patterns.

Several backscatter models exist that calculate the backscattered signal, given soil moisture, soil surface roughness and incidence angle, polarization and wavelength of the radar signal. Soil surface roughness refers to the unevenness of the earth's surface due to natural processes or human activities, and is generally statistically described by the root mean square (rms) height, the correlation length and an autocorrelation function (Ulaby et al., 1982a). Unfortunately, soil surface roughness parameters are difficult to measure as several experiments have shown that roughness parameterization depends on profile length (Callens et al., 2006; Davidson et al., 2000; Ogilvy, 1988; Oh and Kay, 1998) and the measurement technique (Mattia et al., 2003a), meaning that different roughness parameter values can be obtained for the same surface. These problems occur because natural surfaces behave as a self-affine fractal surface (Shephard and Campbell, 1999; Dierking, 1999; Shepard et al., 2001), while most of the backscatter models assume a stationary random surface.

Amongst the various methods that exist to overcome this parameterization problem, Su et al. (1997) suggested the use of an effective roughness parameter, which is estimated by means of remotely sensed data in combination with soil moisture measurements. This parameter then replaces the *in situ* roughness measurements for soil moisture retrieval from successive SAR acquisitions. This concept is applied successfully in different studies (Verhoest et al., 2000; Baghdadi et al., 2002, 2004, 2006; Rahman et al., 2007; Álvarez-Mozos et al., 2008) and will also be used in this study.

SAR retrieved soil moisture maps are often used in hydrological models or in data assimilation schemes. For the latter applications, the Ensemble Kalman filter (Evensen, 2006) is frequently used to assimilate remotely sensed hydrologic information (Reichle, 2008). This method relies on the value of the observed variable and assumes a normal distribution, for which the mean value and the variance of the observed variable are required. Therefore, retrieval algorithms should provide not only soil moisture content, but also a quantification of its uncertainty.

The research questions to be answered in this study are:

1. How can the uncertainty on effective soil surface roughness be quantified?
2. How does this uncertainty influence the uncertainty on retrieved soil moisture?

For this purpose, all other sources of uncertainty were ignored, such as uncertainty on the backscattered signal, uncertainty induced by vegetation cover or by the backscatter model.

2 METHODOLOGY

The methodology used in this study is based on a relationship that was found between effective roughness parameters and backscatter coefficients. A linear regression model was used to model this relationship (Lievens et al., 2010) and can furthermore be used to quantify the uncertainty on the modeled soil roughness as a probability distribution. Using a Monte Carlo method to propagate this probability distribution through an inverse backscatter model, a probability distribution for soil moisture content is obtained.

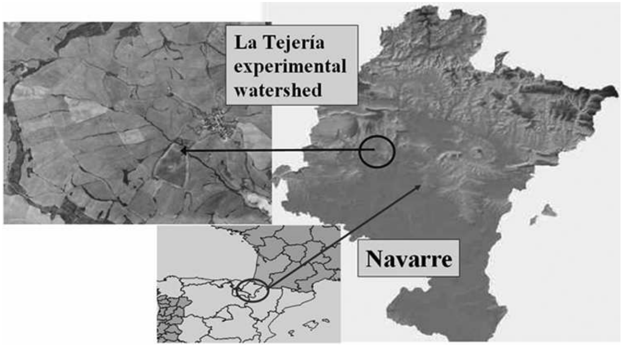

Figure 1: Location of La Tejería experimental watershed

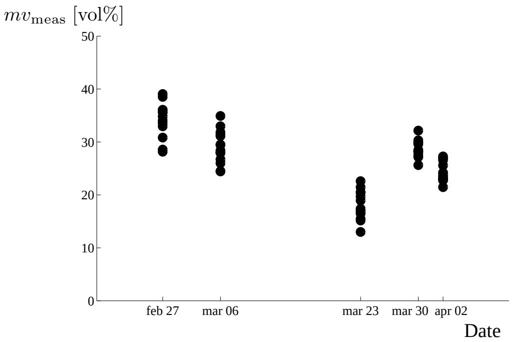

Figure 2: Soil moisture contents (mv_{meas}) measured at different acquisition dates in 2003

2.1 Study site and data

The studied watershed, La Tejería, is situated in the north of Spain (Figure 1), has a humid, submediterranean climate and consists of clayey and silty clay loam textures. It is almost completely cultivated, with an emerging cereal crop covering most of the fields during the experimental period (February - April 2003). A more detailed description of the study site is given by Álvarez-Mozos et al. (2006).

For each acquisition day, field average soil moisture contents were calculated for fifteen seedbed fields based on measurements with a Time Domain Reflectometry (TDR) instrument with 11 cm probes (Figure 2). For a detailed description of the sampling method we refer to Álvarez-Mozos et al. (2006).

Next, five C-band, HH polarized RADARSAT-1 SGF scenes were acquired over the experimental region during spring 2003, at low incidence angles (13°-29°). This configuration has proved to be particularly well suited for soil moisture research over cereal canopies (Ulaby et al., 1982b; Biftu and Gan, 1999; Mattia et al., 2003b). The images have a range resolution of 20 m or 24 m and an azimuth resolution of 27 m, from which field average backscatter coefficients were calculated. Furthermore, in order to reduce the effect of the local incidence angle on the backscatter coefficients, these coefficients were normalized correspondent to a reference incidence angle, according to Lambert's law for optics (Ulaby et al., 1982b; Van Der Velde and Su, 2009):

$$\sigma^0_{\mathrm{l,n}} = \sigma^0_{\mathrm{l}} \frac{\cos^2 \cdot\theta_{\mathrm{ref}}}{\cos^2 \theta}, \qquad (1)$$

where $\sigma^0_{\mathrm{l,n}}$ is the linear normalized backscatter coefficient [-], σ^0_{l} is the linear measured backscatter coefficient [-], θ_{ref} is the reference incidence angle [°], in this case chosen to be 23° and θ is the local incidence angle [°]. The resulting field average backscatter values are shown for every acquisition date in Figure 3.

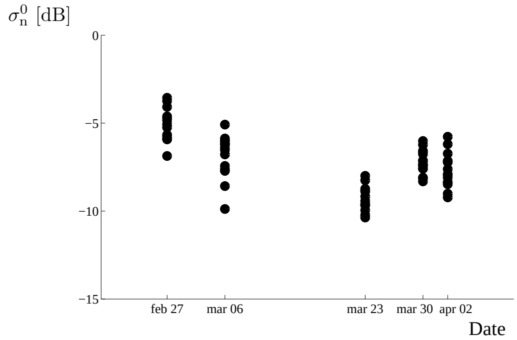

Figure 3: Normalized backscatter coefficients (σ^0_{n}) obtained at different acquisition dates in 2003

2.2 Integral Eqation model

The single scattering approximation of the Integral Equation Model (IEM) (Fung et al., 1992; Fung, 1994) is the most widely used scattering model for bare soil surfaces (Moran et al., 2004). It allows for the calculation of backscatter coefficients based on bare soil surface roughness parameters, soil dielectric constant, local incidence angle, wave polarisation and frequency. The IEM describes surface roughness by three complementary parameters: rms height (s), correlation length (l), and an autocorrelation function. Davidson et al. (2000) and Callens et al. (2006) demonstrated that for smooth to medium rough agricultural bare fields this autocorrelation function is best represented by an exponential function.

The conversion of the dielectric constant to the corresponding soil moisture content is performed by means of the four-component dielectric mixing model of Dobson et al. (1985), for which the residual and saturated soil moisture content used throughout this study are set to 3 vol% and 45 vol% respectively.

It is expected that the emerging crops on the fields influence the results of the inversion of the IEM, since this was developed for bare soil conditions. However, the canopies were only weakly developed and the incidence angles were low, which are reasons to believe that the effect of the vegetation is minimal (Ulaby et al., 1982b; Mattia et al., 2003b). Furthermore, simulations by Lievens et al. (2010) using a water cloud model (Attema and Ulaby, 1978; Prévot et al., 1993) indicated that the attenuation of the backscatter by the cereal canopy was to a large extent compensated by a direct canopy contribution. This led to insignificant vegetation corrections within the relative radiometric accuracy of the RADARSAT observations, *i.e.* +/-1 dB (Srivastava et al., 1999). Therefore this study will not take into account a possible influence of the crop cover on the backscattered signal.

2.3 Effective roughness

The idea of using effective roughness parameters was first introduced by Su et al. (1997). The effective roughness parameters are estimated using backscatter and soil moisture observations. They replace *in situ* measurements of soil surface roughness for the retrieval of soil moisture content from successive SAR images.

In case of the IEM, two effective roughness parameters need to be defined: rms height (s) and correlation length (l). Lievens

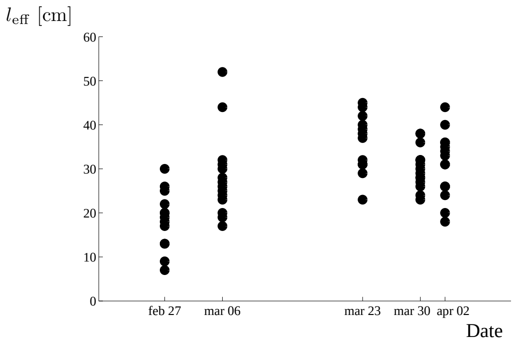

Figure 4: Effective correlation lengths (l_{eff}) obtained with the IEM for the different acquisition dates in 2003

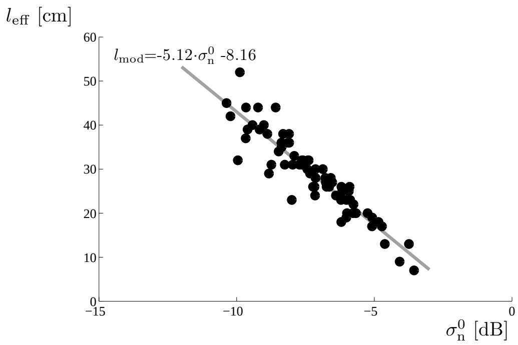

Figure 5: Dependence of the effective correlation length (l_{eff}) on the normalized backscatter coefficient (σ_{n}^0)

et al. (2010) observed that for a large number of different (s,l)-combinations a very small soil moisture retrieval error is obtained. They furthermore concluded that a fixed value for s is best used on which basis the corresponding value for l_{eff} is determined. Therefore s is fixed at 1.0 cm and l ranges from 1.0 cm to 120 cm in the inversion of the IEM. The value resulting in the lowest observation error, l_{eff}, is retained. Figure 4 shows the effective correlation lengths corresponding to the observed normalized backscatter coefficients on every acquisition date.

A comparison of Figures 3 and 4 shows that the behaviour of the field average effective correlation lengths is strongly related to the normalized backscatter coefficients. A plot of the values of l_{eff} versus σ_{n}^0, as presented in Figure 5, reveals this relationship can be modeled by a linear regression model:

$$l_{\text{mod}} = a \cdot \sigma_{\text{n}}^0 + b + \epsilon, \tag{2}$$

with l_{mod} the modeled correlation length, a and b regression parameters and ϵ a random error term, usually considered to be normally distributed. The values of parameters a and b are also shown in Figure 5. Lievens et al. (2010) performed an extensive cross-validation, indicating the robustness of this regression model, however, latter exercise will not be discussed in this work.

The linear regression model can then be further used to estimate the uncertainty around the predicted value. This uncertainty is described by a t-distribution with variance σ^2, calculated as follows (Neter et al., 1996):

$$\sigma^2 = \frac{\sum_{i=1}^{n} e_i^2}{n-2}\left[1 + \frac{1}{n} + \frac{(\sigma_{\text{n},h}^0 - \bar{\sigma}_{\text{n}}^0)^2}{\sum_{i=1}^{n}(\sigma_{\text{n},i}^0 - \bar{\sigma}_{\text{n}}^0)^2}\right], \tag{3}$$

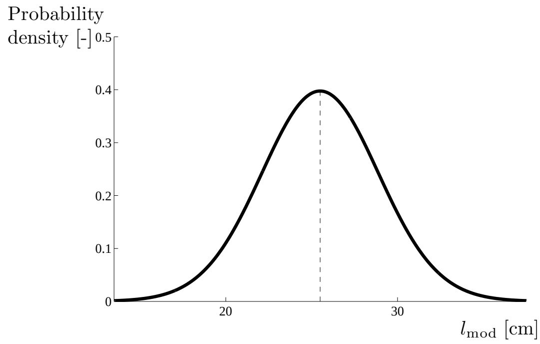

Figure 6: Example of a probability distribution for modeled correlation length (l_{mod})

with n the number of observations, e_i the difference between the ith observed and modeled values of l_{eff}, $\sigma_{\text{n},h}^0$ the normalized backscatter coefficient for which the regression model is applied, $\sigma_{n,i}^0$ the ith observed normalized backscatter coefficient and $\bar{\sigma}_{\text{n}}^0$ the mean of all observed normalized backscatter coefficients. As an example, Figure 6 shows the t-distribution for an arbitrary value of σ_{n}^0, from which it can be seen that this distribution is symmetric around the mean value. The obtained distribution for l_{mod} is propagated through the inversion of the IEM by means of a Monte Carlo method. To this end, 1000 values of l_{mod} are randomly sampled from the distribution and further used as input to the IEM. This results in 1000 corresponding soil moisture contents, representing the histogram of soil moisture.

3 RESULTS AND DISCUSSION

3.1 Soil moisture histogram

Figure 7 shows the histogram of the obtained soil moisture values for the arbitrary example. The histograms are cut off at a minimum soil moisture content of 3 vol% (residual soil moisture content) and a maximum of 45 vol% (saturated soil moisture content), which can influence the mean value. Furthermore, it should be noticed that this example histogram is asymmetric, skewed towards higher soil moisture values and therefore not normal. This was confirmed using a Lillifors normality test (Lilliefors, 1967) for about 70% of the obtained histograms. The remaining histograms were found to be normal, which mostly occurred at low soil moisture values ($<$ 25 vol%). Consequently, using the mean and standard deviation in further applications as representatives for the obtained non-normal soil moisture histograms, may lead to a distorted view of the underlying distributions. Furthermore, the mean value and standard deviation of the normal histograms may be influenced by the fact that the histograms are cut off at the residual and saturated soil moisture content. Therefore it is recommended to use the median value and the interquartile range divided by 1.35 (converted IQR), which are insensitive to the values of residual and saturated soil moisture content.

3.2 Retrieved median soil moisture content

Figure 8 shows a scatterplot of the retrieved versus the observed soil moisture values, where the error bars represent the converted IQR of the resulting histograms. It can be seen that low soil moisture contents ($<$ 20 vol%) are slightly overestimated. Overall, a root mean square error (RMSE) of 3.51 vol% is obtained between the measured soil moisture content and the median of the

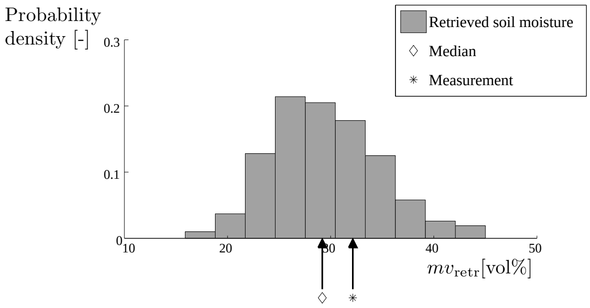

Figure 7: Example of a histogram of retrieved soil moisture content (mv_{retr})

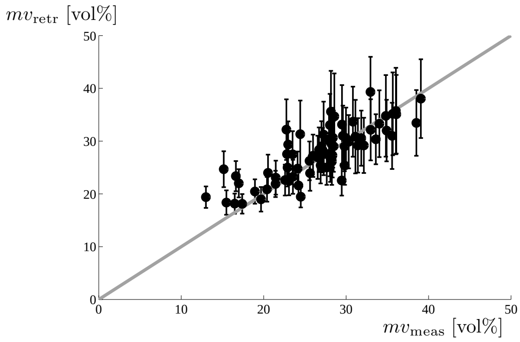

Figure 8: Retrieved (mv_{retr}) versus measured soil moisture (mv_{meas}), the error bars represent IQR/1.35

retrieved histograms. Furthermore a Nash-Sutcliffe model efficiency (Nash and Sutcliffe, 1970) of 0.63 was found, indicating the model predicts much better than the mean value of the observations. It is furthermore observed that the uncertainty on the retrieved soil moisture contents increases with the soil moisture content, which is in accordance with the observations of Verhoest et al. (2007).

4 CONCLUSIONS

This study presents a methodology that allows for the retrieval of soil moisture content and its uncertainty based on modeled roughness. Soil surface roughness, in terms of effective correlation length (l_{eff}) is modeled based on its relationship with normalized backscatter coefficients (σ_{n}^0). The uncertainty on the modeled correlation length l_{mod} is described by a t-distribution, which is then sampled following a Monte Carlo method. The randomly drawn values are propagated through the inversion of the IEM and a corresponding histogram of soil moisture contents is obtained.

Results show that most of these histograms are skewed and non-normal and that a representation of these histograms by means of the mean value and the standard deviation may lead to a distorted view of the underlying distribution. This is particularly important when retrieved soil moisture content and corresponding uncertainty (represented by the mean and standard deviation) are to be used in data assimilation schemes, such as the Ensemble Kalman filter, which rely on normality assumptions of the variables of interest. It would be better to apply the median value and converted IQR in the data assimilation framework. It is furthermore observed that the interquartile range changes with varying soil moisture conditions, larger interquartile ranges are obtained for higher soil moisture contents.

Future research is required to test whether soil moisture content with a variable uncertainty has a large impact when used in a data assimilation framework.

ACKNOWLEDGEMENTS

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