Soil moisture monitoring with ERS SAR interferometry

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Abstract

Soil moisture monitoring with repeat-pass ERS SAR data using interferometric signature analysis was investigated using data acquired over Middle Zeeland, The Netherlands, between January and March 1994 during 3-day repeat orbits.

Bare and sparsely vegetated fields with constant surface roughness were identified based on its interferometric signatures. Such areas are most useful for soil moisture monitoring. Under the assumption of limited vegetation scattering and constant surface roughness, multi-temporal microwave backscattering data show a clear dependence on the soil moisture content of the upper most soil layer.

For eight bare fields without roughness change the backscattering was related to the in-situ measured soil moisture and used to derive retrieval algorithms for:

- relative soil moisture change

- soil moisture.

The relative soil moisture change is retrieved from the relative backscatter change (defined as difference of backscatter values in dB, or ratio [in dB] of absolute backscattering values). The absolute soil moisture can be estimated if the soil moisture is known for one reference data set. In the case of the Middle Zeeland data acquired during a period with frozen soils, i.e. very low soil moisture content, was used as moisture reference. The influence of the surface roughness on the soil moisture retrieval algorithm was also investigated.

In a further step, the algorithms were applied to fields without in-situ data, allowing to retrieve soil moisture maps for larger areas.

Keywords: SAR, SAR interferometry, soil moisture, ERS, Zeeland

Introduction

One of the most often proposed application of microwave remote sensing is the retrieval of soil moisture. The scattering properties of a soil surface are dominated by its geometry and its permittivity or dielectric constant. The permittivity itself depends strongly on the soil moisture content because of the very high permittivity of liquid water. Therefore, the suggested approach is to relate the measured backscattering to the permittivity and the latter to the soil moisture, or what is done even more often, to relate the backscattering coefficient directly to the soil moisture. In practice, it turns out that soil moisture measurement based on the microwave backscattering coefficient is a very difficult task. In order to better understand the scatter properties theoretical models were developed. Based on such models the physical understanding was much improved. Forward models can reasonably well predict the observed backscattering coefficient. The inversion of the models is, unfortunately, much less reliable.

As a result most studies to retrieve soil moisture from microwave backscattering are restricted to bare soils. In addition the approach can be further simplified by interpreting time series of data over specific areas. As long as the surface roughness does not change for those areas the backscatter change originates from the permittivity, respectively soil moisture, change. Under the assumption of constant surface roughness quite reliable soil moisture estimates are obtained from the microwave backscattering coefficient. Surface roughness changes may result in severe errors in the moisture estimate, though.

Here, a new technique is proposed to improve the potential of SAR data for hydrological applications. Repeat-pass SAR interferometry, as successfully demonstrated with data from the ERS satellites, is very sensitive to temporal change (Wegmüller et al., 1995a, Wegmüller et al, 1995b). In a multi-temporal data set this allows to identify areas of unchanged geometry, that is constant surface roughness. The relative changes of the backscattering for those areas can then be used to monitor the soil moisture.

Test Site and Data

Interferometric signatures were extracted from ERS-1 data acquired between January and March 1994 over Middle Zeeland, The Netherlands. Middle Zeeland was selected because of the available in-situ data. Borgeaud et al. (1995) investigated ERS-1 SAR data acquired during the 3-day repeat orbits of Phase D (January to March 1994) together with very detailed descriptions of the soil surfaces of test-fields in Middle Zeeland. The orbital mode (three day repetition rate) together with the detailed in-situ information collected during the ground campaigns and the detailed analysis of the backscatter intensity data (Borgeaud et al., 1995) make this data set ideal for an investigation of the interferometric signatures of bare soils.

The in-situ data were collected and described by Synoptics (Bakker and Huizing, 1994, soil moisture and data) and by Bellini (1994, surface roughness profiles). The location of the 8 test fields is shown in Figure 1. The Middle Zeeland site is very flat. Relatively large fields were selected for the ground campaign (2-10 ha). During field campaigns the air temperature (Figure 2), soil moistures and surface roughness were measured (Bakker and Huizing, 1994). Based on the 1.5 m long surface height profiles the standard deviation of the surface height and the correlation lengths were computed. In Table 1 rms surface height values averaged for each field over the entire observation period are listed. The volumetric soil moisture was measured at depths of 0-5 cm and 0-10 cm. The measurements were repeated in order to monitor soil moisture and surface roughness on the selected fields during ERS-1 Phase D. For a certain period temperature dropped below 0º C and the soils froze. Field averages for the soil moisture of the 0-5 cm depth layer are shown in Figure 3. For days with frozen soil the soil moisture was set to 3%, in accordance with earlier experiments (Wegmüller et al., 1990). The observed soil moistures cover the entire range from the "very dry" (i.e. very low liquid water content) frozen soils to the close to saturated soils often observed during the winter.

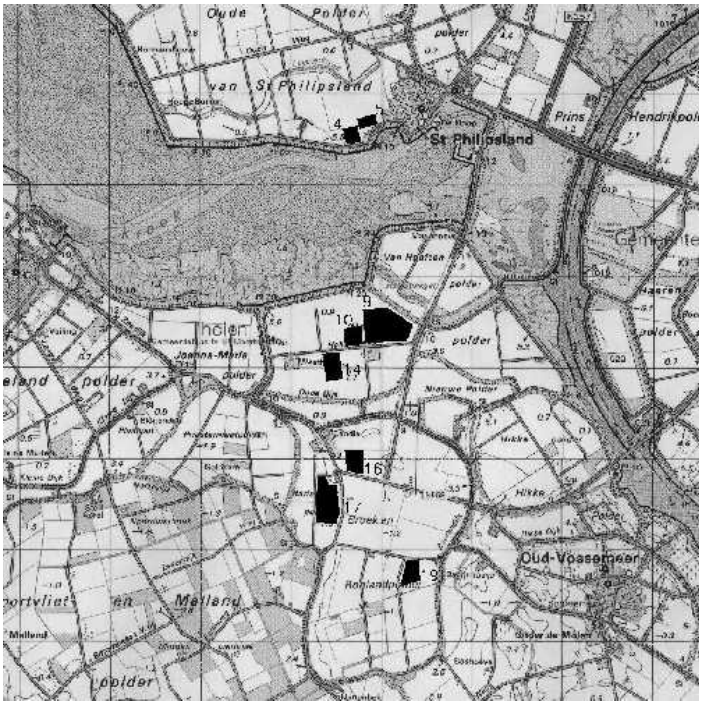

Figure 1: Map of the Middle Zeeland test site with the selected 8 bare soil fields shown in black.

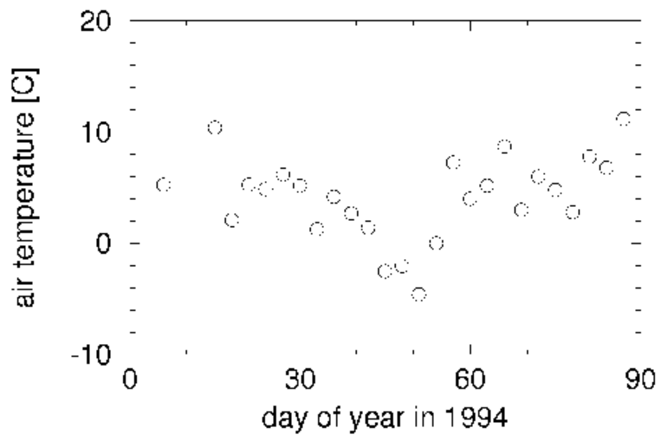

Figure 2: Middle Zeeland experiment winter 1994: Temporal development of air temperature.

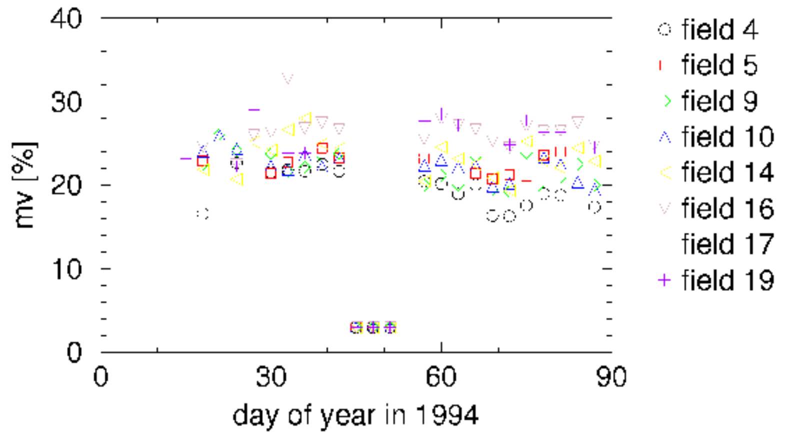

Figure 3: Middle Zeeland experiment winter 1994: Temporal development of volumetric soil moisture m_v (given in %) for selected bare soil fields. For frozen fields the soil moisture (corresponding to liquid water, only) was set to 3% in accordance with earlier experiments (Wegmüller et al., 1990).

Table 1: Average standard deviation of surface height for 8 test-fields at Middle Zeeland observed in winter 1994.

Field number	<rms-height> [cm]
4	1.85
5	2.01
9	4.39
10	2.79
14	1.57
16	3.24
17	1.93
19	0.86

Our investigation focused on the soil moisture monitoring on bare and sparsely vegetated fields. Vegetated fields as well as fields with changing surface roughness are identified based on its low interferometric correlation. For the bare fields without roughness change the backscattering was related to the in-situ measured soil moisture and used to derive retrieval algorithms for:

- relative soil moisture change

- soil moisture.

The algorithms were developed based on the SAR and in-situ data for the 8 test fields. In a second step the algorithms were applied to fields without in-situ data, allowing to retrieve soil moisture information for a larger area.

The influence of the surface roughness on the soil moisture retrieval algorithm was also investigated.

Algorithm Development

Relative Soil Moisture Change

Based on the multi-temporal interferometric correlation (Figure 4), data not useful for soil moisture retrieval were excluded from the analysis. For field 4, data showing low correlation values at the beginning of the time series and, for all fields, data with wet snow (day 54) were excluded. For frozen fields the volumetric soil moisture (liquid water content) drops to very low values. In accordance with ground-based experiments over frozen soils, the volumetric soil moisture was set to 3% (Wegmüller, 1990).

For the 8 test fields the average backscatter intensities were extracted and plotted versus the in-situ measured soil moisture (Figure 5). The backscattering [in dB] shows a clear dependence on the volumetric soil moisture. The linear regressions calculated separately for each field (see Figure 5) have high correlation coefficients between 0.94 and 0.99. The slopes of the regression curves vary only between 0.20 dB/% and 0.27 dB/% (average 0.24 dB/%), the intercepts between -11.9 dB and -7.5 dB (average -9.5 dB).

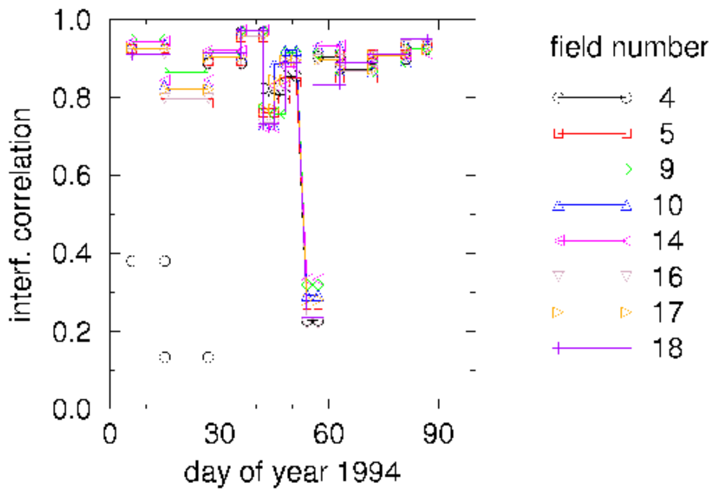

Figure 4: Interferometric correlation of consecutive ERS-1 data acquisitions for 8 bare fields at Middle Zeeland, January to March 1994.

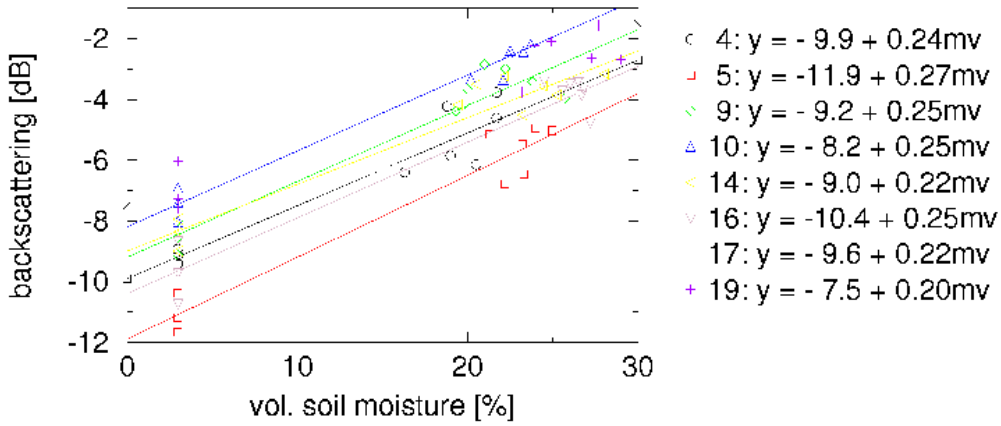

Figure 5: Average backscatter intensities versus in-situ measured soil moisture.

Taking advantage of the result that the slope of the regression curves in Figure 5 is almost the same for all test fields and soil moisture changes, we may retrieve

$$\Delta m_v = m_{v,2} - m_{v,1} \tag{1}$$

using

$$\Delta m_v = 0.042 \Delta\sigma^o |dB| \tag{2}$$

where $\Delta\sigma^o$ is the backscatter change

$$\Delta\sigma^o = \sigma_2^o|dB| - \sigma_1^o|dB|. \tag{3}$$

The advantage of this method is that the errors due to the unknown roughness remain relatively small. The exact slope of the regression slope is approximated with an accuracy of ± 10% leading to a relative soil moisture change estimation error of 10% or an error of 0.01 for a moisture change of 0.1. Another advantage is that calibration errors (for instance caused by local topography, unknown antennae diagram, or other unknown calibration factors) do not affect the quality of the result as long as the same calibration is off by the same factor in both cases. In this relative method most of the influence of the incidence angle dependence of the backscattering coefficient is removed and may therefore be neglected. The main disadvantage of the method is that it is only an estimation of the moisture change but not of the absolute soil moisture level. We conclude that this method is very useful to map moisture changes and particularly to map small moisture changes because the main errors are relative to the change occurring.

The algorithm was first applied for the 8 test fields for four different interferometric image pairs. No frozen soils were included. The soil moisture change estimated from the backscatter change was compared to the in-situ observations of the soil moisture change in Figure 6. Based on the observed in field variability, vertical moisture inhomogeneity, and measurement errors, an uncertainty of at least 0.03 (3%) is expected for a single soil moisture measurement. The difference of two statistically independent measurements with an accuracy of 0.03 is around 0.04 (4%). The accuracy of the estimation of the backscatter change introduces the main error in the moisture estimation. An estimation accuracy of below 0.5 dB may only achieved for very large fields. An error of 0.5 dB translates into a soil moisture change estimation error of 0.02. The soil moisture changes occurring during the experiment were only small, in the range of the errors of both the in-situ and remote sensing method. Therefore, Figure 6 is not sufficient for a profound validation of the algorithm.

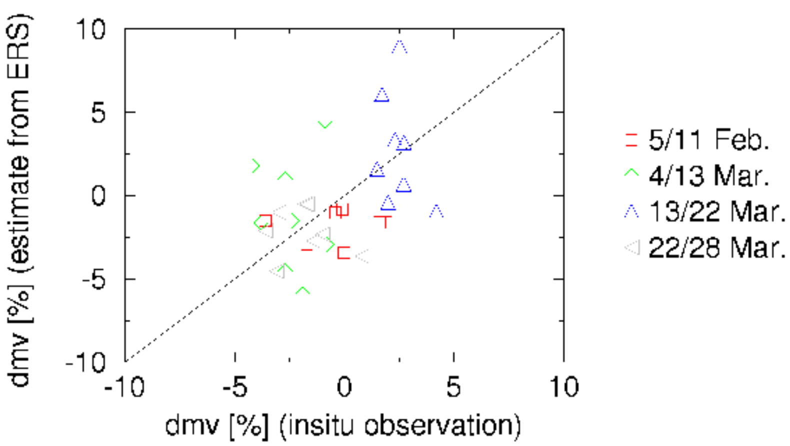

Figure 6: Change in volumetric soil moisture [in %] estimated from ERS data using Equation (2) versus in-situ measured soil moisture change.

Soil Moisture

The algorithm discussed above can be extended to absolute soil moisture estimation if the soil moisture is known for one data set

$$m_v = m_{v,0} + 0.042(\sigma^o[dB] - \sigma_0^o[dB]) \quad (4)$$

where σ_0^o is the backscattering coefficient for the known soil moisture $m_{v,0}$.

Even without in-situ data the soil moisture may be known quite reliably under certain conditions as in the case of frozen soil or very wet (moisture near field capacity) soil after extensive rain.

In Equation (4) the differences in the intercepts shown in Figure 5 were not considered. However, the intercepts may be a measure of the roughness of the fields. Plotting the slope of the regression curves found for the different test fields versus the intercept a high negative correlation is found (Figure 7). Ignoring the one point located far away from the regression curve leads to a correlation coefficient of 0.89 and to a linear regression function as indicated in Figure 7. The fact that the two quantities are related was used to improve the soil moisture retrieval algorithm by replacing the constant slope value with a roughness dependent slope, s, estimated from the intercept, i. According to

$$i = \sigma_0^o - m_{v,0} \cdot s \quad (5)$$

and

$$s = 8.56 - 1.56 \cdot i \quad (6)$$

we found

$$i = \frac{\sigma_0^o - 8.56 \cdot m_{v,0}}{1 - 1.56 \cdot m_{v,0}} \quad (7)$$

The soil moisture retrieval algorithm is therefore

$$m_v = \frac{\sigma^o - i}{8.56 - 1.56 \cdot i} \quad (8)$$

Having two or more data sets with known soil moistures, for example a frozen and a saturated soil, allows us to conduct a regression analysis and derive both slopes and intercepts directly from the data.

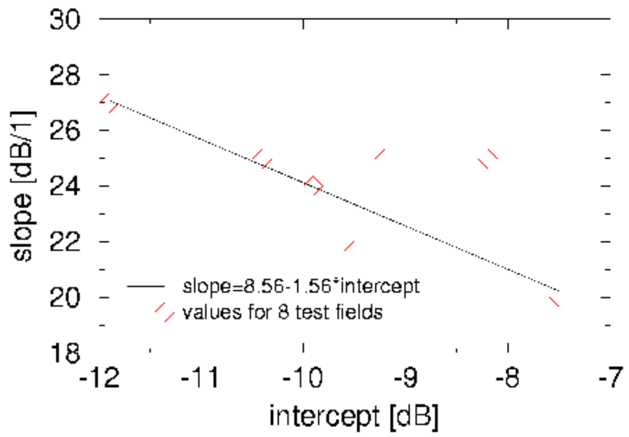

Figure 7: Slope of the regression curves for the different test fields versus the intercept. A high negative correlation is found between the two quantities. Ignoring the point located far away from the regression curve leads to the correlation coefficient of 0.89 and the indicated linear regression function

Results

The described algorithms were applied to the Middle Zeeland data. This allowed to retrieve soil moisture information for fields distributed over the entire ERS scene. The application of the described algorithms is done in two steps, first the classification step and second the parameter retrieval step.

Retrieval of Relative Soil Moisture Change

In order to retrieve soil moisture change over bare soils the *appropriate* bare soils are first classified based on high interferometric correlation (> 0.7) and low image texture (< 0.5). *Appropriate* as used here means bare soil without roughness change between the acquisitions of the two data sets. The low texture condition was used to distinguish the bare or sparsely vegetated fields from urban areas (with high texture).

The soil moisture change was then determined using Equation (2). In the estimation of the backscatter change the speckle noise has to be taken into account. It is recommended to use large enough averaging/filtering windows to determine average backscattering coefficients before the ratio is taken. For the example discussed we applied minimum mean square error (MMSE) filter (Frost et al., 1982) to 7x7 5-look pixels. The ratio was then calculated for averages of 15 x 15 5 look pixels (using a linearly decreasing weighting function). Equation (2) was then applied to calculate the soil moisture change.

The classification and soil moisture change results were then combined. The resulting image contains the soil moisture change values and zero values for areas without soil moisture change estimate. To visualize the result a color scale was used to display the soil moisture change. For the image brightness one of the backscatter images was used. The results obtained for the changes occurred between 4 and 13 March 1994 and between 13 and 22 March 1994 are shown in Figure 8.

For most areas the observed soil moisture change was small (blue color), as expected from the in-situ observations. Decreasing soil moisture (turquoise color) was observed for small parts of the area on the 13 / 22 March pair.

Soil Moisture Retrieval

For simplicity only fields without geometric change throughout the entire experiment were used for the soil moisture monitoring. This was achieved by conducting a classification using the interferogram pair between the first and last data takes, applying a high interferometric correlation (> 0.7) and low image texture (< 0.5) criteria.

In order to have a good reference data set with known soil moisture, the backscattering of the three days with frozen soil were used. The data were first averaged, then a minimum mean square error filter (Frost et al., 1982) with a window size of 7x7 5-look pixels, and finally a running average filter (window size 15x15 5-look pixel) with linear weighting was applied. The result was taken as backscatter reference with an assumed (liquid) soil moisture content of 0.03. The backscatter images to be used for the soil moisture retrieval were treated in the same way as the reference data, i.e. MMSE and average filtering. The resulting backscatter coefficient were then used to estimate the soil moisture using Equation (8).

The classification result and the soil moisture retrieval output were then combined. The resulting soil moisture map contains soil moisture values and zero values for areas without soil moisture estimate. In order to visualize the result a color scale was used to display the soil moisture change. For the image brightness one of the backscatter images was used. The results obtained for the data on 11 and 14 February 1994 are shown in Figure 9.

On 11 February soil moisture values around 0.25 were detected (blue color), with values below 0.20 for a few fields (turquoise color). On 14 February very low soil moistures were detected for all fields as a result of freezing.

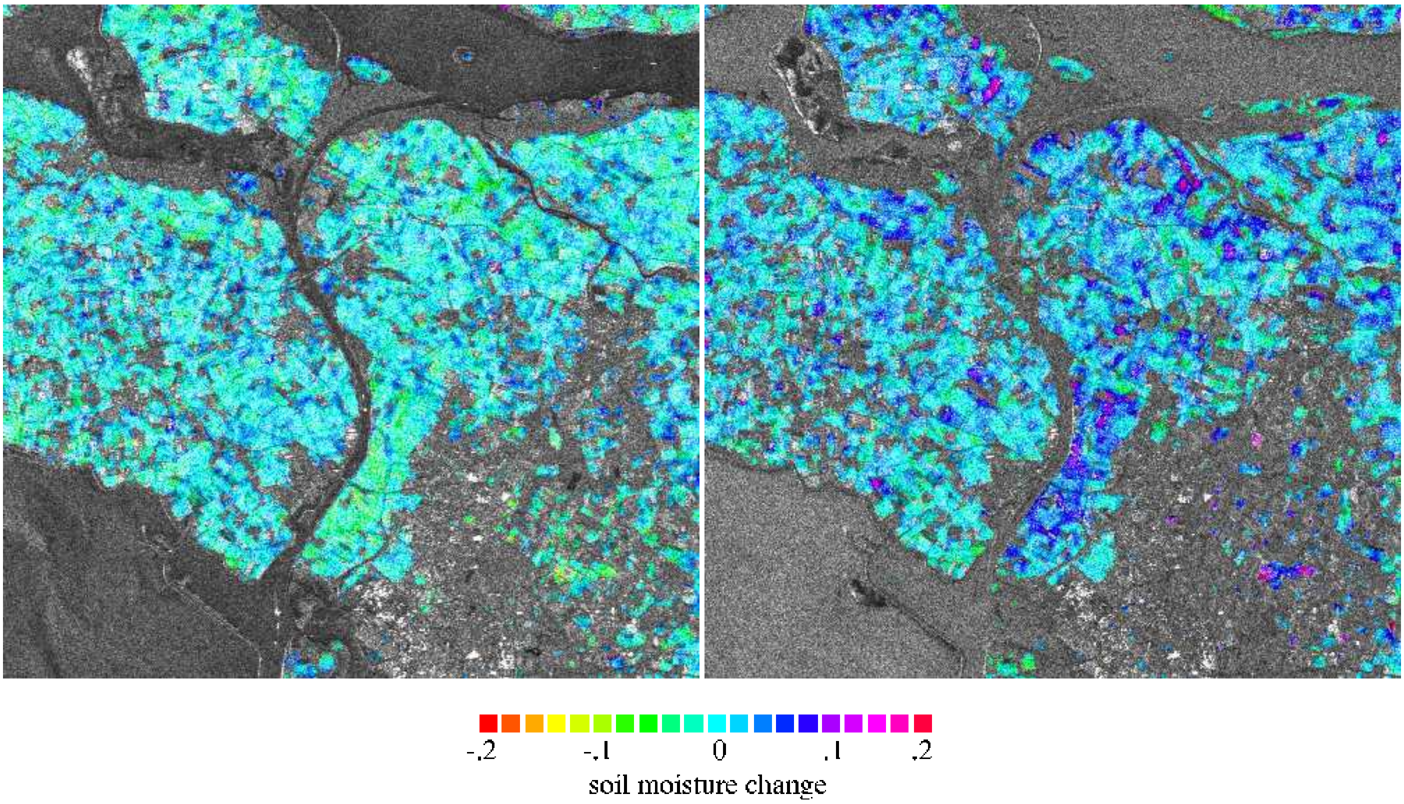

Figure 8: Soil moisture change for Middle Zeeland (NL) test-site occurring between 4 and 13 March 1994 (a, left side) and 13 and 22 March 1994 (b, right side) retrieved from multi-temporal ERS-1 SAR data. The soil moisture change is displayed using a color scale as indicated. The image brightness corresponds to the backscattering on the first date. In order to improve the reliability soil moisture, change was estimated exclusively over bare and sparsely vegetated fields with unchanged surface roughness. For gray areas no soil moisture change information was retrieved.

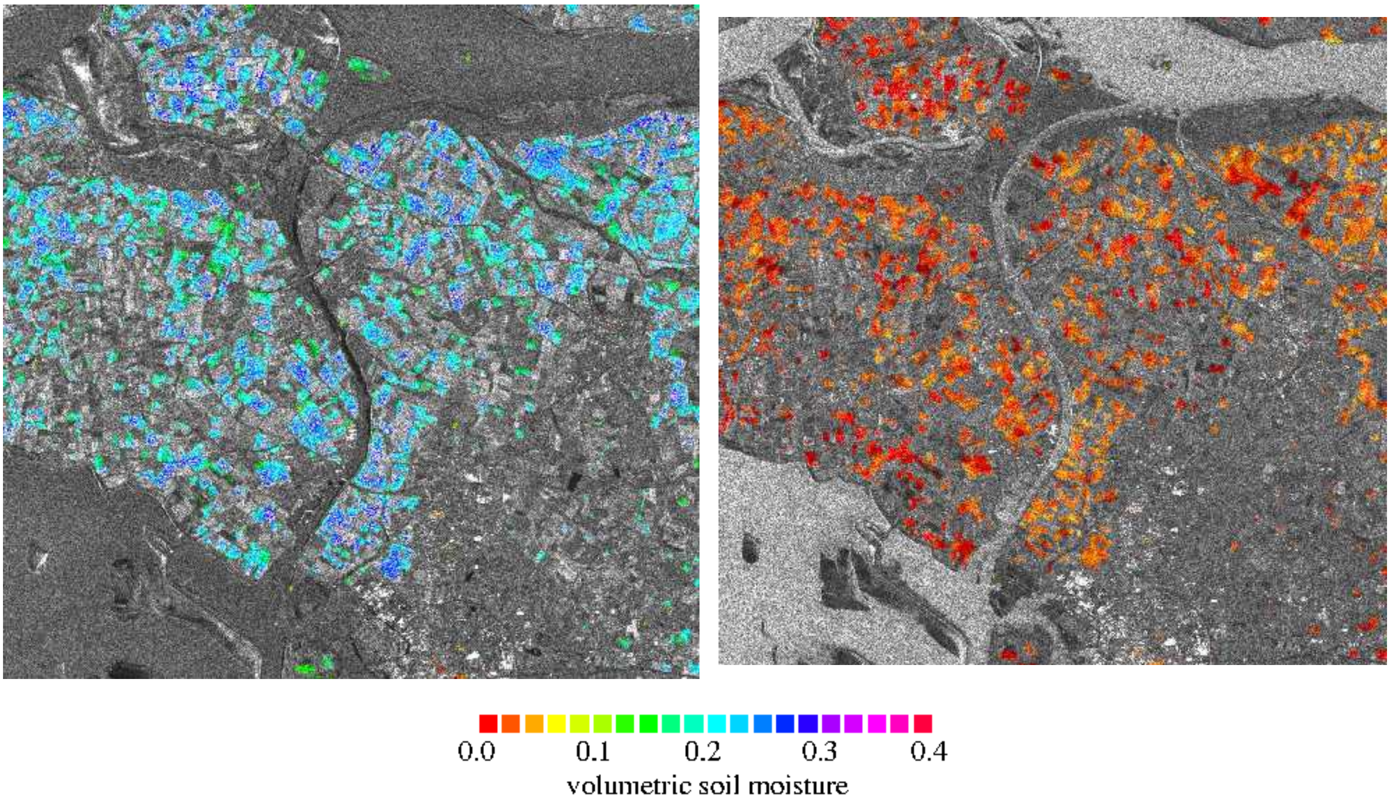

Figure 9: Volumetric soil moisture at 0 to 5 cm depth for Middle Zeeland (NL) test-site on 11 February 1994 (a, left side) and 14 February 1994 (b, right side) estimated from multi-temporal ERS-1 SAR data. The low moisture values on 14 February are a result of freezing. The soil moisture is displayed using a color scale as indicated. The image brightness corresponds to the backscattering on the first date. In order to improve the reliability soil moisture change was estimated exclusively over bare and sparsely vegetated fields with unchanged surface roughness throughout the duration of the experiment. For gray areas the volumetric soil moisture was not retrieved.

Roughness Analysis

The detailed surface roughness data was also used to investigate a possible dependence of the interferometric correlation on the surface roughness. As discussed in detail by Borgeaud et al. 1995 the measurement of the surface roughness and its description with the commonly used statistical parameters, namely the standard deviation of the surface height and the autocorrelation length, is quite problematic. In spite of no obvious changes on the test fields (confirmed by high interferometric correlation!) the average roughness estimates, obtained from roughness measurements taken at different dates throughout the winter, vary strongly. For comparison with the data we reduced the roughness description to one value per field, the average standard deviation of the surface height. These values are listed in Table 1. In spite of the quite large uncertainty in the measurement and description of the roughness, it is clear that the data set includes smooth, intermediate and rough fields.

The differences between the fields on a certain date and between the data of one field on different dates do not show a clear indication of a dependence of the interferometric correlation on the surface roughness. More important factors may be the effects of meteorological conditions, sparse vegetation, acquisition time difference, baseline, etc.

Nevertheless, as mentioned above, the sensitivity of the backscattering to soil moisture change depends on the surface roughness. A multi-temporal data set with some in-situ or meteorological data as the one over the Zeeland test-site allows to determine the slope of the backscattering dependence on the moisture and allows therefore to estimate a surface roughness parameter. For fields without in-situ data the soil moisture has to be "guessed". In the case of freezing the assumption of a low moisture (~ 3%) is relatively accurate with an assumed error below 2%. As a second observation a very wet day, such a day is found either from meteorological data (after a period with much rain) or directly form the SAR data (high backscattering observed on many fields), may be selected. On such a day the soil moisture can either be assumed to be close to saturation or around the moisture values observed for fields in that area (or even better for the same field) during wet conditions. With an assumed "guessing accuracy" of 4% for a moisture value of around 35% the slope can be estimated with a relative error of about 14 %, just about accurate enough to retrieve some roughness information.

Instead of using the relation between the slope and the rms-height (Figure 10) to estimate the rms-height, the slope value itself can be considered as a roughness parameter. This may actually be a more useful description of the "surface roughness as seen by microwaves". In addition, the definition can be extended to fields with vegetation cover which decreases the sensitivity of the backscattering to soil moisture in a similar way as surface roughness but in the case of denser vegetation much stronger.

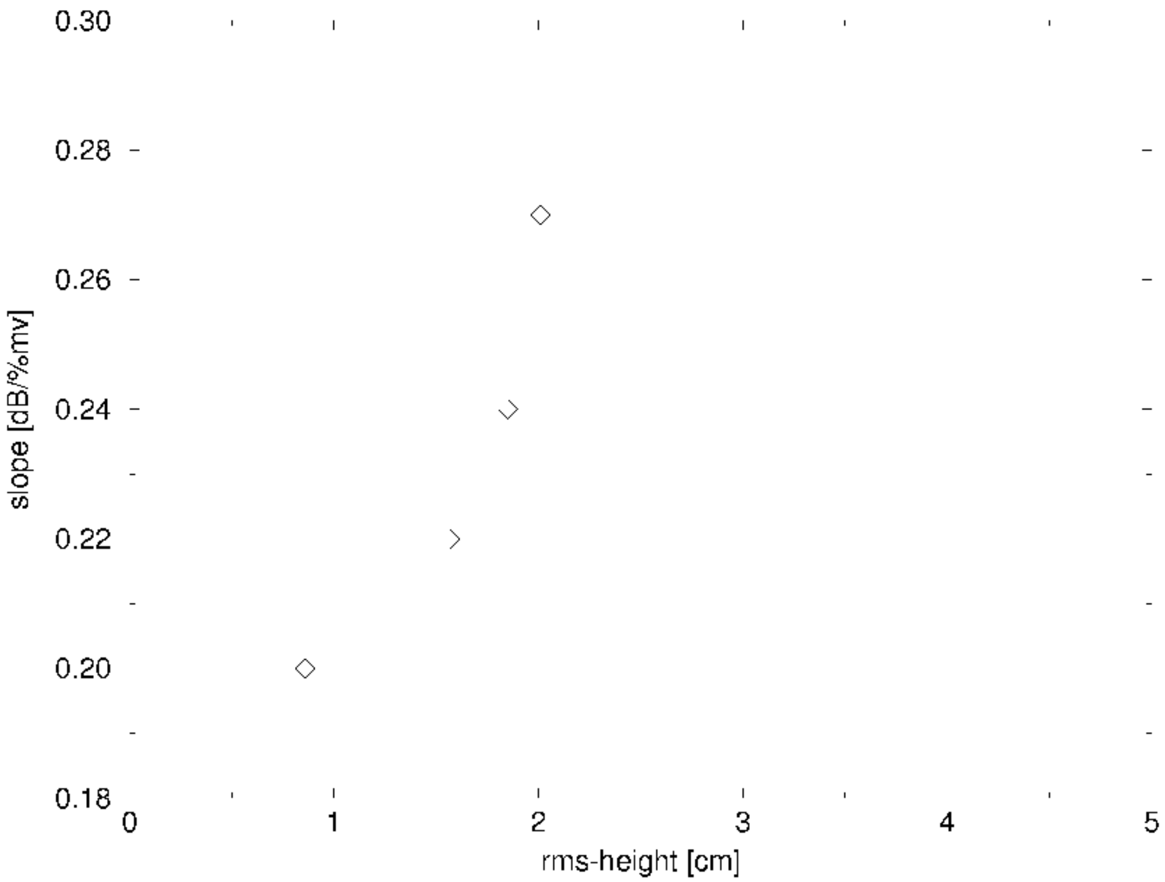

Figure 10: Relation between the slope of the regression curves between the backscatter in dB and the volumetric soil moisture and the rms-height for test fields in Middle Zeeland.

Conclusions

The focus of this study is on soil moisture retrieval with ERS SAR interferometry. Data acquired over Middle Zeeland between January and March 1994 during 3-day repeat orbits were used. The soil moisture monitoring was applied to bare and sparsely vegetated fields with constant surface roughness, which were identify by means of the high interferometric correlation. For eight bare fields without roughness change, where in-situ data were collected, the backscattering was related to in-situ measured soil moisture. The dependence of the backscattering on the volumetric soil moisture was used to derive retrieval algorithms for the relative soil moisture change and the soil moisture.

The algorithms are based on the intercepts and slopes of the regression curves calculated between backscattering and volumetric soil moisture. The algorithm for the retrieval of the relative moisture change is in particular suitable for the map of small moisture changes because the errors are relatively small. The absolute soil moisture can be estimated if the soil moisture is known for one reference data set. In this case study, data acquired during a period with frozen soil were used as reference.

The algorithms were then applied to fields without in-situ data available, leading to soil moisture maps of large areas. At last, the influence of the surface roughness on the soil moisture retrieval algorithm was investigated. In a possible extension of this study, fields with vegetation cover, which decreases the sensitivity of the backscattering to soil moisture, may be investigated.

Acknowledgments

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