Surface soil moisture estimation from the synergistic use of the (multi-incidence and multi-resolution) active microwave ERS Wind Scatterometer and SAR data

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Abstract

This paper presents an original methodology to retrieve surface (< 5 cm) soil moisture over low vegetated regions using the two active microwave instruments of ERS satellites. The developed algorithm takes advantage of the multi-angular configuration and high temporal resolution of the Wind Scatterometer (WSC) combined with the SAR high spatial resolution. As a result, a mixed target model is proposed. The WSC backscattered signal may be represented as a combination of the vegetation and bare soil contributions weighted by their respective fractional covers. Over our temperate regions and time periods of interest, the vegetation signal is assumed to be principally due to forests backscattered signal. Then, thanks to the high spatial resolution of the SAR instrument, the forest contribution may be quantified from the analysis of the SAR image, and then removed from the total WSC signal in order to estimate the soil contribution. Finally, the Integral Equation Model (IEM, [IEEE Transactions on Geoscience and Remote Sensing, 30 (2), (1992) 356]) is used to estimate the effect of surface roughness and to retrieve surface soil moisture from the WSC multi-angular measurements. This methodology has been developed and applied on ERS data acquired over three different Seine river watersheds in France, and for a 3-year time period. The soil moisture estimations are compared with in situ ground measurements. High correlations ($R^2$ greater than 0.8) are observed for the three study watersheds with a root mean square (rms) error smaller than 4%.

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1. Introduction

Surface soil moisture plays a crucial role on the continental water cycle, more specifically on the partition of precipitation between surface runoff and infiltration (Beven & Fisher, 1996; De Roo, Offermans, & Cremers, 1996) and in partitioning the incoming radiation between latent and sensible heat fluxes. As a consequence, soil moisture influences the atmospheric water vapor fluxes and consequently the precipitation. Different numerical weather forecasting models have demonstrated the high sensitivity of the predicted estimation of rainfall to soil moisture conditions (Betts, Ball, Beljaars, Miller, & Viterbo, 1996). Therefore, the ability of measuring soil surface characteristics on a large scale from space with a sufficient repetitiveness is an attractive challenge. Actually, during the last 3 decades, considerable efforts have been devoted to develop remote sensing techniques for characterising the spatial and temporal variability of soil moisture over large regions (Ulaby, Moore, & Fung, 1986) especially active and passive microwave techniques as well as interpretation tools (Jackson, Schmugge, & Engman, 1996).

Passive sensors measure the natural thermal emission of the land surface at microwave wavelengths using very sensitive radiometers. The remote-sensed signal depends on the soil dielectric properties and therefore on its water content. The poor spatial resolution of the existing instruments (of the order of hundred kilometers for the SSMI/platform, Paloscia, Macelloni, Santi, & Koike, 2001; Prigent, Rossov, Matthews, & Marticorena, 1999) prevent land applications but the future sensor SMOS (Soil Moisture and Ocean Salinity, Kerr et al., 2001), an L-band interferometric radiometer is a very promising tool for this purpose with a spatial resolution around 30 km.
Active sensors, particularly the Synthetic Aperture Radar (SAR) onboard the European Remote Sensing satellite (ERS), with a spatial resolution better than 50 m has been largely used in the last past years. The backscattered radar signal depends strongly on soil moisture and roughness for a bare soil (Ulaby et al., 1986). For sparse vegetation, the measured signal depends on the vegetation characteristics and on the soil backscattering signal attenuated by the vegetation layer (Prévot et al., 1993; Ulaby, Aslam, & Dobson, 1982). In the case of dense vegetation like forests, the soil contribution is generally very weak, particularly at high incidence angles (Fung, 1994; Ulaby et al., 1986). Many models have been developed to understand the physics of the interaction between the radar signal and the surface or the vegetation parameters (Fung, 1994; Ogilvy, 1991). For bare soils, the small perturbation model (SPM) for example, which is valid for smooth soil surfaces, and the Kirchoff approximation, valid for rough surfaces have been widely used. A further example is the IEM (Integral Equation Model) developed by Fung et al. (1992) which has been validated by different experimental studies (Rakotoarivony, Taconet, Vidal-Madjar, & Benallegue, 1996; Wu, Chen, Shi, & Fung, 2001). In parallel to these theoretical models, some empirical approaches have been developed (Dubois, Van Zyl, & Engman, 1995; Oh, Sarabandi, & Ulaby, 1992; Shi, Wang, Hsu, O’Neill, & Engmann, 1997; Zribi & Dechambre, 2002). Among them, the linear approach, linking soil surface moisture to radar signal, calibrated and validated with SAR (ERS, SIRC, RADARSAT, . . .) measurements is widely used (Cognard et al., 1995; Quesney et al., 2000).

Recently, some new studies (Frison & Mougin, 1996; Jarlan, Mougin, Frison, Mazzega, & Hiernaux, 2002; Magagi & Kerr, 1997; Wagner, Lemoine, Borgeaud, & Rott, 1999; Woodhouse & Hoekman, 2000) focus on another microwave captor, the ERS wind scatterometer, which was first designed to measure wind speed and direction over the sea surface. The instrument (Fig. 1) consists of three antennae producing three beams looking 45° forward, 45° sideways, and 45° backward with respect to the satellite’s orbit direction. The incidence angle θ varies over the instrument swath from 18° to 47° for the midbeam antenna and from 25° to 59° for the forebeam and aftbeam antennae, giving thus three measurements for each resolution cell. The sensor operates at 5.3 GHz and VV polarisation like the SAR instrument. Its spatial resolution is around 50 km, and measurements are available every 3–4 days. Because of its poor spatial resolution, this signal is difficult to interpret over land. Nevertheless, some methodologies have been proposed for estimating either the soil water content or the vegetation amount from WSC data analysis taking advantage of the multi-incidence capabilities and the high temporal resolution. In the different studies (e.g. Woodhouse & Hoekman, 2000), the estimation of soil moisture is based on a simple model with an incoherent combination of vegetation and bare soil contributions, weighted by their respective percentage within the scatterometer cell. The vegetation contribution is calculated using physical or empirical models (Magagi & Kerr, 2001). Our approach in this paper is similar, except that WSC signal inversion is done using additional SAR information. The SAR data are used to estimate the vegetation contribution in the WSC signal. In our regions of interest (agricultural areas integrating patches of forests and during winter months), the vegetation contribution comes down to the forested areas backscattered signal. This contribution may then be estimated from the keen analysis of the SAR high spatial resolution images and removed from the WSC signal in order to obtain the equivalent “non-forested areas” signal. In the case of agricultural lands, where the non-forested areas are mainly crop fields, this “non-forested areas” signal is related to soil features (soil roughness and moisture) during a large time period. To separate these two effects, we propose first to estimate surface roughness using two incidence angle WSC measurements. Therefore, the inversion can be performed on the only remaining unknown parameter, the soil moisture.

The paper is organised as follows. In Section 2, the proposed methodology to retrieve soil moisture is described. Section 3 presents the application over three agricultural watersheds: the watersheds under study and the database including satellite and ground truth measurements are first presented. Then, the results both in terms of forest signal modelling and soil moisture retrieval are shown. Finally, Section 4 gathers our conclusions.

2. Methodology

Under the assumption that the WSC backscattering signal is the result of the different target contributions included in the resolution cell, it can be decomposed in the sum of the forested areas contribution and the other areas input. Forested areas (as some other types of vegetation) induce a component of volume scattering while the different types of bare soils induce a component of surface scattering. Using the three antennas of WSC, only small azimuthal effects are observed.
over the tested sites in this paper (less than 0.5 dB). Therefore, as for other studies over continental surfaces (Frison & Mougin, 1996, Magagi & Kerr, 1997, Woodhouse & Hoekman, 2000, . . .), we do not consider the azimuthal angle as a main parameter in our approach. For different surfaces, the measured radar signal depends then on polarisation and incidence angle. In particular, soil contribution is more important at low incidence angles (which makes high incidence angles better designed for vegetation characterisation).

In this paper, we propose a simplified backscatter model adapted to the analysis of the WSC instrument measurement. Each cell is described as the mixture of the two land cover types:

- “Forest”;
- “Others” than forest, such as agricultural fields or bare soils.

These two contributions weighted by their respective cover fractions sum up incoherently to give the measured signal $\sigma^0(\theta)$:

$$\sigma^0(\theta) = C\sigma^0_{\text{forest}} + (1 - C)\sigma^0_{\text{others}} \quad (1)$$

where $\sigma^0_{\text{forest}}$ is the backscattering coefficient for forested areas, C the equivalent fractional forest cover, and $\sigma^0_{\text{others}}$ the backscattering coefficient of the non-forested areas. It will be shown in the following how the “forest” signal may be quantified from the SAR image interpretation and introduced in Eq. (1) to estimate the backscattered signal by the other surfaces.

2.1. Forest contribution modelling and removing

The backscattered signal over vegetation depends both on the viewing geometry and on the vegetation characteristics (total biomass, . . .). Then, over temperate forests mostly composed of deciduous trees, one can expect that the radar signal presents a seasonal variation and an incidence dependence. Therefore, a parameterisation of the forest signal has been searched based on the previous studies (e.g. Frison & Mougin, 1996; Kennett & Li, 1989) have shown an approximately linear relationship between the forest signal and the incidence angle. Following this modelling (validated further by the data analysis in Section 3.2.1), we write:

$$\langle \sigma^0_{\text{forest}}(\theta) \rangle = D\theta + E \quad (3)$$

where D and E are coefficients which have to be empirically determined.

Combining Eqs. (2) and (3), $\sigma^0_{\text{forest}}$ writes:

$$\sigma^0_{\text{forest}}(\theta, t) = D\theta + E + A\sin\left(\frac{2\pi}{12}t + B\right) \quad (4)$$

Now, from Eq. (1), we have:

$$\sigma^0_{\text{others}}(\theta) = \frac{(\sigma^0 - C\sigma^0_{\text{forest}}(\theta, t))}{1 - C} \quad (5)$$

Thus, if C (the cover fraction of forests) is known, the “non-forested areas” contribution $\sigma_{\text{others}}$ in the measured signal could be computed.

2.2. Soil roughness estimation

Different analytical and empirical models have been developed to understand the backscattering behaviour of soil surfaces. Bare soil backscattering signal depends on the two parameters: soil roughness and dielectric constant, this latter being linked to soil moisture. Now, different studies (Boisvert et al., 1997; Wegmuller, Matzler, & Schanda, 1989; Zribi & Dechambre, 2002) have shown that the difference $\Delta\sigma$ between signal measurements (in dB) taken at different incidence angles is essentially linked to soil roughness and depends only weakly on soil moisture. Fig. 2 shows simulations of $\Delta\sigma$ (with incidence angles, respectively, equal to 20° and 30°) for three different values of soil moisture: 10%, 20% and 30%, and three different cases of soil roughness. These simulations have been obtained from the IEM (Integral Equation Model, Fung et al., 1992, Appendix A). From Fig. 2, soil moisture effect appears
negligible in comparison with roughness effect on \( \Delta \sigma \). Therefore, we can write:

\[
s^0(\theta_1) - s^0(\theta_2) \approx f(\text{roughness})
\]  

(6)

For WSC data analysis, it means that the simultaneous measurements performed with two different incidence angles present a difference only dependent on soil roughness. In our case, the two different incidence angles correspond to the midbeam and forebeam antennae since the aftbeam acquisitions are often missing.

Then, IEM simulations of the backscattering coefficient have been performed for different kinds of surfaces presenting different root mean square (rms) heights (which is the key parameter for characterising soil roughness in IEM, cf. Appendix A), ranging from 0.3 to 1 cm for a constant water content. The results plotted in Fig. 3 clearly show that the different curves are very close for incidence angles around 15°. In comparison to what happens at high incidence angles, the slopes of the curves corresponding to different roughness show a large dynamic at low incidences. From these results, we use the slope of the curves at low incidence angles, as the differentiating parameter for roughness estimation: the higher the soil rms height, the lower the slope. Consequently, the different incidence angle WSC measurements may be used to estimate this slope parameter and to deduce the soil roughness class. Since, two incidence measurements performed with two different incidence angles present a difference only dependent on soil roughness, the soil moisture effect on the radar signal acquired over bare soil surfaces is approximately linear up to volumetric soil moisture values around 35–40%, and therefore can be written:

\[
s^0_{\text{db}} = \alpha M_v + \beta
\]  

(8)

where \( s^0_{\text{db}} \) is the radar cross-section in dB, \( M_v \) is the volumetric surface soil moisture, \( \alpha \) and \( \beta \) are empirical constants.

IEM simulations have been performed to analyse the links between soil moisture and \( s^0_{\text{db}} \) and to evaluate the chances to inverse the surface soil water content. Fig. 4 shows IEM simulations of the backscattering coefficient versus the surface soil moisture for different rms heights and in the configuration of the SAR instrument (VV polarisation, incidence angle of 23°). The results clearly state that the radar signal saturates quickly with \( M_v \) for values greater than 25%. For \( M_v \) values ranging from 5% to 20%, IEM simulations could be approximated linearly and the fitted slope is independent of the surface roughness. The slope value obtained (0.28) shows a very good agreement with (Quesney et al., 2000) the empirical results. The IEM ability to model radar sensitivity to surface soil moisture was checked for VV polarisation, and an incidence angle of 23° (ERS2/SAR features). The IEM model simulations were used to generalize this result and then to estimate the \((s^0_{\text{db}}, M_v)\) slope (i.e., the \( \alpha \) parameter in Eq. (8)) for different incidence angles. Then, we have:

\[
s^0_{\text{db}}(\theta) = \alpha(\theta) M_v + s^0_{\text{IEM},M_v=0} + b
\]  

(9)

where \( s^0_{\text{db}}(\theta) \) is the backscattering value for a dielectric surface, \( M_v \), the soil moisture, \( \alpha(\theta) \) is deduced from the IEM

![Fig. 3. IEM simulations of backscattering coefficient versus incidence angle, for rms height ranging from 0.3 to 1 cm, and \( M_v = 10\% \).](image)

![Fig. 4. IEM simulations of backscattering coefficient versus surface soil moisture for different rms heights (VV polarisation, 23°).](image)
IEM, \( M_{v0} \) is the IEM backscattering simulation value for a given soil moisture \( M_{v} \) and the considered roughness parameter (estimated as explained in Section 2.2), and \( b \) is a constant used to fit IEM model with real measurements. In our study, based on empirical studies made on our experimental sites (Quesney et al., 2000, Le Hégarat et al., 2002), we take \( M_{v0} = 10\% \) and \( b = -9.6 \text{ dB} \).

In summary, having estimated soil roughness from \( n \) couples of measurements, we can get \( \sigma^{0}_{\text{IEM}, M_{v0}} \) from the IEM model. Then, inverting Eq. (9), we can retrieve the \( M_{v} \) values corresponding to each couple of measurements performed at the different incidence angles. The methodology is summed up in Fig. 5.

### 3. Application and results

#### 3.1. Studied areas and database

##### 3.1.1. Studied areas

The methodology was applied over three different French watersheds for which ERS/SAR, WSC, and ground-truth data were available: the Grand Morin, the Serein, and the Petit Morin. They are all sub-basins of the Seine river’s catchment (cf. Fig. 6). The Petit Morin basin borders the Grand Morin. The Serein watershed is located southern.

These three basins are agricultural areas including forests and grassland areas (mainly pasture lands). Table 1 (Le Hégarat-Mascle, Zribi, Alem, Weisse, & Loumagne, 2002) gives the main features of these three watersheds: size, soil type, and land cover percentages. The crop percentages may slightly vary from one year to the next because of the crop rotation cycles practised in these agricultural regions. We note that, in the case of these three watersheds, the forested areas amount to nearly 30% of the whole area. Soil composition is about the same for the Grand Morin and the Petit

![Fig. 5. Summary of the soil moisture inversion algorithm.](image1)

![Fig. 6. Location of the studied watersheds: Grand Morin, Petit Morin, and Serein.](image2)

<table>
<thead>
<tr>
<th>Watershed</th>
<th>Grand Morin</th>
<th>Serein</th>
<th>Petit Morin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (km²)</td>
<td>1190</td>
<td>1120</td>
<td>605</td>
</tr>
<tr>
<td>Soil texture (%)</td>
<td>rough: 1</td>
<td>rough: 18</td>
<td>rough: 1</td>
</tr>
<tr>
<td></td>
<td>medium: 36</td>
<td>medium: 9</td>
<td>medium: 43</td>
</tr>
<tr>
<td></td>
<td>medium-fine: 59</td>
<td>medium-fine: 53</td>
<td>medium-fine: 41</td>
</tr>
<tr>
<td></td>
<td>fine: 4</td>
<td>fine: 20</td>
<td>fine: 11</td>
</tr>
<tr>
<td></td>
<td>depositing: 12</td>
<td>depositing: 3</td>
<td>depositing: 19</td>
</tr>
<tr>
<td></td>
<td>carbonate and dolomite: 26</td>
<td>carbonate and dolomite: 41</td>
<td>carbonate and dolomite: 45</td>
</tr>
<tr>
<td></td>
<td>sandy rocks and detrital: 1</td>
<td>sandy rocks and detrital: 0</td>
<td>sandy rocks and detrital: 1</td>
</tr>
<tr>
<td></td>
<td>silty rocks: 57</td>
<td>silty rocks: 0</td>
<td>silty rocks: 31</td>
</tr>
<tr>
<td></td>
<td>crystalline and volcanic: 0</td>
<td>crystalline and volcanic: 27</td>
<td>crystalline and volcanic: 4</td>
</tr>
<tr>
<td></td>
<td>marl and clayey rocks: 4</td>
<td>marl and clayey rocks: 29</td>
<td>marl and clayey rocks: 0</td>
</tr>
<tr>
<td>Main kinds of vegetation (%)</td>
<td>forest: 27</td>
<td>forest: 26</td>
<td>forest: 28</td>
</tr>
<tr>
<td></td>
<td>wheat: ( \approx 35 )</td>
<td>grassland: ( \approx 28 )</td>
<td>wheat: ( \approx 25 )</td>
</tr>
<tr>
<td></td>
<td>peas: ( 9 \pm 2 )</td>
<td>wheat: ( 11 \pm 2 )</td>
<td>peas: ( 9 \pm 2 )</td>
</tr>
<tr>
<td></td>
<td>colza: ( 5 \pm 2 )</td>
<td>colza: ( 11 \pm 2 )</td>
<td>colza: ( 9 \pm 2 )</td>
</tr>
<tr>
<td></td>
<td>corn: ( 7 \pm 2 )</td>
<td>barley: ( 6 \pm 2 )</td>
<td>corn: ( 4 \pm 2 )</td>
</tr>
<tr>
<td></td>
<td>barley: ( 5 \pm 2 )</td>
<td>barley: ( 5 \pm 2 )</td>
<td>barley: ( 5 \pm 2 )</td>
</tr>
</tbody>
</table>
Fig. 7. SAR image compositions of the three studied watersheds: (a) Grand Morin, (b) Petit Morin, and (c) Serein.
Morin, but it is different in the case of the Serein watershed. It may also be noted that these watersheds are rather flat areas: over the Grand Morin, 96% of the watershed has a zero to small slope (<8%); over the Serein, 69% of the watershed has a zero to small slope, 14% a small slope (<15%) and 17% a rather large slope (<25%); and for the Petit Morin, 100% of the watershed has a zero to small slope. In the case of the Serein, the area where the slope is greater than 8% is covered by forests.

3.1.2. Database

The data used in this study have been acquired during three vegetation cycles (from 1999 to 2001). We remind that in the case of North European agricultural sites, the agricultural year lasts from November (beginning of soil works in particular for winter crops) to October of the following year (end of harvest).

On the one hand, ERS/WSC data from ERS2 mission from January 1996 to 2001 were analysed. The ERS/WSC main features have already been recalled in Section 1. On the other hand, ERS2/SAR images were used to estimate the forest backscattering signal. The ERS/SAR main features have already been recalled in Section 1. On the one hand, ERS2/SAR images were used to estimate the forest backscattering signal. The ERS/SAR main features have already been recalled in Section 1.

3.2. Results

3.2.1. Signal over forested areas

From SAR series classification, the temporal evolution of the radar signal for each class was retrieved, and particularly for the forest one. This latter class is the most stable along the year: it presents only weak amplitude fluctuation around a mid value. Fig. 8 illustrates the temporal variation of the forest class from 01/1999 to 01/2001, for the Grand Morin and Petit Morin watersheds. The cyclic evolution of the SAR signal is clearly shown and confirmed the assumptions made in Section 2. The maximum value is observed in winter (December or January) and the lowest value is reached around July. Indeed, during winter, the soil component in the backscattered signal (due to leaves, needles, branches, trunks and soil) is significant, and the backscattering signal increases with soil moisture. On the opposite, during the vegetative period (particularly in summer), the influence of the soil surface is negligible and the volume scattering is the dominant mechanism contributing to the backscattering coefficient. From these results, it is possible to fit the annual variations of the backscattering coefficient over forested areas by a sinusoidal function as proposed in Section 2.1.

Fig. 8 illustrates the comparison between the observed SAR and the fitted model given by Eq. (10). For the three studied watersheds, the mean forest signal ($\sigma^0_{\text{forest}}$) has approximately the same level: around $-6.75$ dB. Since the maximum is reached in December, the time offset Eq. (2) may be set to $\pi/2$. Finally, from the results presented in Fig. 8, the amplitude is taken equal to 1 dB. Therefore, in our case Eq. (2) writes:

$$
\sigma^0_{\text{forest}}(t) = -6.75 + \sin[2\pi/12(t + 3)] 
$$

(10)

This model is valid at the SAR incidence, i.e. around $23^\circ$. To generalize this model at other incidences, the coefficients $D$ and $E$ of Eq. (3) have to be determined. For this purpose, only the WSC cells which have a percentage of forest larger than 65%, calculated from CORINE land cover database are considered. In Fig. 9, the WSC/ERS radar signal measure-
ments are plotted against the incidence angle, for the 3 years of data. The area considered for these measurements is the Eastern part of France (about 8° in latitude and 6° in longitude). The linear approximation of this data set is:

\[
\sigma_0^{\text{forest}}(\theta) = \frac{-0.1069 \times \theta - 5.0178}{C_0}
\]

giving a correlation coefficient \(R^2\) equal to 0.81 and a rms value equal to 0.55. We also note the rather small signal dynamics at fixed incidence angle: about 2 dB.

Using Eqs. (5) and (12), the forest contribution in the measured WSC signal can be removed. Remaining contribution corresponds to all other land uses and particularly bare soils. Fig. 10a and b show the “non-forested areas” WSC signal for two periods: (a) December–January and (b) May–June. In the case of the winter period, we clearly observe the very weak value of the slope, due to the fact that scattering is mainly vegetation (dense at this period) volume scattering. In the case of the summer period, the effect of the soil surface is more significant as we have successfully remove the forest contribution. It seems to be the case since the signal dynamic at a given incidence angle has increased (now equal to 6 dB instead of the previous 2 dB of Fig. 9), as well as the slope for small incidence angles, due to the high decrease of the coherent part in rough surface backscattering.

### 3.2.2. Soil moisture retrieval

For the considered sites, like for most of Northern Europe watersheds, from August to February, most of the
non-forested areas are agricultural fields either at bare soil state or with very sparse vegetation. During March–April months, sparse vegetation appears and May–July months correspond to the dense vegetation period. During this last period, it is not possible to retrieve soil moisture. Here, the retrieval of surface soil moisture was only performed during the August–February period.

In the case of the studied watersheds, urban, industrial, and similar areas as well as open water areas are quasi-absent (less than 2.5%). Therefore, between August and February, the “non-forested areas” signal is assumed to only correspond to backscattering over sparse vegetation or bare soil.

Vegetation models (Ulaby et al., 1986) have shown that, in the case of very sparse vegetation (optical thickness lower...
than 0.1) and in a first approximation, the backscattering signal at low incidence angles only depends on bare soil features. Inversely to the contribution from vegetation, which is fairly stable with the incidence angle, the bare soil backscattering coefficient decreases rapidly with the incidence angle. To ensure both that the considered signal is principally dependent on soil moisture and not on vegetation features, and a high dependence of the backscattering slope function with the incidence angle, only the low incidence angles are kept in the soil moisture inversion process. Then, the WSC measurements at incidence angles lower than 30° were kept and the methodology described in Section 3.2.2 was applied.

Fig. 11 shows the soil moisture retrievals in the cases of the Grand Morin and the Petit Morin watersheds during August–February periods and the 3 years studied (1996–1998). Soil moisture estimations are compared with ground truth data acquired by TDR measurements. Each watershed is covered by different WSC cells (eight in the case of the Grand Morin and four in the case of the Petit Morin). At a given date, the plotted soil moisture estimations correspond to the different estimations obtained on each of these cells. The ground-truth TDR data are also represented on the graph. Fig. 11 clearly shows the good performance of the proposed method on the retrieval of soil moisture during winter months. The correlation coefficients $R^2$ are greater than 0.8 and rms errors are lower than 3.5% for the two watersheds. We also observe a bi-modal structure of our database: high (>30%) and low soil moistures (around 20%). Since it could increase the computed correlation coefficient (but does not affect the rms error), it may be interesting to valid our approach also on some data sets showing more uniformly distributed soil moistures.

Finally, Fig. 12 shows, for the 3-year time period and the Grand-Morin and Serein watersheds, the time variation of the soil moisture retrievals compared to ground truth measurements. A small discrepancy (generally lower than 5%) may be observed between volumetric soil moisture measurements performed with TDR probes and gravimetric ones. It is probably mainly due to the fact that TDR are very local measurements whereas gravimetric ones are averaged over the watershed, and/or to a small error in the estimation of the bulk soil density. Fig. 12 shows that the annual cycle of soil moisture is quite well retrieved by ERS data: high moisture level for winter rainy period (November–February) and a lower level for dry period (end of Summer). However, for some dates (day 699 for example), a large difference between measurements and estimations (about 10%) is observed. This is probably due to WSC/ERS calibration, since it is observed for all the tested cells. The data are also compared to rainfall observations: high soil moistures are associated to rainfall events, and the dry periods correspond to a decrease in soil moisture. Unfortunately, the selection of incidence angles lower than 30° limits the number of measurements (approximately two measurements per month remain).

For the Serein watershed, since no daily TDR measurements are available, the comparison is done with the gravimetric measurements for some dates. Consequently, the conclusions for this site are only qualitative.

4. Conclusion

This paper presents a methodology to monitor soil moisture at large scale over sparse vegetation or bare soils areas, based on the synergistic use of the two active microwave instruments of the ERS satellites (the wind scatterometer and the SAR). The WSC signal is represented as the incoherent sum of backscattered signals by different patches of land uses. Over agricultural areas, the two main land uses, which can be distinguished, are forests and agricultural lands. The two contributions may be weighted by their respective fractional cover. More specifically, for the period of August–February, agricultural lands are mostly composed of bare soils or sparse vegetation covers such as wheat fields before raising, but not permanent grassland areas which are generally too dense. Therefore, we consider that the radar WSC signal is an incoherent sum of forest and bare soil effects. Thanks to the high resolution SAR imagery, the forest signal evolution can be retrieved for 2 years over the studied region. A cyclic behaviour is observed, and the forest signal is modelled as a function of time and incidence angle. The fraction of forest within each WSC cell has been known from classification imagery interpretation and the backscattered signal over bare soils can be retrieved. IEM model is used to model the behaviour of backscattering over bare soil. It is shown that the difference between radar simulations acquired simultaneously with two different incidence angles are quasi-independent of soil moisture. Therefore, we propose to use measurements acquired with midbeam and forebeam antennae to estimate roughness parameters. Then, soil moisture is retrieved using a semi-empirical backscattering relationship (linear approximation based on the IEM). Retrieved soil moistures for different cell measurements over the studied watersheds are compared with experimental data. They show a good agreement with correlation coefficients $R^2$ greater than 0.8 and root mean square errors lower than 3.5%. Among the restrictions, we must note that the method described here is specifically developed for agricultural regions principally composed of forests and cultivated areas. Future studies are carried out to generalize this approach for other regions concerned by other types of forests or a higher percentage of grassland areas.

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Appendix A

IEM (Fung et al., 1992) is based on analytical solutions of the integral equations for tangential surface fields on a dielectric interface. The model can be applied for different types of soil surfaces. In IEM, the soil roughness is characterised by two parameters: the root mean square (rms) height, and the correlation length.

For the wave numbers, surface rms heights and surface correlation lengths within the domain validity of the model (small and moderate roughness surfaces), the backscattering coefficient $\sigma_0$ can be written:

$$\sigma_0^{pp} = \frac{k^2}{2} \exp\left[-\frac{k^2s^2}{4}\right] \sum_{n=1}^{\infty} \frac{2n^{2n} \Gamma(2n) \Gamma(2n)}{n!} \cdot n! \cdot \frac{P(n,-2k_0,0)}{P(n,0,0)} \cdot \rho = h, v$$

Where $k_x = k \cos \theta_i$, $k_z = k \sin \theta_i$, $\theta_i$ is the incident angle, $k$ the wave number, and $s$ the rms height of surface. $P_{pp}$ is a function of the incidence angle, soil dielectric constant, $s$, and the Fresnel reflection coefficient. $W^{(n)}(-2k_0,0)$ is the Fourier transform of the $n$th power of the surface correlation function.

This IEM version (Wu et al., 2001) introduces the transversal function in which the Fresnel reflection coefficient $R_p(T)$ is not evaluated for an incidence angle $\theta_i$, but for an angle ranging from $\theta_i$ to the normal incidence. It writes:

$$R_p(T) = R_p(\theta_i) + lR_p(\theta_{sp}) - R_p(\theta_i)\gamma_p^{sp} \cdot \rho = h, v$$

where $R_p(\theta_i)$ is the Fresnel reflection coefficient calculated at the incidence angle, $R_p(\theta_{sp})$ is the Fresnel reflection coefficient calculated at the specular angle and $\gamma_p$ is a transition function dependent on polarisation, incidence angle, and surface parameters.

The IEM input parameters are the dielectric constant derived from the surface volumetric moisture content and the soil texture (Hallikainen, Ulaby, Dobson, El-Rayes, & Wu, 1985), and the correlation function of surface heights, or its corresponding spectrum. In the case of agricultural soil studies, an exponential correlation function generally gives a good fit with the majority of experimental surfaces.

References


Giordano, A., et al. (1990). CORINE soil erosion risk and important land resources. Publication of the European Communities, 12323, EN.


