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New methodology for soil surface moisture estimation and its application to ENVISAT-ASAR multi-incidence data inversion

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Abstract

This paper presents an original methodology to retrieve surface soil moisture based on the use of the ENVISAT-ASAR multi-incidence angle sensor. Previous studies using ERS and RADARSAT SAR have shown the potential of radar signals to monitor surface soil moisture with one incidence-angle data and a simple linear relationship. This work aims at developing this linear approach to estimate mean soil surface moisture of a small watershed using ASAR multi-incidence angle data.

A method of normalisation of all radar data acquired at different incidence angles is first described. Secondly, the effects of roughness and soil texture on the linear relationship between moisture and radar signals are discussed. Finally, the proposed methodology to reduce these effects is developed. The validation of our approach is based on eight experimental campaigns with different ASAR incidence angles, and different surface moisture conditions. The processed radar signal shows a linear relationship with the mean measured soil surface moisture, with very high correlation ($R^2=0.97$) and a slope of 0.28. These results illustrate the high potential of the developed approach and ENVISAT-ASAR to monitor surface moisture.

Keywords: Radar; ENVISAT-ASAR; Soil moisture; Inversion; Backscattering

1. Introduction

Surface soil moisture plays a crucial role on the continental water cycle, specifically on the partition of precipitation between surface runoff and infiltration (Beven & Fisher, 1996; De Roo et al., 1996) and in partitioning the incoming radiation between latent and sensible heat fluxes. Therefore, the ability to measure soil surface characteristics on a large scale from space with sufficient repetitiveness is an attractive challenge.

Different studies based on remote sensing have been realised in recent years in order to retrieve and monitor this parameter from satellite measurements (Jackson et al., 1996; Le Hégarat-Mascle et al., 2002; Quesney et al., 2000; Ulaby et al., 1986). Surface soil moisture can be derived by using either passive or active remote sensing instruments. In the passive microwave domain, different studies have shown the potential of low frequencies for the restitution of surface moisture (Bindlish et al., 2001; Jackson & Hsu, 2001; Paloscia et al., 2001). The future Soil Moisture and Ocean Salinity (SMOS) sensor will propose an operational global restitution of surface moisture (Kerr et al., 2001). However, these sensors have a very small resolution (about 50 km) better adapted to climatic than to hydrological or regional studies.

In the active microwave domain, the measured signal over bare soil depends on two parameters: soil moisture, which is directly linked to the dielectric constant, and surface roughness (Ulaby et al., 1986). Several forward and inversion studies have been made in recent years. First, different theoretical and analytical backscattering models have been developed (e.g. Small Perturbation model, Integral Equation Model (IEM), etc., Fung et al., 1992; Ulaby et al., 1986). Other semi-empirical and

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empirical models (Baghdadi et al., 2002; Dubois et al., 1995; Oh et al., 1992; Shi et al., 1997; Zribi & Dechambre, 2002) propose a simultaneous estimation of roughness and moisture. They are based on multi-configuration data (multi-polarisations, or multi-incidence angles). These models are well adapted to the retrieval of surface moisture of agricultural fields. However, it is difficult to generalize them to different soils.

Secondly, many experimental studies have tried to estimate only surface moisture by using different hypotheses in addition to surface roughness. Ulaby et al. (1986) proposed a linear relationship between surface moisture and radar signals. This approach was validated with a large number of experimental studies (Cognard et al., 1995; Le Hégarat-Mascle et al., 2002; Quesney et al., 2000; Wang et al., 1997; Zribi & Dechambre, 2002). This is generally considered as a reliable approximation for a studied site, where we can assume that the mean surface roughness is approximately unchanged between successive radar measurements. However, the coefficients describing the linear relationship are often different from one watershed to another and also from one year to the next and need to be calibrated. For example, with ERS/SAR data, the slope is 0.33 for Le Hégarat-Mascle et al., 2002, 0.28 for Quesney et al. (2000), 0.42 for Taconet et al. (1996), 0.55 for Weimann et al. (1998).... For this reason, it is still very difficult to use this relationship for radar signal inversion without a time-consuming calibration work.

This paper proposes to analyse and to improve the robustness of the coefficients characterising the linear relationship between soil moisture and radar signal.

The previously mentioned experimental studies are based on one-incidence angle radar measurements (particularly with ERS/SAR). The problem with such data lies in its measurement time repeat: 35 days. This seems insufficient in comparison with the needs of hydrologic studies. The new ENVISAT-ASAR radar (Rosich, 2002) is a multi-mode sensor. It operates in C band (5.3 GHz) at several polarisations, incidence angles and spatial resolution configurations. The angular diversity, which is the case also of RADARSAT, allows for high repetition measurements with few days between two successive observations of the same site at two different incidence angles. Here, the surface moisture is estimated using ASAR radar data by a multi-incidence angle data normalisation.

This paper is organised as follows. In Section 2, the methodology proposed to retrieve soil moisture from different incidence angle radar data is described: An analysis of radar signals as a function of roughness, moisture and incidence angle is proposed. Then, an approach for normalising the radar signal acquired at different incidence angles is presented. A discussion of the effects of roughness and texture on the linear relationship between soil moisture and radar signals follows. A new methodology reinforcing the robustness of the soil moisture inversion process is then proposed. Section 3 describes the results obtained using experimental data acquired over the Villamblain test site in the Beauce region (near Paris, France). Finally, Section 4 gathers our conclusions.

2. Methodology

This section presents the strategy for soil moisture estimation from ASAR multi-incidence data. As mentioned in the Introduction, until nowadays, the inversion of radar signal was based for a large number of studies on a simple linear relationship between the mean signal at one incidence angle (σ_0) and the mean soil surface volumetric moisture (W_s):

$$\sigma_0(\mathrm{dB}) = a \cdot W_s(\%) + b \tag{1}$$

where the a and b coefficients depend on incidence angle, roughness and polarisation. In our case, ASAR data correspond to different incidence angles. Therefore, applying the relationship (1) is not possible without normalising measurements corresponding to different angles.

In the second part of this section, the reasons for the variation of the a, b coefficients from one site to the next are then analysed and a new approach to make the method more stable is proposed.

As the radar data set of our experimental campaigns is limited to HH polarisation radar data, this study will only pertain to this polarisation.

2.1. Methodology for incidence angle normalisation

The normalisation of radar data acquired at different incidence angles requires an in-depth understanding of roughness and moisture effects on backscattering as a function of incidence angle. Therefore, the first step proposed in this section, before the normalisation methodology, is to analyse the behaviour of the backscattering coefficient using different theoretical simulations.

We use an exact numerical backscattering model based on the moment method (Chen et al., 1989). This model has been validated with different experimental SAR measurements and different types of roughness (Zribi et al., 2005). The simulations are made using generated surfaces with predefined surface roughness parameters (root mean square height (s), correlation length (l), correlation function shape) and different surface moistures.

2.1.1. Effects of incidence angle, soil roughness and moisture on radar signal

Different simulations have been made with different surface conditions to analyse the effects of roughness and moisture on the radar signal. First, Fig. 1 illustrates the model simulations at an incidence angle of 40° with five different rms height values ranging from s = 0.5 cm to s = 2.5 cm.

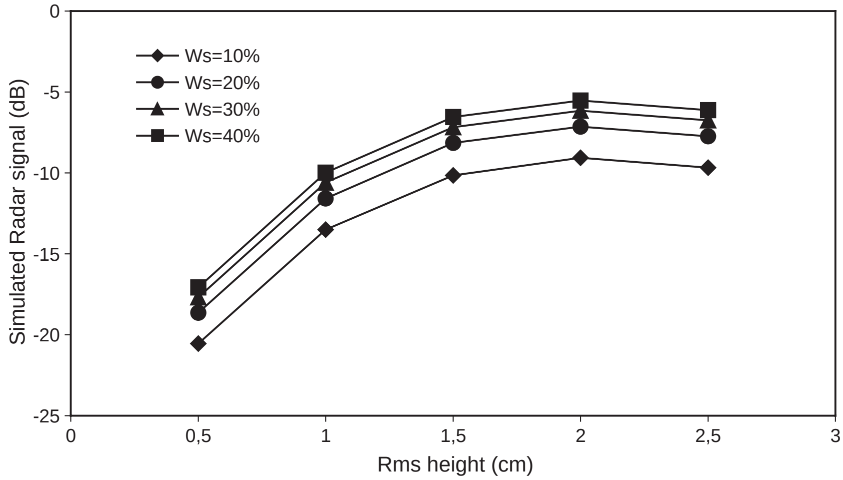

Fig. 1. Illustration of the effect of soil moisture and roughness on radar signal simulations at 40° incidence angle.

Based on (Zribi et al., 2005), the correlation function is written as:

$$\rho(x) = s^2 \exp(-(x/1)^{\alpha}) \tag{2}$$

where

$$\alpha = 0.84\log(s) + 0.96 \tag{3}$$

and x is the horizontal distance between two points.

In order to simplify the analysis of the correlations between roughness and moisture effects on the radar signal, we choose to fix the correlation length to one value (l=9 cm). In spite of the importance of this parameter on the backscattering signal, it shows a large variation even on a single homogenous agricultural field (Oh & Kay, 1998). Taking only one value for the correlation length has no effect on our conclusions in this section. The 40° incidence angle is chosen as the reference incidence angle for data normalisation in the next sections.

For rms heights greater than 2 cm, simulations show an approximate saturation of the radar signal. On the first hand, we note that the effect of moisture is approximately independent of roughness values. For example, between W_s=10% and 20%, the backscattering difference is 2 dB with s=0.5 cm and 1.95 dB with s=2 cm. On the other hand, the effect of roughness on the radar signal is also approximately independent of the surface moisture effect. For example, the difference between the backscattering signal at s=0.5 cm and the backscattering signal at s=2 cm is 11.5 dB for W_s=10%, 11.55 dB for W_s=20%, 11.53 dB for W_s=30% and 11.52 dB for W_s=40%. Based on these results, we consider, as a first approximation, that roughness and moisture are separable variables and that the radar signal is a product of the separate contributions of roughness and moisture (or dielectric conditions):

$$\sigma_0 = f(W_s, \theta) \cdot g(R, \theta) \tag{4}$$

or in logarithmic scale:

$$\sigma_0(\mathrm{dB}) = 10\log[f(W_s, \theta)] + 10\log[g(R, \theta)] \tag{5}$$

where θ is the incidence angle and R the roughness.

Fig. 2 shows $\Delta\sigma_0$ simulations between 23°and 40° for three different values of soil moisture and different roughness parameters. The soil moisture effect on $\Delta\sigma_0$ appears to be negligible in comparison with the roughness effect. This observation has been made in different experimental studies (Zribi & Dechambre, 2002; Srivastava et al., 2003).

Therefore, the normalisation of the radar signal relative to the incidence angles a priori only requires surface roughness knowledge. The radar signal at any incidence angle can be deduced from the radar signal measured at one incidence angle and under the same roughness conditions, using a numerical backscattering model simulation. Thus, as a first step of signal normalisation, we build a library of simulations with a large range of surface roughness conditions and incidence angles. This library will be the tool for actual data correction as a function of incidence angle variations. As a second step, we identify the distribution of roughness in the studied site.

2.1.2. Library realisation

The objective here is to build a library corresponding to a large range of roughness parameters. The rms height ranges from 0.5 to 2 cm. For s>2 cm, the radar signal is considered to be nearly saturated. For each case, we consider the correlation function shape computed directly from the rms height by applying relationship (3). Three values of the correlation length are considered, which represent a large variation interval (l=3 cm, l=6 cm and l=9 cm). Using the approach described by Fung and Chen (1985), different surfaces characterised by these parameters were simulated. The backscattering coefficients were simulated for each surface roughness as illustrated in Fig. 3. They have been performed assuming constant volumetric moisture: 30%. Backscattering values cover a large dynamic interval.

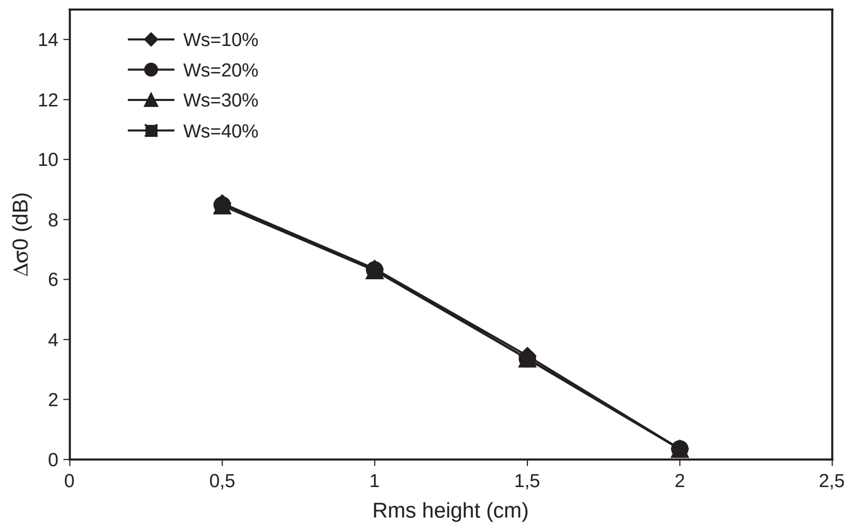

Fig. 2. Illustration of radar signal difference between two incidence angles (23° and 40°) as a function of roughness for different moisture values.

2.1.3. Description of the spatial variation of the radar signal due to roughness

In Section 2.1.1, we have seen the key role of roughness in the variation of the radar signal versus incidence angle. Assuming a small spatial variation of surface moisture, the radar signal variations at the studied scale over bare soil are mainly due to speckle noise and surface roughness. In order to validate this hypothesis, we consider two cases of IEM simulations, a first one with a constant surface moisture and a variation of surface roughness over 100 different fields in the studied site, which follow, for example, a Gaussian distribution for the rms height (s between 0.5 and 2.5 cm with $l=9$ cm), a second case with the same roughness variations for 100 different fields but with a variation of surface moisture, which follows, for example, a Gaussian distribution with the same mean value as the first case. The variations of surface moisture are taken to be larger than the maximum observed in our studied site for the different dates between the means of test field measurements. Table 1 illustrates the mean value and the standard deviation of the radar signal distribution in the different studied cases. It clearly appears that the effect of soil moisture variation is negligible on radar distribution characteristics and that the hypothesis made in this section is valid for a moderate variation of surface moisture. However, it is important to note that our studies mainly concern flat sites. For large topographical variations, moisture variations could be larger and our hypothesis could be invalidated.

In order to remove the effect of speckle from spatial variations in the radar signal, the mean radar signal is considered for each agricultural bare field (assuming homogenous roughness). Using the size and mean signal for all selected fields, the radar signal probability density function is retrieved. The radar distribution corresponds only to surface roughness variations.

Each roughness produces one radar signal value. In our case, we correspond from the minimum (σmin) up to the maximum (σmax) values of radar signal distribution, each 1 dB step to one roughness.

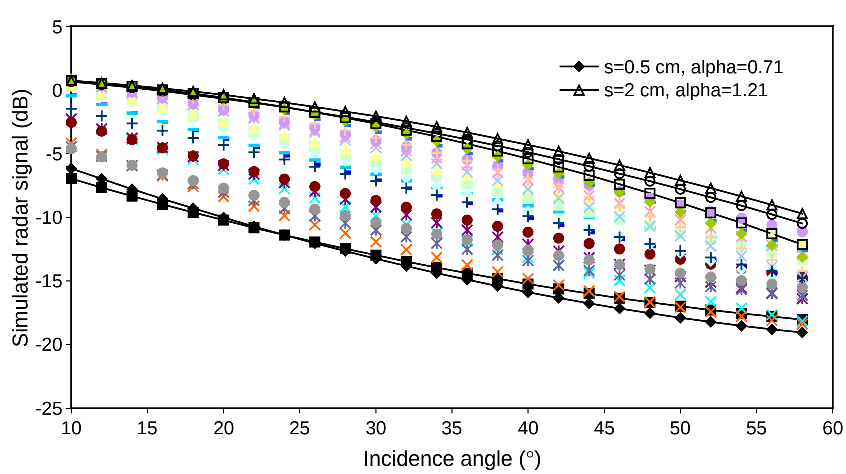

Fig. 3. Illustration of library simulations of the backscattering coefficient for wide ranges of surface roughness parameters (rms height, α parameter) and incidence angles.

Table 1
Discussion of moisture variation effects on radar signal distribution over a studied site

	Mean (Mv)=10% and std=0	Mean (Mv)=20% and std=0	Mean (Mv)=30% and std=0
Radar signal mean value (dB)	−14.59	−12.54	−11.84
Standard deviation of variations "std" (dB)	2.41	2.34	2.87
	Mean (Mv)=10% and std=3 vol.%	Mean (Mv)=20% and std=4 vol.%	Mean (Mv)=30% and std=5 vol.%
Radar signal mean value (dB)	−14.5	−12.78	−11.61
Standard deviation of variations "std" (dB)	2.6	2.7	2.6

2.1.4. Confrontation of measured data with library simulations and incidence angle correction

Radar signal distribution retrieved in Section 2.1.3 is confronted to the library of radar simulations covering a large range of roughness and incidence angles.

For a studied agricultural site (several square kilometer in size), different types of surface roughness from smooth to rough surfaces (as observed during experimental campaigns in agricultural regions) are generally present. With the crop rotation practiced in agricultural regions in Europe (wheat, corn, colza, etc. . . .), during the yearly cycle, we can observe smooth surfaces after sowing ($s \sim 0.5$ cm), and ploughed soils for future cultivations ($s > 2$ cm).

Considering a roughness interval ranging from about 0.5 cm to a large roughness (2 cm or more) as realistic, we can assume that the central values $\sigma_c^0 = \frac{\sigma\min + \sigma\max}{2}$ in the radar signal distribution and in library simulations correspond, as illustrated in Fig. 4, to $s \sim 0.85$ cm.

Therefore, as illustrated in Fig. 5, we first translate the radar signal distribution in order to make it centred using the library simulations. The offset added for this translation will be subtracted after normalisation. It is due to the difference in surface moisture between data and library simulations. Then, for each 1 dB step (corresponding to one roughness value) for example, the radar signal, from minimum to maximum values in the radar distribution, is normalised to the reference incidence angle (40°) by using the closest numerical simulation in the library simulations.

After the last operation, the new radar signal distribution at the reference angle θ_n (=40°) is retrieved. We consider the found radar values as the signals corrected for the incidence angle effect but with the same roughness and moisture features.

2.2. Methodology to reduce variations in the a, b coefficients

Once the normalisation of radar data acquired at various incidence angles has been performed, our objective in this section is to propose an approach for minimising the large variations observed in the a and b coefficients.

Three parameters could be important in the variation of the a, b coefficients: the scale of the studied site, soil roughness and soil texture.

In this study, the question of spatial scale effect will not be investigated in great detail. However, it can be noted that the spatial scale used to apply the linear relationship between mean radar signal and mean surface moisture is very important. At the field scale, it is not possible to neglect the effects of surface roughness variation over a long time period. The hypothesis often made that the surface roughness does not vary in time is inadequate for this scale, and if used, leads to large variations in a and b coefficients. Nevertheless, a very large scale could induce large errors in the surface moisture retrieved because of large heterogeneities (moisture, roughness, vegetation, topography, . . .). Empirically, it may be assumed that a scale of a few square

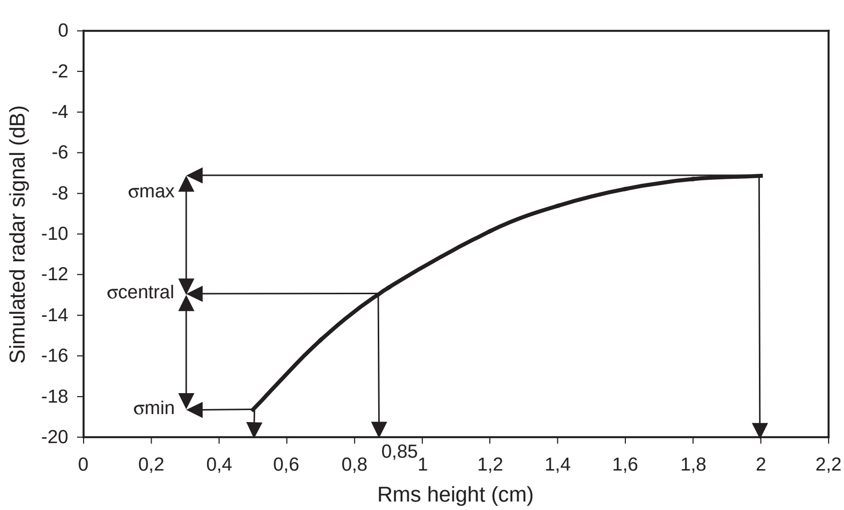

Fig. 4. Illustration of the central value of simulations for roughness ranging from 0.5 to 2 cm (or more).

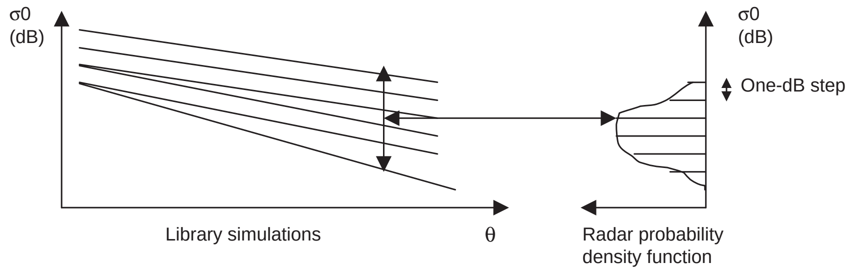

Fig. 5. Illustration of the confrontation between library simulations and measured radar distribution.

kilometers is relevant for this application. This scale is well suited to hydrological or risk studies.

The first step of this study is to identify the effects of roughness and soil texture through different simulations.

2.2.1. Effects of roughness on the a, b coefficients

In order to understand the effect of surface roughness on the *a* and *b* coefficients, different case studies based on IEM simulations will be shown illustratively. We first consider the monitoring of surface moisture over one site at four dates corresponding to the successive surface moistures ($W_{s1}=10\%$, $W_{s2}=15\%$, $W_{s3}=20\%$ and $W_{s4}=25\%$). The restriction to 25% is due to two reasons: the first one being that saturation is not reached at this value of surface moisture. The second reason is that IEM simulations show saturation behaviour before the actual radar signals. Therefore, in order to avoid other effects on the linear relationship behaviour, it was decided to restrict simulations to this maximum value. We then assume four roughness distribution cases (d_1, d_2, d_3, d_4) as illustrated in Fig. 6. These different cases can be observed in actual agricultural sites. We assume, for each date, a roughness distribution chosen from the 4 presented distributions. We consider the different possibilities of mixing one roughness distribution with one moisture value (d_i, W_{sj}, $i=1, \ldots, 4$, $j=1, \ldots, 4$) on the four dates. For each roughness distribution, 100 rms heights are generated using a Monte Carlo approach (Nougier, 1987). We compute for each combination (d_i, W_{sj}, $i=1$, ...4, $j=1$, ...4) the mean backscattering coefficient value corresponding to the different rms heights. Linear relationships between moistures and IEM mean simulations are retrieved for all possible cases. Coefficients *a* and *b* are calculated for the 256 (4^4) cases. The values of coefficients *a* and *b* show a large variability, as illustrated in Fig. 7, with a mean value of coefficient *a* of 0.16 and a standard deviation of 0.09 (56%). For coefficient *b*, the mean value is −16.5 dB with a standard deviation of 1.65 dB. In conclusion, roughness effects may explain an important part of *a*, *b* variation observed in different experimental studies.

2.2.2. Effect of soil texture on the a, b coefficients

Saturation moisture W_{sat} depends on soil texture. For sandy soil, $30\% < W_{sat} < 45\%$; for loamy soil, $40\% < W_{sat} < 60\%$; and for clayey soil, $30\% < W_{sat} < 65\%$ (Musy & Soutter, 1991). The radar signal reaches approximately its maximum value at saturation. Let us consider now moisture values smaller than W_{sat}. Four dates with the successive volumetric moistures (10%, 15%, 20% and 25%) and one distribution of soil roughness (d_1) are considered. As noted

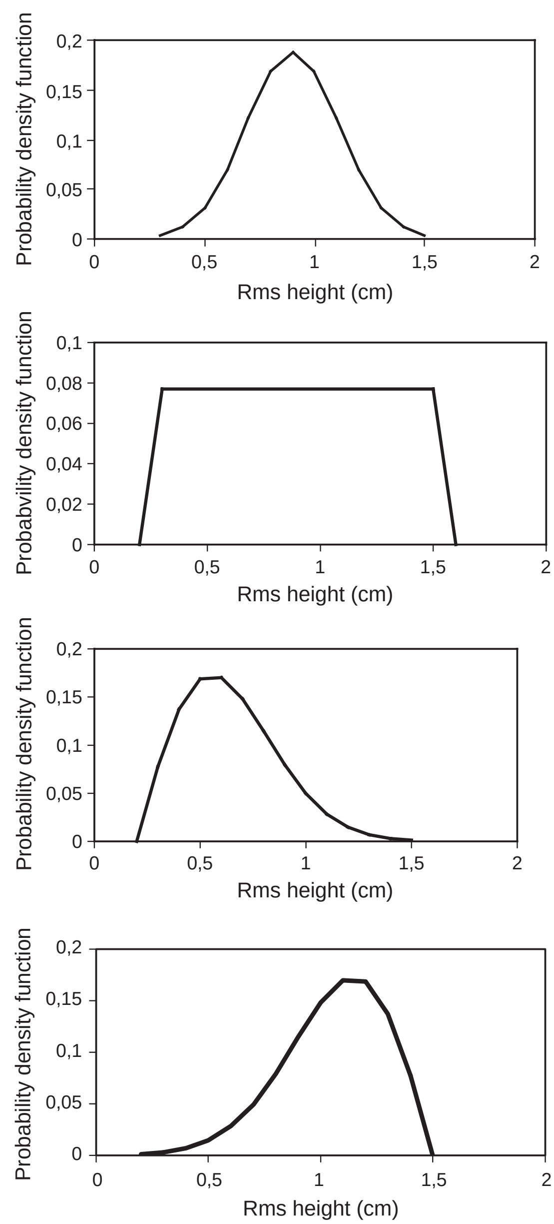

Fig. 6. Illustration of four roughness distributions.

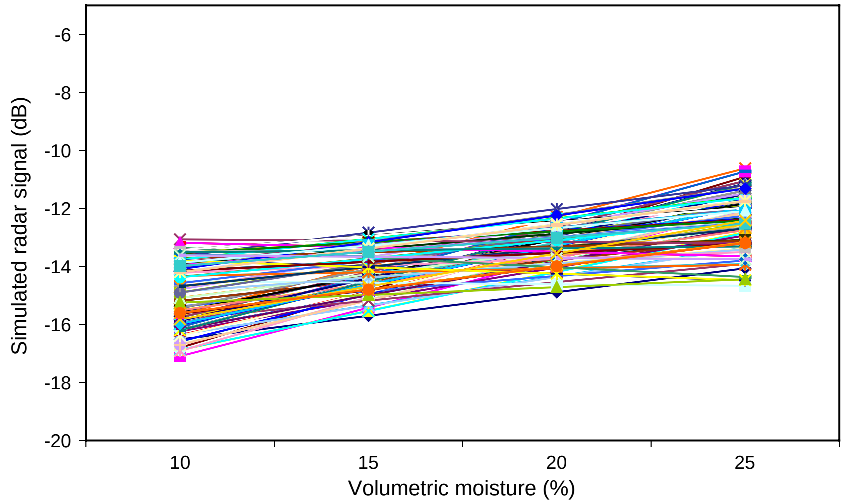

Fig. 7. Illustration of the effects of roughness variations on the linear relationship between surface moisture and radar signal.

in Section 2.2.1, the restriction of surface moisture up to 25% is taken in order to avoid other effects due to moisture saturation. The three considered texture types are detailed in Table 2. The Hallikainen empirical model (Hallikanen et al., 1985) is used to compute the relationship between surface moisture, soil texture and dielectric constant. Results in Fig. 8 show a very limited variation of coefficients a, b. The variation observed for coefficient a is less than 0.01. Therefore, as a first approximation, the soil texture effect can be considered to be negligible for soil moisture ranged between 10% and 25%. This effect is certainly more important for higher moistures because of the differences in the saturation moisture values.

2.2.3. A methodology for reducing the effect of roughness on the a, b coefficients

As underlined in Section 2.2.1, the roughness distribution has a strong effect on coefficients a and b. Here, we propose a new two-stage approach to reduce this roughness effect:

1) The radar signal distribution due to roughness spatial variation is computed using the approach described in Section 2.1.3.
2) From the minimum to the maximum radar values in the radar distribution, each 1 dB step (σ_0^i) corresponds to one roughness R_i. The percentage of each roughness R_i in the studied site is deduced directly from the radar distribution.

For the reference angle θ_n (=40°), we can only derive the effect of moisture by removing the roughness contribution from radar signal measurements in the studied site, as follows:

$$10\log(f(W_s, 40°)) = \sigma_0^i/\mathrm{dB} - 10\log(g(R_i, 40°)). \tag{6}$$

With the hypothesis taken in Section 2.1.4 concerning the roughness range in the agricultural sites studied, the central radar value in the radar distribution corresponds approximately to 0.85 cm in rms height. Then, g is suppressed for all (σ_0^i) values in the radar distribution to leave only the influence of moisture: knowing that the radar distribution is due only to roughness variation, for each roughness i, g corresponds to the g signal computed for s=0.85 cm ± the variation observed in the radar distribution. This could be written in logarithmic form as:

$$g(R_i) = g(0.85) + \left(\sigma_0^i - \sigma_c\right). \tag{7}$$

In conclusion, based on this approach, we consider a reduced effect of roughness on moisture monitoring. We note that if the roughness is really stable between observation dates (without changes in roughness distribution), we must retrieve the same slope as with the conventional approach based on a direct relationship between the mean radar signal over bare soils and mean soil moisture.

Table 2
Characteristics of three soil texture types

	Texture 1 (%)	Texture 2 (%)	Texture 3 (%)
Sand	43	92	10
Loam	34	5	50
Clay	23	3	40

3. Application and results

3.1. Studied area and data base

3.1.1. The studied area

In this study, data acquired during eight experimental campaigns at the Villamblain site in the Beauce region were used. The study site is located in the centre of France with a very flat topography. It is about 80 km west of Paris (latitude 48° 10′N and longitude 01° 48′E) with an area of 5 km^2 approximately. This site is characterised by large agricultural fields with homogenous soil composed of about 60% loam, 30% clay and 10% sand (Macaire, 1971). The

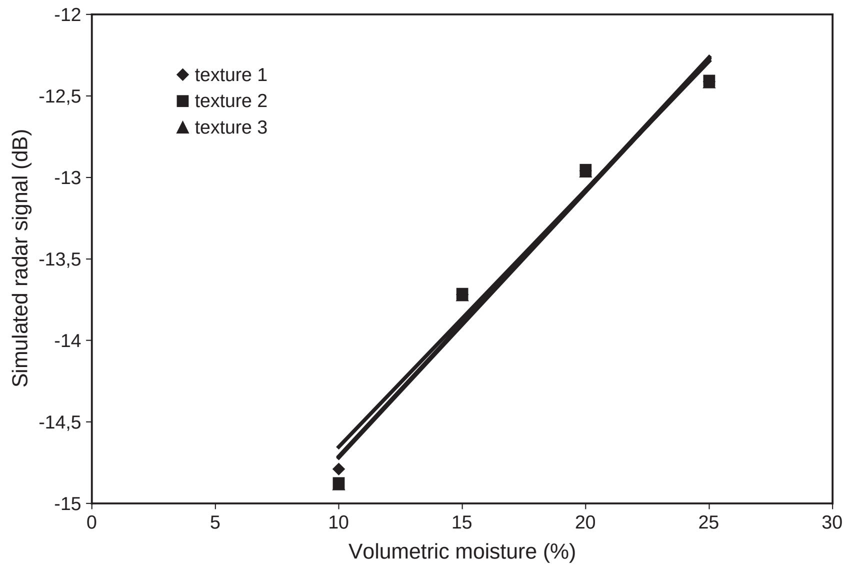

Fig. 8. Illustration of the effects of soil texture on the linear relationship between soil moisture and radar simulated signals.

main crops in the Beauce region are wheat and corn. Therefore, from September to December, many bare soil fields are found before wheat sowing. For the spring period, other bare soils are prepared for corn sowing. Therefore, for all dates, approximately a half of the fields are bare soil. For each date, simultaneously to ENVISAT-ASAR radar measurements, ground truth measurements were acquired for a great number of bare soil test fields. Radar acquisitions have been made with different incidence angles in HH polarisation. Details of satellite images are presented in Table 3. A SPOT image (September 2003) was used to assess the boundaries between fields.

3.1.2. Ground truth measurements

Ground truth measurements were made for eight experimental campaigns at the Villamblain site. Measurements of the soil moisture were made within the top 5 cm using a gravimetric method with more than 10 samples per field. For each date, measurements were made on more than 20 fields. Three bulk density measurements were carried out for each training site using cylindrical samples of 500 cm^3 at a depth of 9 cm. Roughness measurements were made using a pin profiler (a total length of 2 m with a resolution of 1 cm). For each date a large roughness range from smooth to rough surfaces is observed. Table 2 shows mean soil moisture values and variations for each experimental campaign.

3.2. Results

3.2.1. Radar data processing

The proposed approach is applied to Villamblain site for all radar data. The eight ENVISAT-ASAR images are acquired with different incidence angles and different moisture conditions. Absolute calibration of the ASAR images was carried out to transform the radar signal (a digital number) into a backscattering coefficient (σ^0). No corrections for topography were needed since, as mentioned in Section 3.1.1, the region is completely flat.

All images were georeferenced using topographic maps with a root mean square error of the control points of about 20 m. For each one of them, an identification of bare soil fields is made. This identification is based on a ground survey (GPS measurements) and a SPOT optical image. Based on the size and mean radar value of the different fields, a probability density function (distribution) of radar

Table 3
Main characteristics of satellite images used in this study and ground truth data (soil moisture)

Date (dd/mm/yy)	Incidence angle (°)	Sensor/ mode	Polarisation	Pixel spacing (m)	Mean soil moisture "W_s" (%)	Standard deviation of moisture variation vol (%)
09 February 03	37.5	ASAR/IS5	HH	12.5 by 12.5	27.8	1.7
23 September 03	40	ASAR/IS6	HH	12.5 by 12.5	16.3	1.6
26 September 03	34	ASAR/IS4	HH	12.5 by 12.5	6.7	1.3
09 October 03	43	ASAR/IS7	HH	12.5 by 12.5	24.2	3.2
09 November 03	37.5	ASAR/IS5	HH	12.5 by 12.5	26.1	2.9
02 December 03	40	ASAR/IS6	HH	12.5 by 12.5	32.3	4
14 December 03	37.5	ASAR/IS5	HH	12.5 by 12.5	28.6	4
23 April 04	34	ASAR/IS4	HH	12.5 by 12.5	12.5	2.6
04 September 03	–	SPOT4	–	20 by 20		

signal variations is determined for each date. As a first approximation, this distribution originates from surface roughness. Fig. 9 shows the radar signal distributions for the different dates. The eight distributions illustrate clearly differences in roughness from one date to another. They are consistent with roughness data measurements. For example, on 09/02/2003, we observe more large signals and then a majority of fields with a large roughness. On the other hand, 23/04/2004 corresponds to a majority of soils with smooth surfaces.

For each date, the radar signal distribution is confronted to library simulations, as described in Section 2.1.4. All data are then corrected relative to the reference incidence angle 40°. Incidence angles data range from 34° to 43°. It is important to note that normalisation of radar data is more robust for high incidence angle data. In fact, for low incidence angles, large-scale roughness (such as rows) greatly contribute to the radar signal (Zribi et al., 2002) and may induce other effects on the angular behaviour of the radar signal. After normalisation, the roughness distribution effect is eliminated thus only leaving a processed signal dependent on soil moisture.

3.2.2. Relationship between soil moisture and radar signal

Fig. 10 shows the processed radar signals at 40° versus the mean measured surface soil volumetric moisture W_s

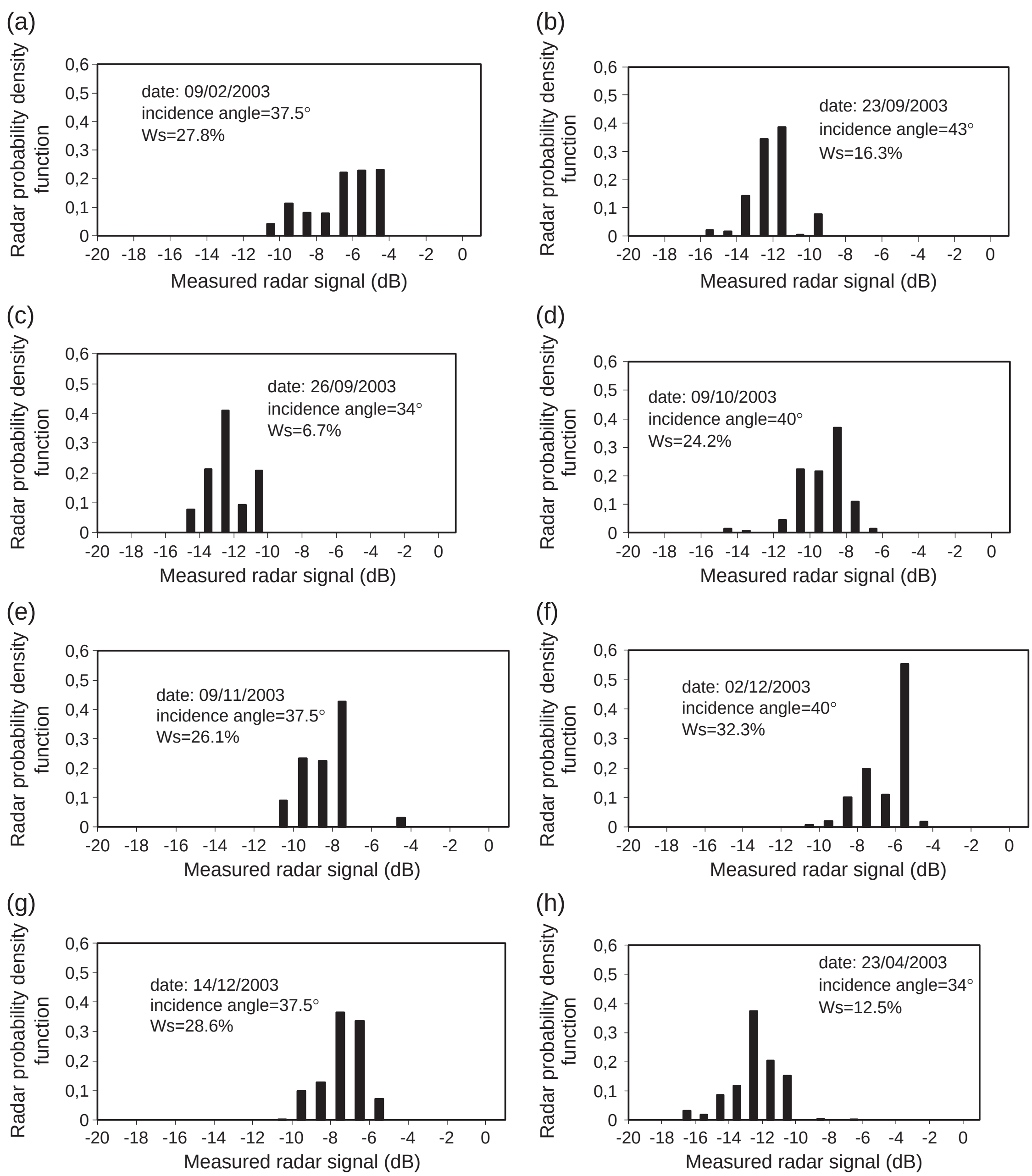

Fig. 9. Radar signal distribution in the study site characterising roughness variations for the eight different ASAR-ENVISAT dates.

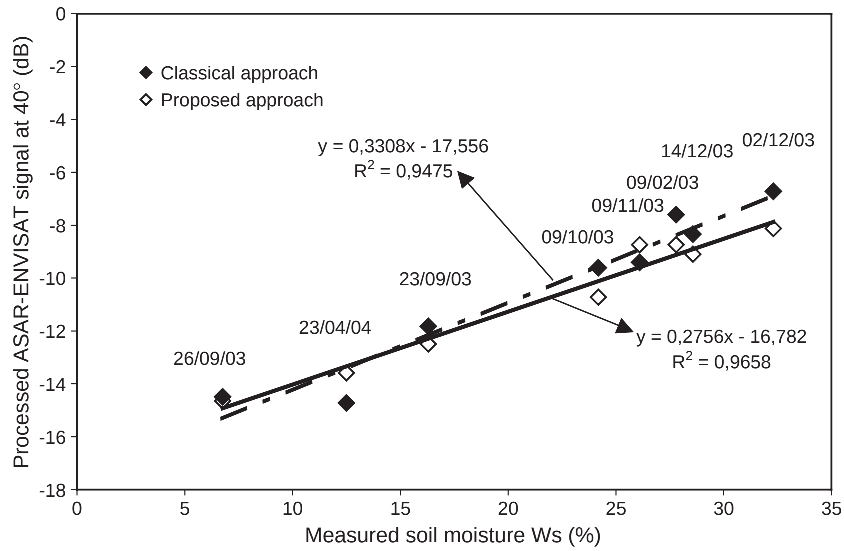

Fig. 10. Processed ASAR signal (in dB) at 40° incidence angle versus measured volumetric soil moisture W_s (in %) for eight different dates with the classical approach and the proposed methodology.

according to two approaches, namely the conventional one and the methodology proposed here, in which the roughness effect is removing as detailed previously. For the conventional approach, a linear relationship is searched between the mean radar signal over bare soils on the studied site and the mean surface moisture. This approach assumes no variation of roughness from date to date. Each point illustrated in Fig. 10 corresponds to a different date.

For the two approaches, a very good correlation coefficient, greater than 0.95, is observed. The radar signal increases clearly with soil moisture. It is difficult from just one studied site to analyse the difference between the two approaches. However, for the studied site, we observe a discrepancy between the slopes of the relationships. This difference is due to the fact that the effect of roughness changes is taken into account only in our methodology. For our approach, the slope is 0.28 whereas in the conventional one, it is 0.33. In the studied application, the 23/04/2004 example shows clearly the difference between the two approaches. This date is characterised by a large majority of fields with smooth surfaces. Therefore, if we consider the mean radar signal without change in roughness between dates, we underestimate the value of moisture because the roughness effect is smaller than those on the other dates. On the other hand, for the proposed approach, with the reduction in the roughness effect based on the radar distribution, the proposed processed signal does not underestimate moisture. A similar remark can be made for the 09/02/03 date with a majority of large roughness in bare soil fields.

As conclusion, although our application was restricted to only one studied site and therefore is not entirely sufficient clearly underline the contribution of our approach to the improvement of moisture estimation, the examples shown illustrate the advantage of eliminating the effect of roughness in moisture estimation.

4. Conclusion

This paper proposes to monitor the surface moisture using multi-incidence angle ENVISAT-ASAR data by an adaptation of the conventional empirical linear relationship approach ($\sigma_0(\mathrm{dB}) = a \cdot W_s(\%) + b$) between radar signal and surface moisture. This conventional approach directly uses the mean value of the radar signal over one studied site (for one incidence angle) to monitor mean surface moisture by assuming no variation of roughness during the studied period.

In this study, a new methodology is proposed to normalise multi-incidence angle radar signals to one angle and to correct for roughness on the a, b coefficients.

A methodology to normalise radar signal acquired with different incidence angles is proposed:

1) A backscattering simulation library is built based on the numerical backscattering model with a large range of roughness conditions and incidence angles.
2) A large sample of bare soil fields is identified in the studied site to characterise the radar signal variation due to surface roughness assuming an approximately constant moisture. A radar signal distribution is defined.
3) Assuming that in the studied sites, smooth and rough surfaces are presented and then that the central value in the radar signal distribution corresponds approximately to a medium roughness (about 0.85 cm), a normalisation of data with different roughnesses over the site is made

using library simulations. A new radar distribution is found at the reference angle used for normalisation.

A discussion of the stability of the linear relationship between surface moisture and radar signal has been made. The effects of scale, roughness and texture have been shown. It is clearly observed from different simulation examples that the temporal roughness variation on the linear relationship coefficients has a strong effect.

Two steps are proposed to reduce the effect of roughness on the processed signal:

1) The distribution of the radar signal due to roughness is defined.
2) We propose an approach based on the separation of roughness and moisture contributions from the distribution of the radar signal distribution. The processed signal must depend only on soil surface moisture.

This approach has been applied to eight radar ENVISAT-ASAR images acquired over a study site with different incidence angles (between 34° and 43°) and moisture conditions. Simultaneously to radar measurements, different experimental ground truth measurements, particularly of moisture and roughness, have been made. Excellent correlation is found between the measured mean soil moisture and the processed signal. A linear relationship is proposed to inverse the radar signal and to retrieve surface moisture. It is important to note that validity of this type of linear model is limited for high surface moistures close to saturation, for which radar signals do not respect this linear relationship behaviour.

The actual efficiency of this approach will be discussed in forthcoming studies based on a large number of experimental sites.

This approach is developed for HH polarisation. However, it can also be applied to vertical (VV) polarisation. In the forthcoming studies, it will be important to validate a more operational mapping of surface moisture for a large region and also to introduce fields with scattered vegetation that can be corrected using a radiative transfer model. In order to obtain a very large repetition rate, it will be possible to use combined ASAR and RADARSAT multi-incidence angle data.

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